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Assessment of the Impact of the Operation of Light Commercial Vehicle (LCV) on their Failure Rate and Transport Safety

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Abstract:

Purpose: *The main aim of the research was to determine the impact of the intensity of use of LCV on their failure rate. The impact of vehicle failures on the costs and safety of freight transport was determined.*
Design/Methodology/Approach: *The research was carried out on a data set that describes the operation of LCV. The most important variables were identified and indicators were developed to assess the vehicle operation process. Statistical analysis of the Kruskal-Wallis test was used for the research, which provided the basis for determining the range of variable values determining the highest probability of vehicle failure. The impact of failure rates on the safety of transport and vehicle operating costs was analyzed and assessed.*
Findings: *Analysis of the data set allowed us to determine the failure rate for the group. For the group of emergency vehicles, the three most important variables that may affect the failure rate of delivery vehicles were identified. This is the age of the vehicle, overload factor and fuel consumption. The failure rate of vehicles was verified for three models: Renault Master, Renault Mascott, Fiat Ducato and Citroen Jumper. The analysis showed failure-free operation of the Renault Mascott model. It was also calculated what type of failure generates the highest costs in the group of emergency vehicles.*
Practical Implications: *The research results presented in the article can be used to plan the operating strategy of delivery vehicles in transport companies. The fleet manager can use the vehicle failure rate, verify the overload factor and determine the probability of failure. The presented results constitute the basis for safe transport and planning of operating costs.*
Originality/Value: *Most available research focuses on the analysis of operating costs and the analysis of basic indicators. The authors do not analyze the impact of vehicle overload on the safety of deliveries. To assess the failure rate of delivery vehicles, the overload factor of delivery vehicles was used and the group of vehicles with the highest probability of failure was identified.*

Keywords: *Light Commercial Vehicle (LCV), transport safety, vehicle operation, failure rate.*

JEL classification: *C10, R42.*

Paper type: *Research article.*

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1. Introduction

The planning and execution of the exploitation process for Light Commercial Vehicle (LCV) in a complex transport system involve solving multi-criteria decision-making problems. Excessive exploitation of vehicles affects their failure rates, driving safety, driver security, and the effectiveness of transport tasks. Research in this area addresses significant issues related to fleet management and the economic consequences of improper vehicle exploitation for businesses.

The literature increasingly discusses the problem of rising failure rates in vehicles operated beyond normative indicators, which leads to increased costs related to repairs and maintenance. This also disrupts the continuity of transport operations and negatively affects the company's image. Studies confirm that excessive vehicle loads result in accelerated wear of key components, such as the drive system, suspension, and braking system, which ultimately shortens vehicle lifespan and increases the risk of unforeseen failures.

The specifics of LCV exploitation continue to raise many controversies, and a range of legal ambiguities persist, which contributes to the limited literature in this area. Each month, new data are released by Poland's General Road Transport Inspectorate on the results of LCV inspections. For several years, the percentage of overloaded vehicles among inspected delivery vehicles has averaged 93% (GITD, 2024).

Modern transport companies provide a wide range of door-to-door services, meaning that vehicles travel on various roads with both asphalt and unpaved surfaces. The conditions under which a vehicle operates and how it is exploited directly influence the pattern of operational loads that change over time. While performing transport tasks, LCV and their structural components are subjected to variable loads that are usually random.

These loads result from various factors, primarily impacting the vehicle's suspension, such as road irregularities, engine vibrations, load distribution and weight, driving maneuvers, and speed. Over time, exploitation leads to a decline in the technical condition and functionality of vehicles, manifested in reduced mechanical efficiency.

A key aspect of fulfilling transport assignments is to ensure that the conditions for vehicle exploitation enable safe and effective performance of operational tasks.

The research presented in this article was conducted on 24 LCV that transported goods over a period of two years. The dataset comprises 13101 observations, based on which a set of indicators describing the vehicle exploitation process was developed. A failure rate coefficient was calculated for all observations. Statistical analysis using the Kruskal-Wallis test provided a basis for identifying variable ranges with the highest probability of vehicle failure.

The subsequent sections of the article include an analysis and evaluation of the impact of failure rates on the safety of transport operations and vehicle operating costs.

Available studies in the field of vehicle exploitation mainly focus on evaluating operating costs and identifying their causes. Results are typically considered relative to mileage, working time, types of roads, vehicle model, and age. This study also includes a new factor—the vehicle overload coefficient.

2. State of Research in the Studied Area

Previous studies on the evaluation of vehicle exploitation processes primarily focus on minimizing Vehicle Operating Costs (VOC) (Ranawaka and Pasindu, 2017). The current practice is to update VOCs in the literature based on price indexes, which do not accurately reflect variations in the main factors influencing operating costs (Cahyono and Wibowo, 2021). Generally, VOC determination is based on adjusting for price increases in components such as fuel, oil, and tires (Kumarage, 2000).

Vehicle exploitation intensity is assessed, among other factors, through the analysis of selected parameters, such as mileage, engine capacity, vehicle age (Caban *et al.*, 2019), repair costs (Tey and Rahizar, 2019), revenues from transport services (Owczarek *et al.,* 2022), technical readiness, and vehicle downtime (Knopik and Migawa, 2018).

Research mainly focuses on analyzing exploitation data, showing correlations between vehicle exploitation intensity and fleet maintenance costs. Results indicate that regularly monitoring parameters, such as mileage and fuel consumption, can significantly aid in forecasting and reducing failure rates. Using models like HDM-4 or HDM-VOC, companies can optimize vehicle utilization processes and avoid excessive loads, positively impacting both financial stability and operational efficiency (Thube, 2013).

In sustainable development, there is an increasing search for methods to evaluate vehicle exploitation in urban environments (Linneusson *et al.*, 2018). Using the Pacific Consultant International (PCI) method, the impact of road congestion and transport time on vehicle exploitation is analyzed (Yuni *et al.*, 2021). Research is increasingly conducted to evaluate vehicle exploitation in terms of emissions (Zhou *et al.*, 2015) and environmental safety (Mrozik and Merkisz-Guranowska, 2020).

Given the dynamically changing conditions in vehicle exploitation systems, assessing these complex processes using traditional mathematical models may not yield satisfactory results. In such cases, alternative computational methods are proposed, such as models using Markov processes, reliability phase diagrams (Bokrantz *et al.*, 2017), and Monte Carlo simulations (Kowalski *et al.*, 2011).

Numerous publications also explore heavy vehicle studies using the expert-based FMEA (Failure Mode and Effect Analysis) method, aimed at systematically identifying potential defects and minimizing associated risks (Ling *et al.,* 2011).

The exploitation process can be monitored in real time through modern telecommunications techniques that enable continuous data transmission from vehicles to dispatchers. Exploitation process optimization is possible by controlling diagnostic data, which allows the analysis of vehicle structural component status (Siergiejczyk *et al.,* 2018). Research focuses on analyzing the causes of vehicle damage, and, based on the obtained parameters, reliable transport systems are modeled (Andrzejczak *et al.,* 2018; Malec *et al.,* 2021).

One of the main causes of vehicle failures is damage resulting from non-compliance with exploitation rules or the influence of external factors beyond the intended conditions. This leads to premature wear of parts and unplanned vehicle downtime (Rögnvaldsson *et al.,* 2018).

Negative consequences of improper vehicle exploitation can include timing belt fractures and crankshaft damage, which ultimately lead to engine failure (Woźniak *et al.,* 2017) or drive shaft failure (Zha *et al.,* 2019).

The macroscopic results of damaged crankshaft inspections in engines presented in (Caban *et al.,* 2013) do not allow for conclusive identification of failure causes, but it is confirmed that they may result from improper vehicle exploitation.

An assessment of usage conditions on brake system wear in Renault vehicles confirmed that factors like season (time of year) and traffic type (suburban vs. non-urban) influence the wear of discs and brake pads (Świderski *et al.,* 2019). The highest brake system wear was recorded during summer months (May to September) and in urban traffic. It was also demonstrated that uneven braking force distribution increases wear in front brake components – by over 20% for pads and over 40% for discs.

Research evaluating the impact of vehicle usage on the technical condition and reliability of their systems and components usually seeks to identify factors determining exploitation costs and transport safety (Nallusamaya *et al.,* 2015). A reliability description of systems in two brands of heavy vehicles is presented in (Ślęzak *et al.,* 2018). The most failure-prone systems identified were the engine, drivetrain, electrical system, braking, and exhaust systems within the observed time frame.

Reliability verification of LCV includes operational reliability indicators, assessing mileage to first failure, mileage between subsequent failures, and failure intensity. These criteria help determine the brand with the lowest failure rate and the lowest exploitation costs over the monitored period (Dziubak *et al.*, 2021).

A study (Niewczas *et al.*, 2016) presents findings on reliability, costs, and failures of selected functional systems in medium-duty trucks of three brands (Iveco, MAN, Mercedes). Repair costs are highest for wear-prone suspension and wheel systems (18%-25%), engine and gearbox (0.16%-16%), braking (12%-13%), exhaust (0.5%-7%), and electrical systems (0.3%-4%). The average annual number of failures for all brands was: suspension – 3, engine and gearbox – 1, braking system – 2, exhaust – 1, and electrical system – 3.

Research on LCV exploitation processes is still conducted on a small scale. Due to the lack of regulations governing the usage of these vehicles, transport companies are not required to record all operations performed by a vehicle. This is also the reason why these vehicles are often overloaded, which can create dangerous situations for both drivers and other road users.

3. The Impact of LCV Exploitation Intensity on Failure Rates

The specifics of fleet management in transportation focus on safely and effectively completing transport assignments. Companies should monitor exploitation intensity and costs to develop appropriate exploitation strategies based on this data.

The research sample consisted of 24 LCV operated by transport companies providing services within the country. These vehicles were manufactured between 2004 and 2011 by three manufacturers (Renault, Fiat, Citroen), encompassing four models: Renault Master, Renault Mascott, Citroen Jumper, and Fiat Ducato. Initial vehicle mileages at the start of the study ranged from 52,000 km to 396,000 km, and permissible load capacities varied between 720 kg and 1,300 kg. Over two years, each vehicle completed daily transport assignments, forming the basis for the dataset used to assess delivery vehicle exploitation and failure rates. Based on the dataset, variables describing the exploitation process were identified (Table 1).

***Table. 1**. Characteristics of Exploitation Process Variables for LCV*

No.	Variable Name	Symbol	Label/Unit	Description
1	Vehicle Age	W_p	Years	The vehicle's age calculated from the difference between the data analysis year and the year of vehicle production
2	Daily Mileage	P_u	[km]	The number of kilometers traveled during a given transport assignment
3	Driving Time	J_u	[h]	Driving time, excluding stops, breaks, or other work (e.g., loading, unloading)
4	Working Time	C_u	[h]	Total working time, including driving, stops, breaks, and other work (loading/unloading)
5	Fuel Consumption	S_u	[dm^3/100 km]	Fuel consumption in dm^3 per 100 km
6	Overload	W_u	[%]	Numeric percentage indicating the relation

	Coefficient			between $\frac{M_u - \text{Cargo weight}}{L_p - \text{Vehicle capacity}}$
7	Seasonality	Z_u	Format 0; 0,5; 1	Periods identified for food product transport, with specific sale levels per season 0 – The peak season, during which the highest product sales are recorded, falls within the months: 10; 11; 12; 1; 0,5 – The medium season, during which an average level of product sales is recorded, falls within the months: 2; 3; 4; 5; 1 – The low season, during which the lowest product sales are recorded, falls within the months: 6; 7; 8; 9
8	Planned Revenue	P_r	[pln]	Planned revenue based on unit price per km in the transport order and planned daily mileage
9	Transport Order Cost	K_k	[pln]	Total cost of completing the transport order

Source: *Own work.*

During the study period, the vehicles completed:

$$L_z = 13101 \tag{1}$$

L_z – liczba zrealizowanych zleceń przewozowych.

Denotes the total number of completed transport assignments. The number of assignments interrupted due to vehicle failure is:

$$L_a = 17 \tag{2}$$

L_a – represents emergency breakdowns.

From the above data, a failure rate coefficient was calculated for the dataset:

$$E_g = \frac{L_a}{L_z} \cdot 100\% = 0{,}13\% \tag{3}$$

The large discrepancy between completed assignments and those interrupted by breakdowns precludes modeling the relationship between potential determinants and failures. This discrepancy also prevents parametric analysis of variance to identify statistically significant differences between occurrences of failures and their hypothetical parameters. However, to suggest a hypothetical relationship between quantitative vehicle characteristics in the failure and non-failure groups, the non-parametric Kruskal-Wallis test was used.

This test is an alternative to one-way ANOVA, based on observation ranks, applicable when parametric test assumptions are unmet or when the dependent variable is ordinal. The Kruskal-Wallis test does not require normal distribution or homoscedasticity and is resistant to unequal group sizes and outliers. The mean rank in the Kruskal-Wallis test serves as the equivalent of the arithmetic mean in classic variance analysis.

Table 2. *Failure Analysis for all observations*

Variable	Failure Status	N	Average rank
W_p [years]	No failure	13084	6555,56
	Failure	17	3039,76
	Total	13101	
P_u [km]	No failure	13084	6549,8
	Failure	17	7477,15
	Total	13101	
J_u [h]	No failure	13084	6549,96
	Failure	17	7349,15
	Total	13101	
C_u [h]	No failure	13084	6550,34
	Failure	17	7057,82
	Total	13101	
W_u [%]	No failure	13084	6545,85
	Failure	17	10511,79
	Total	13101	
S_u [dm^3/100km]	No failure	13084	6546,66
	Failure	17	9888,41
	Total	13101	
P_r [pln]	No failure	13084	6548,67
	Failure	17	8341,32
	Total	13101	
K_k [pln]	No failure	13084	6548,87
	Failure	17	8192,91
	Total	13101	

Source: *Own work.*

Table 3. *Kruskal-Wallis test analysis*

Variable	H Kruskala-Wallisa	df	Significance
W_p [years]	15,349	1	0
P_u [km]	1,026	1	0,311
J_u [h]	0,762	1	0,383
C_u [h]	0,306	1	0,580
W_u [%]	19,088	1	0
S_u [dm^3/100km]	14,441	1	0
P_r [pln]	3,888	1	0,049
K_k [pln]	3,208	1	0,073

Source: *Own work.*

Analysis results show a statistically significant difference between the mean ranks for the "failure" and "no-failure" groups for variables *Vehicle Age* W_p,

Overload Coefficient W_u and Fuel Consumption S_u. Statistical significance ($p < 0.05$) suggests a large difference between means, potentially impacting vehicle failure probability for the indicated variables.

Table 4. *Descriptive Statistics for Vehicle age W_p, Overload Coefficient W_u, Fuel Consumption S_u in the "Failure" Group*

W_p [years]	Average		11,290
	95% Confidence Interval	Lower bound	11,050
		Upper bound	11,540
	Standard Deviation		0,470
W_u [%]	Average		1,476
	95% Confidence Interval	Lower bound	1,385
		Upper bound	1,566
	Standard Deviation		0,176
S_u [dm^3/100km]	Average		15,710
	95% Confidence Interval	Lower bound	14,980
		Upper bound	16,430
	Standard Deviation		1,404

Source: *Own work.*

Results presented in Table 4 indicate a 95% probability that, compared to averages for non-failure assignments, vehicles at higher risk of failure include:

- Younger vehicles, aged between 11.05 and 11.54 years;
- Overloaded vehicles, with an overload factor between 138% and 156%;
- Vehicles with fuel consumption between 14.98 and 16.63 dm^3/100 km.

An analysis of the *Vehicle Age variable* W_p for the entire sample showed that 12 vehicles, representing 50% of observations, fall within the $14 \leq W_p \leq 15$ age range. The Overload *Coefficient variable* W_u shows that in the study sample, 65.8% of all observations involved overloaded vehicles (i.e., $W_u > 100\%$).

Within the range $138\% \leq W_u \leq 156\%$, there are 698 observations out of 13,101, which constitutes 8.1% of all overloaded vehicles. For the *Fuel Consumption variable* S_u, observations within the $14.98 \leq S_u \leq 16.63$ range make up 31.37% of all observations, with W_u having an average value of 148.5% within this range.

For a detailed analysis of vehicle exploitation and its impact on failure rates, an evaluation of qualitative variables—Vehicle Model and Seasonality—was conducted concerning the variables Fuel Consumption and Overload Coefficient.

Table 5. *Failure Analysis by Fuel Consumption and Vehicle Model*

	Fuel Consumption					**Total**
Vehicle Model	13	14	15	16	17	
Renault Master	1	0	2	1	1	5
Fiat Ducato	0	2	2	0	2	6
Citroen Jumper	0	1	0	0	5	6
Total	**1**	**3**	**4**	**1**	**8**	**17**

Source: *Own work.*

The analysis shown in Table 5 reveals that the Renault Master model had five failures, which occurred at average fuel consumption levels of 13, 15, 16, and 17 dm³/100 km. The Fiat Ducato recorded six failures with an average fuel consumption of 14, 15, and 17 dm³/100 km. The Citroen Jumper also had six failures, five of which occurred at an average fuel consumption of 17 dm³/100 km. The Renault Mascott model was failure-free. The analysis thus confirms that vehicle failures occurred at various fuel consumption levels and not when vehicles had the highest fuel consumption, i.e., 18 dm³/100 km.

Table 6. *Failure Analysis by Vehicle Model and Overload Coefficient*

	Overload Coefficient													Total
Vehicle Model	1,11	1,25	1,33	1,39	1,40	1,46	1,50	1,54	1,55	1,58	1,64	1,77	1,79	
Renault Master	0	1	0	0	1	0	0	0	1	0	2	0	0	5
Fiat Ducato	0	0	1	1	0	0	1	1	0	1	0	1	0	6
Citroen Jumper	1	0	0	3	0	1	0	0	0	0	0	0	1	6
Total	**1**	**1**	**1**	**4**	**1**	**1**	**1**	**1**	**1**	**1**	**2**	**1**	**1**	**17**

Source: *Own work.*

Results in Table 6 confirm that most failures (4) were recorded for the Citroen Jumper model with $W_u = 139\%$. This indicates that failures generally occurred just above the average overload level of 123%, without a direct correlation with the maximum overload level of 274%. Failures thus typically accompany average fuel consumption and overload values within the confidence interval. Further analysis explored the relationship between seasonality and vehicle failure rates in relation to the variables *Overload Coefficient* and *Fuel Consumption*. This analysis was necessary because of the defined seasons by the examined companies, where season "0" (good season) represents the highest product sales and transport assignments.

Table 7. Failure *Analysis by Seasonality* and *Fuel Consumption*

	Fuel Consumption					**Total**
Season	13	14	15	16	17	
peak	0	1	1	1	2	5
medium	1	0	3	0	4	8
low	0	2	0	0	2	4
Total	**1**	**3**	**4**	**1**	**8**	**17**

Source: *Own work.*

Table 8. Failure Analysis by *Seasonality* and *Overload Coefficient*

	Overload Coefficient													**Total**
Season	1,11	1,25	1,33	1,39	1,40	1,46	1,50	1,54	1,55	1,58	1,64	1,77	1,79	
peak	0	0	0	2	0	0	1	0	1	1	0	0	0	5
medium	0	1	1	1	1	0	0	1	0	0	1	1	1	8
low	1	0	0	1	0	1	0	0	0	0	1	0	0	4
Total	**1**	**1**	**1**	**4**	**1**	**1**	**1**	**1**	**1**	**1**	**2**	**1**	**1**	**17**

Source: *Own work.*

The analysis in Table 7 indicates that vehicle failures occurred in each season. In season "0" (peak season), 5 failures were recorded; in season "0.5" (medium), 8 failures; and in season "1" (low), 4 failures. No correlation was found between vehicle failure rates and seasonality, though more failures occurred during the moderate season.

The analysis of failure rates in relation to seasonality and overload coefficient confirms that $W_u = 139\%$ resulted in 2 failures in the good season. Failures generally occur within typical observations, within the confidence intervals for variables such as *Vehicle Age* W_p , *Overload Coefficient* W_u, and *Fuel Consumption* S_u

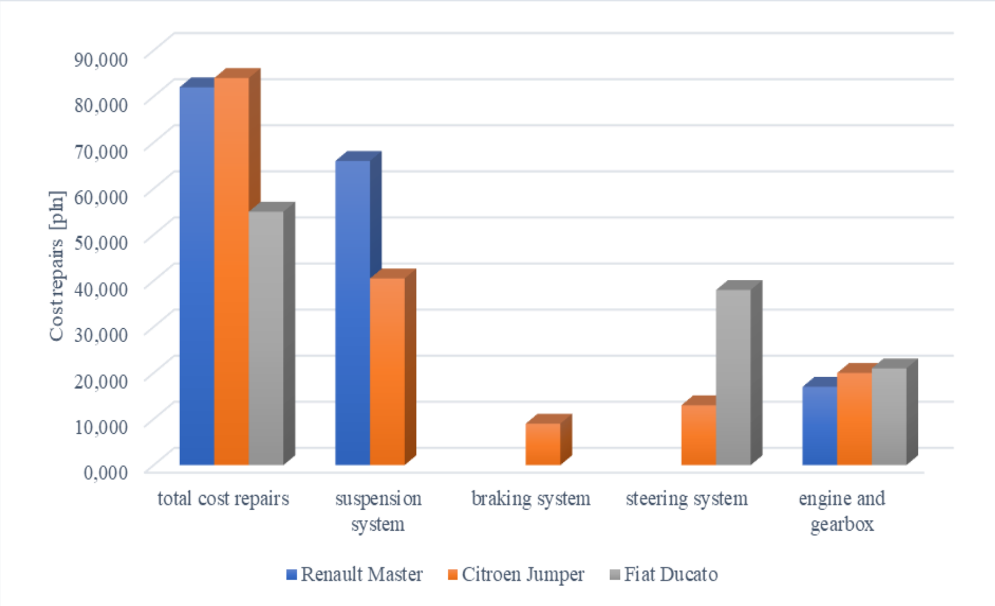
4. Assessment of the Impact of Vehicle Exploitation on Costs and Transport Safety

The lack of ongoing monitoring of vehicle exploitation and the cause-effect relationships of performed tasks can lead to disruptions in transport continuity due to unforeseen failures. Such situations may increase the risk of technical failures, leading to dangerous road conditions and interruptions in the logistics chain.
Vehicle exploitation intensity has a direct impact on transport safety, influenced by several key factors:

Accelerated Component Wear*:* Intense vehicle exploitation causes faster wear on key mechanical components, such as brakes, suspension, and the drive system.
Reduced Effectiveness of Preventive Maintenance*:* Vehicle overloads and intense usage may necessitate more frequent inspections and maintenance. Consequently, maintenance schedules should be adjusted to reduce the probability of breakdowns during transport tasks.
Decreased Material Fatigue Resistance*:* Vehicles operated beyond normative indicators reach a fatigue threshold sooner, where material wear leads to failures. This phenomenon can be particularly hazardous when transporting high-value goods or hazardous materials.
Impact on Driver Performance*:* Intense vehicle exploitation may influence drivers' driving styles, leading to stress and reduced attentiveness, which can pose a danger on the road.

For the examined group of LCV prone to failures, encompassing three brands (Renault Master, Citroen Jumper, and Fiat Ducato), a cost analysis of repairs for individual functional systems was conducted (Figure 1).

Figure 1. *Repair costs for selected functional systems in examined vehicle brands*



Source: *Own work.*

The brand generating the highest repair costs was the Citroen Jumper, which recorded six failures during the study period, including issues in the suspension system (2), braking system (1), steering system (1), and engine and gearbox (2). Repair costs for the suspension system accounted for 50% of total repair costs.

The second brand with high repair costs was Renault Master, which recorded five failures: suspension system (damaged springs, shock absorbers, cracked frame) – 3; engine and gearbox – 2. Suspension repairs represented 81% of the total repair costs.

The brand with the lowest repair costs was Fiat Ducato, where six failures primarily affected the steering system (4), generating 63% of total repair costs. Theory and practice show that for the studied vehicle group, the most costly failures occur in the suspension system, potentially due to improper exploitation. Figure 2 shows a failure of the Renault Master vehicle due to a cracked frame.

Among the three studied, failure-prone vehicle brands, the Fiat Ducato was the least costly in terms of failure-related expenses. Table 9 suggests that certain technical and operational characteristics may influence the probability of suspension system failures.

Figure 2. *Cracked Frame in Renault Master Vehicle*

Source: *Own work.*

Table 9. *Analysis of selected technical-operational characteristics for failure-prone vehicles by brand*

	Renault Master	Citroen Jumper	Fiat Ducato
Average Daily Mileage [km]	452	477	392
Average Working Time [h]	10	11	8,38
Average Overload Coefficient [%]	149	152	142
Average Vehicle Age [years]	12,5	11,5	8,5

Source: *Own work.*

For Fiat Ducato, compared to the other two brands, lower average daily mileage, shorter working hours, and younger vehicle age were observed. These characteristics may influence the occurrence of suspension system failures, thereby impacting exploitation costs and transport safety.

It is confirmed that vehicle failures not only generate unplanned repair costs but also pose significant risks to road users. Given that the goal of a transport company is profit from service sales, it should also verify vehicle reliability by identifying operational damages and their possible causes.

This analysis, both theoretical and practical, confirms that exceeding permissible standards, such as the allowable vehicle load, accelerates component wear and causes failures, generating unplanned costs and potentially leading to breakdowns. Unplanned vehicle downtime disrupts the transport process, negatively impacting the company's financial stability.

Maintaining safe transport operations thus requires ongoing monitoring of exploitation parameters. In delivery vehicle exploitation, overload is particularly critical, so ensuring compliance with allowable load limits is a primary priority.

5. Conclusions

The conducted research on assessing the impact of delivery vehicle exploitation on their failure rates and the safety of transport operations indicates that:

In the studied sample, comprising 13,101 observations, only 0.13% represent failure case – 17 instances where the transport process was interrupted.

Failure rates may be influenced by variables such as *Vehicle Age* W_p, *Overload Coefficient* W_u and *Fuel Consumption* S_u. but only within specific ranges.

In the failure-prone group, vehicles aged 11–12 years constitute 50% of all studied vehicles, with an average daily mileage of 400 km, overload coefficient of 138%, and fuel consumption of 15 dm³/100 km.

- Failures do not result from extreme overloads.
- No relationship was observed between failure rates and seasonality.
- The Renault Mascott model (7 out of 24 vehicles) proved to be failure-free.
- Fuel consumption [dm³/100 km] for the failure-prone vehicle group is within the range (14.98; 16.63), with an average overload coefficient of 148.5%.

The analysis confirms, both in theory and practice, that exceeding permissible limits, such as the allowable load of the vehicle, can lead to accelerated wear of parts and functional systems, ultimately resulting in failures and downtimes, which generate additional costs. The available literature does not address the aspect of overloaded delivery vehicles or attempts to assess its negative impact on the exploitation process within transport companies.

Conducting a reliable assessment of vehicle exploitation requires continuous monitoring of parameters and indicators, forming the foundation for building optimal exploitation strategies aimed at the safe implementation of transport processes.

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