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CIVIL ENGINEERING

Seasonal and predictive analysis of transport fleet availability and reliability using long-term operational data

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Abstract. This study introduces a novel empirical approach to analyzing seasonal variations in the availability and reliability of a transport vehicle fleet. While previous research has examined fleet reliability, few studies have integrated long-term operational data with complementary technical indicators and statistical modeling of seasonality.

Using three key metrics – fleet availability rate (FAR), mean time between failures (MTBF), and mean time to repair (MTTR) – data from 10 distribution vehicles operating over three years (2022–2024) were analyzed to identify recurring seasonal patterns. A linear regression model with seasonal dummy variables was applied to quantify the impact of weather conditions and operational intensity on vehicle availability.

The results reveal a clear seasonal cycle: the lowest availability and highest failure rates occur between February and May, while summer and early autumn show near-optimal performance. The model demonstrated statistically significant differences between quarters and indicated a gradual long-term improvement in FAR.

This study introduces a novel analytical and predictive framework that combines three reliability indicators with long-term operational data and regression-based seasonal modeling. The approach facilitates not only the identification of seasonal effects but also the prediction of fleet availability trends to support data-driven maintenance planning.

These findings support more accurate forecasting of fleet availability and provide actionable guidance for optimizing maintenance schedules, resource allocation, and downtime risk management in transport operations. Overall, the results demonstrate how integrating operational data with seasonal regression models can improve predictive decision-making and optimize transport fleet reliability.

Keywords: fleet availability; reliability modeling; seasonal effects; predictive maintenance; transport logistics; regression analysis.

1. INTRODUCTION

In the dynamic environment of contemporary logistics and distribution, managing fleet availability has become one of the key factors in ensuring operational continuity and maintaining a company's competitive edge. Although fleet reliability has been studied extensively, limited research has addressed how seasonal factors influence key performance indicators using long-term operational data. Most previous studies focused on short-term observations or single metrics, leaving a gap in understanding the full scope of seasonal effects. The globalization of markets, rising customer expectations regarding delivery timeliness, and growing cost pressures mean that any disruption in vehicle availability can result not only in financial losses but also in the erosion of trust among business partners. At the same time, fleet operation inevitably involves technical downtimes, stemming from both scheduled maintenance activities and unforeseen breakdowns.

In this context, tools enabling continuous monitoring of vehicle technical condition and reliability analysis over time play a crucial role. The use of reliability and availability indicators such as FAR, MTBF, and MTTR has been extensively discussed in reliability modeling studies [1–3]. In transport fleet management practice, particular importance is attributed to three key indicators:

- Fleet availability rate (FAR), which reflects the percentage of time that vehicles are operational and available relative to the scheduled operating time.
- Mean time between failures (MTBF), which measures the average operational time between successive failures.
- Mean time to repair (MTTR), which indicates the average duration required to restore a vehicle to service following a failure.

The application of these metrics allows not only for the assessment of the current technical condition of the fleet but also supports the identification of trends, forecasting of downtime risks, and implementation of preventive measures. In the age of digitalization and the advancement of real-time monitoring technologies, these indicators are becoming increasingly vital as a foundation for predictive maintenance strategies [4].

However, the effectiveness of optimization efforts depends on a thorough understanding of the operational conditions un-

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der which the most significant challenges arise. In practice, fleets operating in the Central European region are subject to notable seasonal variability – both in terms of operational intensity and weather conditions. Factors such as low temperatures, road icing, and road salting measures contribute to increased mechanical wear and failure rates [5]. Therefore, research spanning three years and capturing full annual cycles is especially valuable from the perspective of operational fleet management.

This article aims to provide an in-depth analysis of the seasonal availability of a transport fleet using the indicators FAR, MTBF, and MTTR. Based on three years of operational data from 10 vehicles (2022–2024), the study investigates trends in failure rates, repair durations, and vehicle availability, with breakdowns by month and quarter. The analysis is complemented by a regression model incorporating seasonal variables, enabling a statistical assessment of the impact of seasonal changes on fleet availability.

The purpose of the study was not to statistically generalize the results to the entire population of transport enterprises, but rather to identify the mechanisms of seasonal variability in reliability and to verify the applicability of the proposed analytical model based on FAR, MTBF, and MTTR indicators, supported by seasonal regression analysis.

The findings are of an applied nature and may support planners and fleet managers in making more informed operational decisions, such as optimizing maintenance schedules, planning for service buffers, and selectively deploying vehicles with higher reliability during critical periods.

This study contributes to the existing body of knowledge by combining three key reliability indicators – FAR, MTBF, and MTTR – with a three-year dataset of real-world fleet operations. Unlike previous research, which often relied on short-term observations or focused on a single metric, our approach enables a comprehensive assessment of seasonal effects on both vehicle failures and availability. In addition, the study utilizes a regression model with seasonal dummy variables, allowing for the quantification and forecasting of seasonal impacts on fleet performance. These elements collectively provide a practical framework for predictive maintenance planning and operational decision-making, which has not been addressed in earlier studies.

Recent developments in artificial intelligence and data-driven reliability assessment have significantly influenced maintenance management across various industries. Predictive maintenance models based on machine learning and telematics data now enable early identification of failure risks, adaptive scheduling of technical resources, and data-supported decision-making. Integrating these AI-based approaches with long-term operational datasets provides new opportunities for quantifying the seasonal effects that impact fleet reliability. The present study builds on these advancements by applying regression-based seasonal modeling to real-world fleet data, aligning with contemporary international research trends in predictive maintenance.

The remainder of this paper is structured as follows. Section 2 presents a review of the relevant literature on fleet reliability and seasonal effects. Section 3 describes the materials, data sources, and research methods applied in the study. Section 4 reports and analyzes the results, while Section 5 discusses the main findings in the context of practical implications. Finally, Section 6 summarizes the key conclusions, provides recommendations for fleet management, and outlines directions for future research.

2. LITERATURE REVIEW

In recent years, there has been growing interest in research on the reliability and availability of transport fleets, particularly in the context of seasonal variability and its impact on the operational efficiency of logistics systems.

2.1. Reliability and availability indicators

Key indicators commonly used in such analyses – namely fleet availability rate (FAR), mean time between failures (MTBF), and mean time to repair (MTTR) – facilitate a comprehensive assessment of the technical condition of the fleet and support the optimization of maintenance and servicing strategies.

2.2. Reliability: seasonal and environmental influence

The literature frequently highlights the considerable influence of seasonal conditions on the availability and failure rates of transport systems. Particularly adverse operational parameters are typically observed during winter and early spring transition period, when vehicle wear intensifies due to extreme temperatures, moisture, and road salting. These conditions simultaneously place greater pressure on maintenance facilities, leading to longer repair durations and an increased number of downtimes [6].

In contrast, summer and autumn periods are characterized by more stable operating conditions, resulting in improved MTBF and FAR values. It has also been shown that seasonality can be effectively modeled using linear regression incorporating cyclical variables, allowing for accurate prediction of fluctuations in fleet availability.

Similar seasonal reliability issues and maintenance challenges have also been observed in the aviation sector – particularly in ground support equipment and regional aircraft operations. These systems are exposed to environmental stressors such as temperature fluctuations, moisture, and varying surface conditions, which contribute to increased failure rates during specific times of the year. Notably, incidents involving landing gear tend to rise during transitional weather periods, emphasizing the importance of predictive diagnostics and preventive maintenance strategies [7,8]. Incorporating these insights broadens the scope of the analysis and demonstrates its interdisciplinary relevance.

2.3. Predictive and machine-learning approaches

Organizational factors also play a significant role in fleet reliability management. Research demonstrates that strategies such as spare parts buffering, flexible maintenance scheduling, and failure forecasting based on telematics data can significantly reduce downtime and improve fleet availability [9]. Predictive diagnostics and historical data analysis not only reduce reaction times but also lower the frequency of corrective interventions.

Predictive models based on artificial intelligence are also gaining traction, particularly in identifying seasonal failure patterns. Studies using neural networks and machine learning algorithms demonstrate high effectiveness in predicting service downtimes and optimizing maintenance cycles. Especially promising in this regard are models that integrate meteorological, operational, and technical data to identify nonlinear relationships between seasonality and failure rates [10, 11].

In summary, the available body of research clearly indicates the necessity of seasonal planning in fleet maintenance strategies. Considering environmental variability, operational rhythms, and predictive data can significantly enhance the performance of transport systems and mitigate losses associated with technical downtime.

3. MATERIALS AND METHODS

3.1. Company profile

The subject of this study is a retail company operating in the beauty segment, specializing in the distribution of cosmetics as well as personal care and hygiene products. The company conducts its operations on a nationwide scale across Poland, supplying a network of 160 brick-and-mortar stores located in major and medium-sized cities across all voivodeships. The retail network is supported by a central distribution warehouse and regional cross-docking hubs, enabling the execution of daily, scheduled, and campaign-based deliveries.

The company's transport fleet comprises 10 delivery vehicles with payload capacities ranging from 2.5 to 5 tonnes, all of which are used daily. At the beginning of the study period, these vehicles had been in operation for between 2 and 4 years, with an average mileage of approximately 80 000–120 000 km. All vehicles were serviced in accordance with the manufacturer's maintenance schedule. Throughout the three-year observation period, no new vehicles were added to or withdrawn from the fleet, which ensured the consistency and comparability of the dataset. Each vehicle operates between 2 and 4 routes per day, servicing eight to twelve retail locations. The nature of the distribution model requires a high degree of operational flexibility and consistently high technical availability of transport assets – particularly during peak trading seasons.

Two distinct periods of intensified logistical activity are observed in the annual delivery cycle. The first occurs from March to May and is associated with the launch of new product lines and brand campaigns. The second takes place from October to December, driven by increased demand related to holiday promotions and year-end budget spending. In contrast, summer months (July–August) are characterized by markedly reduced operational intensity, due to decreased customer activity, seasonal closures of retail outlets in shopping centers, and a limited number of product launches.

Given the company's broad geographic coverage, varying weather conditions, and high delivery frequency, maintaining a high level of fleet reliability represents a key operational challenge.

This study aimed to identify seasonal patterns in vehicle failure rates and technical availability, which could serve as the basis for formulating operational recommendations applicable to similar organizations.

The study was conducted as a case study, which is a commonly applied research approach in reliability analysis of technical systems when detailed operational data and process-level examination over time are required [12]. The research sample included a fleet of 10 distribution vehicles observed over 36 consecutive months, providing a total of 360 monthly operational records.

In this study, the analysis was performed at the fleet level, which corresponds to the research objective focused on identifying seasonal reliability patterns. The input data analysis showed that the number of failures was relatively evenly distributed among all vehicles (6–12 failures per vehicle over 36 months), indicating the absence of dominant cases or outliers. Therefore, the use of aggregated indicators (FAR, MTBF, MTTR) at the fleet level was justified, enabling the identification of periodic cycles of reliability and availability. A detailed breakdown of reliability at the individual vehicle level will be addressed in further research.

Although the analysis covers a single organization, the structure of the analyzed fleet reflects the characteristics of the Polish transport market, where most transport and logistics enterprises are small and medium-sized companies operating fleets of up to 20 vehicles [13, 14]. The authors emphasize that the aim of the study was not to statistically generalize the results to the entire population of transport companies but to identify the mechanisms of seasonal variability in reliability and to verify the applicability of the proposed analytical model based on FAR, MTBF, and MTTR indicators and seasonal regression analysis.

3.2. Scope of data and indicator definitions

The research process consisted of several clearly defined stages, combining data collection, statistical analysis, and forecasting. The sequence of steps is shown in Fig. 1.

Figure 1 presents the workflow of the research process, showing the main stages of analysis from data collection to interpretation and recommendations. Each step indicates the methods applied and how the results from one stage were used in the next.

All repair activities within the analyzed fleet were conducted internally by the company's in-house maintenance team, equipped with a dedicated workshop and the necessary technical resources. The MTTR values presented in this study, therefore, reflect the actual efficiency of the internal service process, without outsourcing to external providers. The repair time records include both minor technical interventions (e.g., replacement of consumable parts) and more complex mechanical repairs.

The analysis was conducted based on operational and maintenance data from a fleet of 10 distribution vehicles operated by a logistics company over the period from January 2022 to December 2024. The data were compiled every month for each vehicle, resulting in a total of 360 observations (10 vehicles across 36 months). For each case, the following parameters were recorded:

- Scheduled operational time for the vehicle in the given month (H_{total}, expressed in hours)
- Number of failures occurring within the month (N)

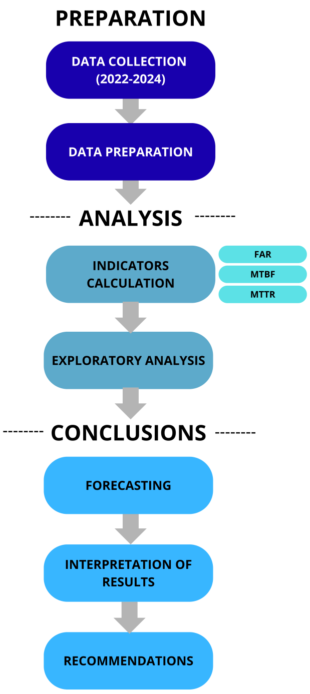

Fig. 1. Research process presented as a diagram

- Total repair time during the month (H_{repair}, expressed in hours)

Based on these values, three reliability indicators were calculated using the following formulas:

Fleet availability rate (FAR) expressed as a percentage:

$$\text{FAR} = \frac{H_{\text{total}} - H_{\text{repair}}}{H_{\text{total}}} \cdot 100\%, \tag{1}$$

where

H_{total} – the number of hours scheduled for vehicle operation in the given period,

H_{repair} – the total number of hours of downtime due to technical repairs in the same period.

Mean time between failures (MTBF) – average time between failures, expressed in hours:

$$\text{MTBF} = \begin{cases} \dfrac{H_{\text{total}}}{N}, & \text{if } N > 0, \\ \text{no data}, & \text{if } N = 0, \end{cases} \tag{2}$$

where N – the number of recorded failures for the vehicle in the analyzed period.

Mean time to repair (MTTR) – average repair duration, also expressed in hours:

$$\text{MTTR} = \begin{cases} \dfrac{H_{\text{repair}}}{N}, & \text{if } N > 0, \\ \text{no data}, & \text{if } N = 0. \end{cases} \tag{3}$$

In cases where no failures were recorded for a given month ($N = 0$), the values of MTBF and MTTR were marked as no data and excluded from the calculation of quarterly averages. All values were calculated to one decimal place. The correctness of the formulas was verified across the entire dataset.

To analyze the impact of seasonality on the variability of fleet availability, a linear regression model was applied using binary explanatory variables (so-called dummy variables) representing individual quarters of the calendar year. This approach aimed to quantitatively capture the differences between seasons while maintaining interpretative clarity of the results and ensuring the model suitability given the limited number of time-series observations. The model was structured as follows:

$$\text{FAR}_t = \beta_0 + \beta_1 Q_2 + \beta_2 Q_3 + \beta_3 Q_4 + \beta_4 t + \varepsilon_t\,. \tag{4}$$

Q_2, Q_3, Q_4 are the binary variables representing the individual calendar quarters (with Q_1 serving as the reference category), t denotes the time trend variable, and ε_t is the error term. This model enabled the estimation of both seasonal differences and the overall trend in fleet availability over the analyzed period. The choice of a linear regression model over more complex time series models (e.g., ARIMA, Holt-Winters) was driven by practical considerations: the limited number of quarterly observations and the need to maintain a clear interpretation of results in a managerial context. Furthermore, seasonality was analyzed at the level of quarterly aggregates, which allowed for the identification of significant operational changes without the risk of overfitting the model to short-term fluctuations.

4. RESULTS

The analysis of operational data from the period 2022–2024 led to the identification of seasonal fluctuations in the reliability and availability of a fleet of 10 vehicles used for daily distribution across a network of 160 retail outlets. Variations in the values of the FAR, MTBF, and MTTR indicators – as well as overall operational availability – were examined on both a monthly and quarterly basis, with particular attention given to key operational seasons (March–May and October–December). The following section presents a detailed analysis of the results for each of the defined indicators.

4.1. Analysis of the FAR indicator and the number of failures

Seasonal peak in failures during February–May

In the first stage, an analysis was conducted of the results for the fleet availability rate (FAR), calculated using (1) as presented in the preceding section of the article.

The analysis of monthly fleet availability rate (FAR) values, presented in Fig. 2, reveals a clear operational seasonality that directly affects the company's ability to conduct transport tasks continuously and efficiently. The chart illustrates seasonal fluctuations in fleet availability, showing the lowest FAR between February and May and near-optimal performance in late summer and early autumn. The blue line represents the overall upward trend over the three years. The lowest FAR values, ranging between 92–94%, consistently occur from February to May, i.e., during the transition from winter to spring. This period also coincides with a significant increase in the number of failures – averaging 2.0–2.6 failures per vehicle per month, and prolonged repair times, reaching 6–8 hours on average. This indicates a strong accumulation of fleet stress factors, including both adverse weather conditions (low temperatures, road salting, variable traction) and increased operational intensity due to the start of the first seasonal retail peak.

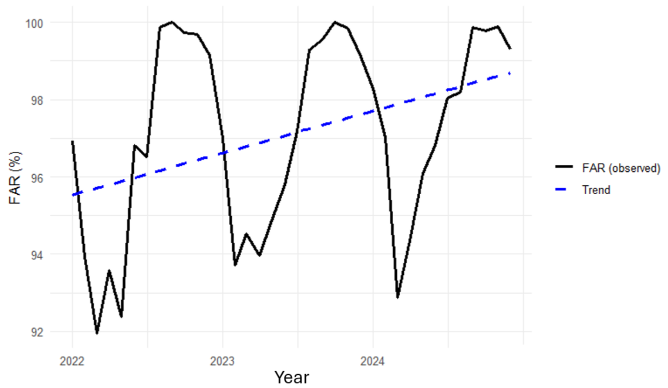

Fig. 2. Monthly fleet availability rate (FAR) values for the period 2022–2024

In contrast, summer and early autumn months, especially August, September, and October, are characterized by near-full fleet availability (FAR at the level of 99–100%), a marginal number of failures (0–0.2 failures per vehicle), and shortened service intervention times (MTTR of 2–4 hours). This seasonal distribution indicates the existence of recurring technical load cycles on the fleet and suggests the potential for applying balancing and predictive measures aimed at minimizing downtime risks in the most critical months.

The blue line in the chart represents the linear trend. It is noteworthy that the trend is upward, which means that, in the long term, the average fleet availability is systematically increasing, even though individual months may show greater or lesser deviations from the general pattern.

To deepen the analysis and enable predictive capabilities, quarterly variations in fleet availability were modeled using linear regression with seasonal "dummy" variables. The model assumes that the variation in FAR depends not only on the linear trend but also on cyclical effects specific to individual quarters of the year. This approach facilitates capturing the regularity of seasonal fluctuations previously identified at the monthly data level.

Regression confirms upward trend in FAR

The linear regression model in (4), describing the fleet availability rate (FAR), was found to be statistically significant, providing an excellent fit to the data ($F(4,7) = 69.090$, p-value < 0.001), with a very high coefficient of determination ($R^2 = 0.975$; adjusted $R^{=}0.961$).

The estimated model parameters are presented in Table 1.

The intercept ($\beta_0 = 94.621$) represents the baseline level of fleet availability in the first quarter, which serves as the reference category in the model.

Table 1

Estimated parameters of the linear regression model for fleet availability rate (FAR)

Variable	Coefficient (β)	Std. Error	t-value	p-value
(Intercept) β_0	94.621	0.320	295.945	< 0.001
Quarter 2 β_1	−0.277	0.361	−0.767	0.468
Quarter 3 β_2	3.373	0.367	9.181	< 0.001
Quarter 4 β_3	4.167	0.378	11.039	< 0.001
t (trend) β_4	0.104	0.039	2.664	0.032

The time trend variable ($\beta_4 = 0.104$; p-value = 0.032) has a positive and statistically significant coefficient, indicating a gradual improvement in fleet availability over time.

The dummy variable for the second quarter ($\beta_1 = -0.277$; p-value = 0.468) is not statistically significant, suggesting that fleet availability in this period does not differ significantly from the first quarter.

The seasonal dummy variables for the third ($\beta_2 = 3.373$; p-value < 0.001) and fourth ($\beta_3 = 4.167$; p-value < 0.001) quarters are positive and statistically significant.

These results indicate that the highest levels of fleet availability are recorded in the third and fourth quarters of the year, confirming the seasonal impact on the FAR indicator.

Figure 3 presents the course of fleet average quarterly availability from 2022 to 2024, as well as forecasted FAR values for the following two years, covering eight future quarters. On the left-hand side of the chart, empirical data are shown, revealing a recurring pattern: a decline in availability in the first quarter, a rebound in the second, peak values in the third, and then stabilization or a slight decrease in the fourth quarter. On the right-hand side, the forecast component of the model is displayed, where the linear path of the average FAR value is surrounded by confidence intervals (95%) – shaded areas presented in Fig. 3. The predicted availability distribution indicates a continuation of the current seasonal dynamics, along with a gradual increase in overall availability levels on an annual scale.

The regression model incorporating quarterly dummy variables achieved a high level of fit (R^2 above 0.9), confirming its

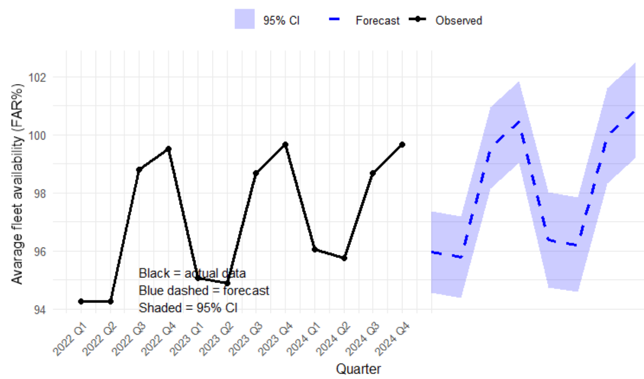

Fig. 3. Historical and forecasted quarterly FAR values with 95% confidence intervals (shaded area)

usefulness in forecasting future fluctuations in fleet availability. The confidence intervals indicate greater forecast uncertainty during transitional periods between quarters, which may result from variations in operational intensity across the individual months within a given quarter. Nevertheless, the results obtained represent a valuable tool for fleet management – supporting the planning of technical resources, maintenance schedules, and vehicle allocation in line with expected changes in operational availability.

Integrating the forecasting model into the company's operational practice enables not only the prediction of potential declines in the FAR indicator but also the timely implementation of preventive measures, in accordance with the recommendations presented in earlier sections of the study. The model can also support service budgeting, route scheduling, and downtime risk management-contributing, on a year-round basis, to increased logistical efficiency across the entire distribution system.

4.2. Analysis of MTTR and MTBF indicator results

Maintenance duration variability indicates changing workload patterns

As part of the study, an analysis was also conducted of the MTTR and MTBF indicator values. In the first stage, the total number of fleet failures was examined and described for each of the months under consideration.

Further analysis was conducted based on a monthly breakdown of the total number of vehicle failures across the fleet, as shown in Fig. 4. The data presented in the chart confirm the cyclical and strongly seasonal nature of technical failure rates. In each of the analyzed years, the peak in failure occurrences was observed during late winter and early spring periods – particularly in February and March – when as many as 20 to 30 service reports were recorded per month. Although the number of incidents gradually declines in April and May, it remains elevated (15–25 failures per month), confirming that the entire first quarter represents a period of heightened operational risk.

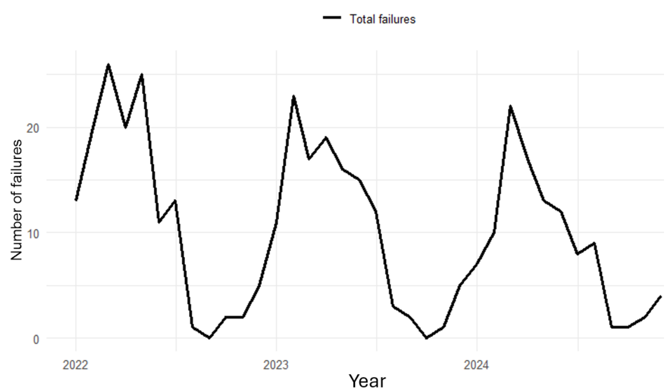

Fig. 4. Total number of fleet failures by month over the three-year study period

In the second half of the year, a consistent decrease in failure rates is observed. During summer months (June–July), the number of failures generally ranges from 10 to 15, while in August and September, it reaches minimum values, often approaching zero (0–2 failures per month). This phenomenon suggests the presence of a natural "service window" in the operational calendar, during which the risk of technical downtime is marginal. In autumn, there is a moderate increase in service activity, with 5 to 10 failures recorded in October and November, while December typically ends the year at a level of 10 to 15 cases, coinciding with the company's second major retail campaign.

The seasonal failure pattern can be explained by the operational conditions and the specific nature of the company's annual activity cycle. Winter months, particularly the transition from winter to spring, are associated with increased strain on mechanical and braking systems due to low temperatures, road salting, moisture, and sharp daily temperature fluctuations. Additionally, the beginning of the calendar year brings a surge in transport activity following the holiday period, which intensifies component wear and increases the likelihood of failures. In contrast, summer conditions are significantly more favorable, and operational intensity decreases, thereby reducing pressure on the technical system and lowering failure rates.

The conclusions from this part of the analysis further reinforce the validity of previously outlined recommendations regarding seasonal management of service resources, planning of preventive actions, and selective vehicle allocation based on historical reliability performance. The identified pattern of cyclical failures also provides a valuable foundation for short-term forecasting and for aligning operational and maintenance schedules with the actual rhythm of fleet utilization.

To analyze the recurrence of annual failure cycles more precisely, the data were aggregated into the form of the average number of failures per calendar month. This allowed for the identification of the most critical periods from the perspective of operational reliability and their interpretation in the context of the company's seasonal logistics activity.

Figure 5 presents the monthly profile of the average number of fleet failures per vehicle, showing a distinct failure peak occurring in February and March. During these months, the average number of failures ranges from 1.8 to 2.6 per vehicle, reaching the highest level in the entire annual cycle. In April and May, a transitional decline is observed, down to 1.5–2.0 failures per vehicle; however, the risk of technical faults remains elevated. In June and July, values drop to approximately 1.0–1.2, and in Au-

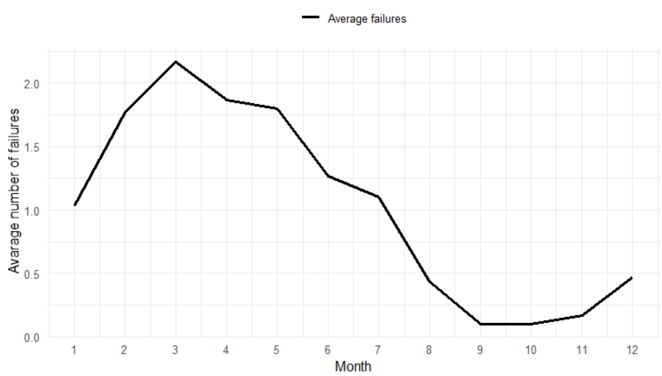

Fig. 5. Average number of failures per vehicle by calendar month

gust and September, they reach a minimum, below 0.2 failures per vehicle, making this period practically fault-free and optimal for conducting maintenance activities or route restructuring. In autumn, a slight rebound occurs, with average failure rates in October and November ranging from 0.1 to 0.4. Winter months of December and January bring a renewed increase to 0.6–1.4, serving as a transitional phase before the February peak.

The seasonal variability in average failure rates aligns with the operational profile of the company, which functions under conditions of highly fluctuating demand. This includes a consistent increase in distribution intensity following the New Year (January–March), and variable weather conditions in the first quarter that increase the technical load on drivetrain and braking systems. The peak in February and March can also be attributed to the cumulative effects of winter operation and the increased number of delivery routes following the holiday break. The averaged data confirm earlier monthly and quarterly observations, and their distinct cyclicality indicates the necessity of adjusting technical and operational activities to specific calendar months rather than relying solely on standard service intervals.

Most repair cases (approximately 70–80%) were completed within a single working day, typically between 5 and 8 hours, while around 15–20% of interventions exceeded this threshold due to higher complexity. This distribution of repair times indicates that the MTTR metric accurately reflects the real operational capabilities of the workshop and provides a reliable basis for assessing the impact of seasonal variability on fleet availability.

To assess the distribution of repair durations, the mean time to repair (MTTR) indicator was analyzed, with the corresponding histogram shown in Fig. 6. The data indicate that repair times ranged from approximately 0.5 hours (short, minor technical interventions) to a maximum of 10.9 hours (the most complex cases). The highest number of observations occurs within the 5- to 8-hour interval, corresponding to the typical duration of technical inspections and standard operational repairs. It is worth noting that most cases are completed in under 8 hours, indicating that most repairs can be conducted within a single working day.

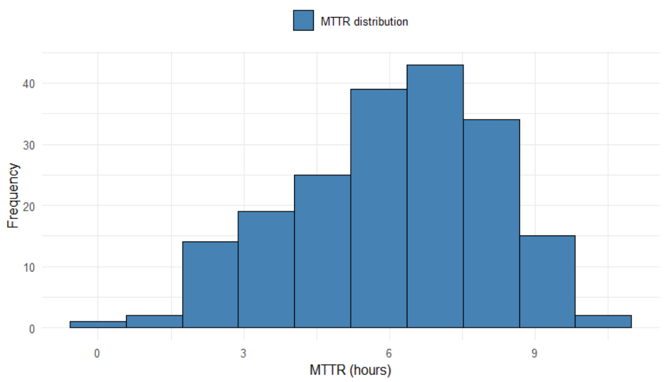

Fig. 6. Histogram of repair duration

An estimated 15–20% of technical interventions exceed 8 hours, highlighting the need to account for such cases in service schedules, particularly during peak failure periods. From an operational planning perspective, effective management of the maintenance team's workload requires the assumption of a time buffer of at least 8 hours per service request. For approximately one-fifth of cases, it is also advisable to consider alternative measures, such as involving a second technician, reserving a service bay for two days, or having the flexibility to reassign transport tasks to other vehicles.

The MTTR distribution confirms that proper workshop organization and realistic planning of technical resources are essential for maintaining high fleet availability. From the standpoint of operational continuity, it is also important to identify early those faults that may lead to time-consuming repairs, further reinforcing the rationale for investing in predictive monitoring systems, as discussed earlier.

Figure 7 presents the monthly distribution of the mean time to repair (MTTR) indicator, calculated based on data from all years covered in the study. The box plot analysis reveals significant variation in repair times depending on the month, indicating the presence of seasonal fluctuations in the efficiency of maintenance interventions. MTTR values in most months revolve around a median of 6–8 hours, although the spread of data and the presence of outliers vary substantially.

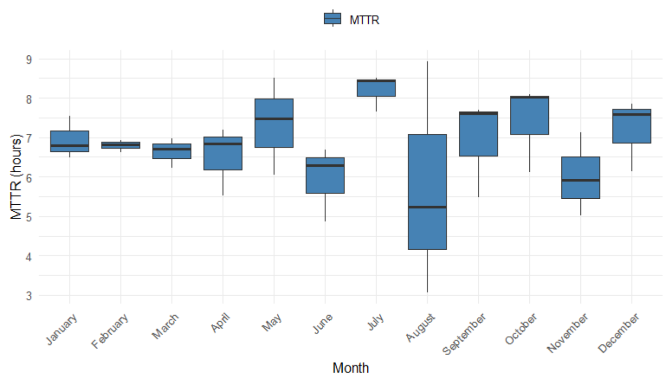

Fig. 7. Monthly distribution of mean time to repair (MTTR)

The longest average repair times were observed in May, August, and October, when the upper quartiles exceeded 8 hours. In August, in particular, an exceptionally wide range of data dispersion is visible, suggesting the occurrence of both noticeably short and unusually long repair events. August and November also show the lowest lower quartile values, reaching as low as 4 hours, which indicates both very efficient technical service in those months and a certain degree of instability in service processes.

Conversely, the shortest MTTR medians were recorded in June and November (approximately 6 hours), which may reflect greater availability of technical resources and reduced operational pressure during these periods. A relatively stable and narrow MTTR spread was observed in the first quarter of the year (January–March), suggesting that despite a high number of failures in this period, repair durations remain relatively predictable. This may result from earlier organizational preparation for winter-related faults or a high level of repeatability in repair types during these months.

The monthly variability in MTTR distribution confirms the need for dynamic management of maintenance capacity throughout the year. In particular, it highlights the necessity of increased flexibility in allocating technical resources during months with greater repair time dispersion and the need for further analysis of the causes of extremely long interventions, which can significantly affect the operational availability of the fleet.

Figure 8 presents the monthly distribution of the mean time between failures (MTBF) indicator, which reflects the average time a vehicle operates without failure between successive faults. The boxplot reveals considerable variation in technical reliability depending on the month, indicating the presence of clear seasonal cycles in the intervals between failures.

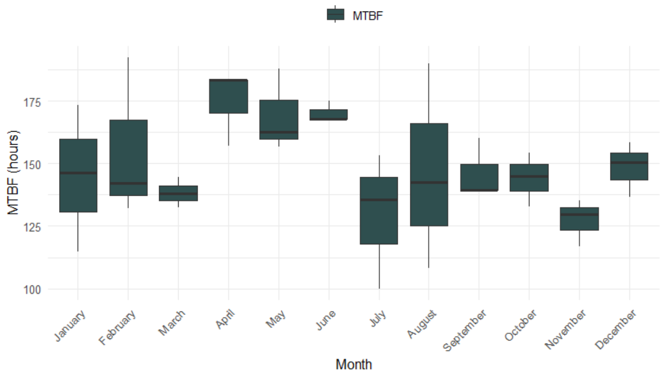

Fig. 8. Monthly distribution of mean time between failures (MTBF)

The lowest MTBF medians, ranging between 130 and 140 hours, are observed in March, November, and July, confirming earlier observations regarding increased failure rates during these periods. These months also show relatively narrow interquartile ranges, suggesting that shorter intervals between failures are both recurring and typical at these times. Conversely, the highest MTBF medians, exceeding 170 hours, were recorded in April, May, and June, indicating significantly longer fault-free operating periods in these months. Exceptionally high MTBF values were also noted in January and August, although August also displayed high data variability, pointing to instability in operational conditions.

In the remaining months, such as September, October, and December, MTBF values remain moderate and relatively stable (median approximately 145–155 hours), with no significant outliers. The data distribution suggests that the greatest reliability predictability can be achieved in spring and early summer months, while the highest risk of failure accumulation occurs during transitional periods between retail seasons, specifically at the turn of winter to spring and autumn to winter.

The monthly variability of MTBF underscores the importance of dynamic fleet task planning. Vehicles with the shortest failure-free intervals should be subject to more intensive technical oversight or assigned to less demanding routes during critical months. Maintaining high MTBF values, particularly during periods of increased logistical demand, remains a key factor in ensuring operational continuity and cost-efficiency across the entire transport system.

5. DISCUSSION OF RESEARCH FINDINGS

The results demonstrate a strong seasonal pattern, with February–May representing the most challenging period for fleet availability and August–September serving as a natural low-risk window. These findings confirm that environmental factors and operational peaks have a direct and recurring impact on reliability indicators.

The disparities between seasons necessitate a flexible approach to technical maintenance management. The data indicate that during peak periods, buffer strategies should be implemented, including increased staffing in service departments, guaranteed availability of spare parts, and the execution of comprehensive technical inspections prior to the February–March failure peak. The adoption of predictive systems and real-time monitoring of the fleet condition (e.g., through telematics data) could further improve the accuracy of risk identification and optimize response times.

Monthly variability in MTTR and MTBF values, not only in terms of medians but also in range and dispersion, suggests that workshop planning should account for more than just average repair durations. Specifically, attention should be given to the proportion of outlier cases. Approximately 15–20% of repairs exceed 8 hours, which requires the scheduled allocation of additional mechanics, technical resources, and potentially backup vehicles.

It is also worth noting that although the second operational peak occurs in autumn (October–December), its impact on failure rates and fleet availability is significantly weaker compared to spring season. This may reflect greater organizational preparedness during that period or more favorable environmental conditions. These differences should be considered when developing long-term vehicle maintenance strategies.

These findings are consistent with previous studies that reported higher vehicle failure rates in winter months due to low temperatures and increased operational stress. Ružinskas *et al.* demonstrated that challenging winter conditions, such as slush and low-temperature road surfaces, negatively affect vehicle performance and safety, leading to increased wear and risk of failures. Similarly, Jack *et al.* highlighted the impact of seasonal factors on operational characteristics of vehicle fleets, showing that variations in temperature and demand patterns significantly influence system performance [5, 6]. However, the magnitude of seasonal variation observed in this study was greater than that reported in these works, likely due to the higher operational intensity in the analyzed fleet. This highlights the need to consider both environmental and workload factors when planning maintenance and distribution strategies.

The primary objective of this study was to evaluate seasonal patterns of fleet reliability and availability at an aggregated level rather than to assess the performance of individual vehicles. Nevertheless, the distribution of failures among the 10 vehicles was relatively balanced (6–12 failures per vehicle over three years, corresponding to 2–4 failures annually), which supports the validity of the aggregated indicators. No vehicle was failure-free, and no single unit dominated the statistics. This confirms that the seasonal patterns identified in the MTBF and MTTR indicators reflect the overall fleet condition rather than being driven by individual outliers. The applied methodological approach (FAR, MTBF, MTTR) can also be directly transferred to the level of individual vehicles, creating opportunities for more detailed diagnostic analyses in future research.

From a practical perspective, the results underline the importance of adapting both maintenance strategies and distribution planning to seasonal patterns. Maintenance resources should be flexibly allocated, and vehicle rotation should be planned to minimize downtime during high-risk periods. These strategic considerations are further developed into specific, actionable recommendations in the Conclusions section.

6. CONCLUSIONS AND RECOMMENDATIONS

The study demonstrated that the operation of the analyzed retail transport fleet was strongly influenced by seasonal cycles, affecting both failure rates and vehicle availability. The period from February to May is the most challenging, as it combines high transport demand, low ambient temperatures, and increased pressure on maintenance facilities. In contrast, July and August are characterized by minimal failures and high FAR values, making them the optimal months for conducting planned technical interventions.

The results provide actionable insights for applying seasonal reliability modeling in transport fleet management. The proposed regression-based approach enables the forecasting of quarterly variations in fleet availability, helping organizations allocate maintenance resources more efficiently, plan service activities in low-risk periods, and mitigate downtime during high-failure months. The model can also be integrated into predictive maintenance systems, supporting data-driven decision-making and long-term reliability improvement in logistics operations.

Based on these findings, the following specific recommendations are proposed to improve fleet management:

- Increase service capacity during February–May by adding maintenance staff, pre-purchasing critical spare parts, and securing backup vehicles to manage peak failure periods.
- Schedule preventive inspections in January and September to detect and address potential issues before seasonal peaks.
- Use telematics and predictive diagnostics for real-time monitoring of vehicle condition and early failure detection [15].
- Allocate the most reliable vehicles (highest FAR and MTBF) to critical routes during high-risk months, while assigning less dependable units to less demanding tasks or preventive maintenance.
- Plan major technical interventions during summer low-failure period to minimize disruption of distribution operations.

Although this study focused on aggregated indicators for the entire fleet to capture seasonal effects, the methodology used can also be adapted to the level of individual vehicles. This would enable detailed diagnostic analysis and support targeted maintenance and servicing strategies.

The study was impacted by some limitations. The analysis was based on a relatively small fleet of 10 vehicles, which limits the generalizability of results to larger fleets. The dataset lacked detailed information on the causes of failures, which restricts the interpretation of seasonal patterns. Behavioral factors such as driving style were not considered, though they may significantly affect vehicle reliability.

In addition, the research was conducted within a single enterprise and therefore reflects the operational and organizational conditions specific to that company. Nevertheless, the extended observation period of 36 months and the resulting 360 operational records strengthen the robustness and representativeness of the findings. Another limitation concerns the adopted level of data aggregation, with the analysis performed at the fleet (system) level rather than for individual vehicles. While this approach aligns with the study's objective of identifying seasonal reliability trends, it does not capture potential variability between units.

Future studies should therefore expand the scope of analysis to include multiple transport companies and fleets of varying size, structure, and operational intensity. It is also planned to incorporate vehicle-level statistical analyses, including the construction of reliability curves, Weibull modeling, and significance testing of differences between individual units. Such an extension would provide a more granular understanding of reliability behavior and enhance the external validity of the model.

Additionally, given the growing trend of fleet electrification, it is worth noting that the behavior of key indicators such as FAR, MTBF, and MTTR may differ for electric vehicles due to distinct failure profiles, maintenance cycles, and component wear characteristics. Future studies should explore these differences to ensure accurate modeling across diverse vehicle technologies.

Future research should also extend the analysis to larger fleets, incorporate correlations with route types and weather conditions, and develop predictive models using machine learning techniques, such as XGBoost or LSTM neural networks, trained on historical telematics, weather, and operational data. Such models could enable accurate forecasting of FAR and MTBF values under varying seasonal and usage conditions. This would allow not only for the description of seasonal fluctuations but also for their precise prediction and proactive mitigation.

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