Predictive Reliability Analysis of a Transportation Fleet A Case Study from Jordan

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Abstract: - Transport fleets in transportation and distribution networks strive to maintain service quality, operational efficiency, and effectiveness in terms of service reliability, cost and time-vital objectives for these companies. Consequently, a case study covering a five-year operational period was conducted to investigate the reliability, maintainability, and availability of vehicles comprising the fleet of a major Jordanian transport company (JTC1).

Breakdowns (1380) experienced by the company's fleet of 23 operational vehicles were monitored. The methodology focused on analyzing them and collecting data, aiming for improvement through better maintenance management and planning. Data were modeled and analyzed using MINITAB software.

Results showed that the Johnson transformation yielded the lowest Anderson-Darling statistics (0.350 – 0.621), respectively, and high p-values (0.467 and 0.104). Therefore, it was the most suitable distribution for the data. Data analysis was continued, and reliability and maintainability were analyzed. The average availability level was 36%, indicating promising potential for improvement. A correlation was observed between the fleet's reliability pattern and the company's maintenance practices. This study provides practical scientific insights, contributing to the management of maintenance across various systems.

Key-Words: - Fleet Maintenance, Reliability, Time Between Failures, Transportation, Predictive Maintenance, Operational Availability, Maintenance Optimization

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1 Introduction

Reliable transportation systems and the safety of their fleets enable the smooth movement of people and goods, enhance commercial, tourism, and industrial activities, and play a supporting role in community and economic development. Therefore, transportation network maintenance departments are keen to protect these fleets to ensure their safe, reliable, and sustainable operation by working to reduce various malfunctions- mechanical, electrical, operational, and other- and eliminate their causes. These malfunctions disrupt or delay, and sometimes lead to legal liabilities and ethical and societal consequences.

Therefore, there has been a growing demand for implementing various maintenance programs designed, such as proactive, preventive, and corrective maintenance, to extend the life of vehicles, reduce breakdowns, lower operating costs, and improve stakeholder satisfaction. This, in turn, enhances the quality and performance of transportation and disruption operations. It has also become beneficial to identify all relevant variables that affect overall performance, such as vehicle design, manufacturing features, design characteristics, operating conditions, technical and financial constraints, and so on.

This paper presents a proposed framework for evaluating the efficiency and reliability of maintenance activities applied to a case study of a transport fleet at Jordanian Transport Company in Amman, the capital of Jordan, which will be referred to hereafter as JTC1. JTC1 provides passenger transport services and owns a diverse fleet consisting of several vehicles.

1.1 Key Performance Indicators of JTC1's Maintenance Strategy

The company targeted a set of selected key performance indicators that measure the efficiency and effectiveness of implemented maintenance activities and their resulting outcomes. These indicators are intended to be used to identify ways to enhance maintenance efficiency and improve fleet reliability. Providing measurable performance indicators positively contributes to maintenance management decisions, promotes operational improvement, and identifies strengths and weaknesses in maintenance management.

1.1.1 Measuring Reliability and Failures

JTC1 strives to find ways to ensure its fleet operates with high reliability and considers this a top priority. JTC1 is keen to find effective solutions and adopts a mechanism that establishes measurable key performance metrics that clearly reflect the frequency of breakdowns. These metrics include:

1. Mean time between failures (MTBF) represents the average time from the moment of breakdown to the moment of the next one for the same vehicle.
2. Mean time to repair (MTTR) represents the period of time a vehicle undergoes repair.
3. Mean time to failure (MTTF) represents the average period from the moment a vehicle starts operating until its first breakdown occurs.

To evaluate these indicators, it is necessary to track various breakdowns, all related data, and to know the relevant statistics and frequency. This is a necessary and fundamental requirement without which the maintenance department at JTC1 cannot identify, diagnose, understand maintenance activities, and identify the strengths and weaknesses of fleet maintenance.

1.1.2 Spare Parts Management and Scheduling

Anticipating maintenance schedules means having a precise schedule and having the right parts available when needed; see Table 1. Therefore, JTC1 uses the key performance indicators (KPIs) mentioned above to achieve these two purposes. The minimum spare parts inventory indicator enables JTC1 to maintain a sufficient quantity of spare parts at a minimum, without unjustified accumulation, delays, or resulting downtime. This ensures that the necessary maintenance is performed on time as scheduled.

Monitoring KPIs maintains the company's operational efficiency and avoids waste, delays, and poor planning.

1.1.3 Controlling Maintenance and Energy Costs

To prevent fleet maintenance from becoming costly, the JTC1 Maintenance Center pays close attention to operating costs. The company has implemented an improvement program that regulates the reduction of maintenance costs and overall service-related expenses. This includes measures to reduce maintenance costs, rationalize energy consumption, and eliminate or reduce waste to optimize the fleet's use of resources consumed during maintenance operations and fleet operations. Maintenance management's focus does not stop at these aspects; it also extends to managing operations to ensure long-term resource sustainability.

Table 1: JTC1 Preventive Maintenance Schedule by Failure Category.

Failure Category	Inspection Frequency (days)	Common Failures Identified	Recommended Action
Mechanical	Every 10-12	Gearbox failures, water pump degradation	Lubrication, adjustments, targeted part replacements
Electrical	Every 7-10	Wiring faults, Battery depletion,	Diagnostics, fuse checks, Reconfigurations
Fluids and Tires	Every 15	Tire wear, brake fluid depletion	Fluid refill, pressure checks, rotational check
Air Conditioning	Every 20	Gas leakage, Compressor failures,	Fan inspections, Prev. coolant maintenance,
Glass and Body	As needed	Mirror damage, Structural integrity issues,	Door alignment, Frame support, Glass repairs,

"Source: created by the authors"

1.1.4 Encouraging Improvement and Knowledge Sharing

JCT1 believes that maintenance management is not just about repairing equipment and vehicles. Rather, it encompasses multiple aspects, including the application of tools related to continuous improvement of services and products, such as Kaizen, continuous improvement methodologies, lean principles, and agile maintenance management. Therefore, JTC1 is committed to integrating various tools that preserve knowledge and facilitate organizational learning. It also takes preventive measures and procedures for operations based on maintenance records to eliminate the root causes of failures and identify corrective actions for each problem.

1.1.5 Making KPIs Part of the Bigger Picture

JTC1's comprehensive maintenance management system is integrated with maintenance key performance indicators. Real-time data from breakdown logs and maintenance activities enables the identification of recurring failure patterns, which are then used to evaluate performance and inform operational decisions. All of this is easily analyzed using Minitab, a reliable, proven, and user-friendly statistical analysis tool.

Practical solutions are then proposed to prevent and predict maintenance problems, enhancing fleet reliability, efficiency, and long-term operational cost.

1.2 Overview of Previous Studies

Using both conventional methods and advanced analytic practices, this paper investigated multiple methods to improve fleet reliability and maintenance efficiency in the transportation industry. Many papers and academic studies have considered that, including, for example, Bruchon's [1] contribution to improving shared transportation, which examined reducing congestion and its environmental impacts. In another academic research, [2] identified and studied recurring failures in metro vehicle braking and door systems and their impact on metro availability and reliability. In a similar study [3], the weaknesses of early-stage diesel generators and their impact on the reliability and availability of diesel generators were highlighted. The research has increasingly expanded to include the use of machine learning and digital twins to manage and improve maintenance systems [4], [5], [[6]. Other methods have also been used to develop various maintenance systems, some employed data-driven approaches [7], [8]. In others, the Ant Colony optimization methodology was employed [9], while other maintenance systems were developed and analyzed by integrating DEMATEL with ANP [10], and applying reliability-centric maintenance systems [11].

Many of the issues facing maintenance management systems and reliability have been addressed in numerous studies. Other studies focused on maintenance economics and the need to balance maintenance costs with reliability [12], [13]. In another study, the issue of improving spare parts inventory management and its impact on the performance of maintenance systems was addressed [14]. Studies have also expanded and spread to include transportation fleets used in emergency and public safety systems and military fleets. This expansion has revealed various challenges and advantages related to reliability challenges and highlighted the need for efficient prediction models supported by artificial intelligence [5].

A structured overview of previous studies is tabulated in Table 3 (Appendix). These studies are tabulated by title, attained methodology, main findings, and a brief review.

In addition, previous studies provide important insights into maintenance practices and reliability analysis for fleets in regions far from the Middle East zone. It is noted that most studies focus on the tradeoff between quality of maintenance and cost of maintenance, leaving a research gap in the study of vehicle reliability in the transportation sector in Jordan.

1.3 Contribution of the Current Research

This paper presents an assessment of maintenance performance within JTC1 in terms of fleet availability and reliability. The assessment was carried out based on 1,380 recorded repair incidents covering all types of failures that occurred during the operation of the 23 vehicles over five years. Failure patterns are identified; accordingly, the effectiveness of existing maintenance practices is investigated using Minitab software. The investigation implies the determination of the best-fit probability distributions; the best probability is then used for predicting expected failures and the associated reliability indicators, including Availability, Time between Failures (TBF), and Time to Repair (TTR). The investigation also implies how the vehicle brands influence the operational performance. Spare parts availability and technician expertise are other factors that influence the failure rate. By investigating the JCT1 maintenance structure, this paper will contribute to getting a better understanding of transportation reliability and explaining the association between maintenance techniques and fleet performance, providing insights that empower the employment of best maintenance techniques in the field. The outcomes of this paper will also lead to practical maintenance recommendations that enable maintenance techniques to reduce downtime, enhance reliability, and endorse data-driven decision-making in fleet management.

2 Problem Formulation

Like other businesses facing challenges, transportation companies face ongoing and continuous challenges of ensuring the reliability as well as the availability of their vehicle fleets.

Unforeseen breakdowns and repetitive mechanical problems generate communal dissatisfaction, particularly customer dissatisfaction, and disruptive and irregular service. This results in increased operating costs, underutilization of resources, and waste. Old-style maintenance programs frequently fail to correctly predict failures because they focus on preventative and corrective measures. This calls for different maintenance strategies to mitigate these obstacles and improve maintenance proficiency and equipment availability.

Although JTC1 is committed to implementing the established maintenance procedures, it seeks to manage its relatively large fleet innovatively and systematically based on real-world data. This approach aims to improve the efficiency of its fleet maintenance management with higher reliability and availability by reducing recurring breakdowns. Therefore, this study was proposed.

This paper examines JTC1's maintenance records over five years. The paper aims to identify recurring failure patterns, analyse them, and accordingly suggest recommendations for improvements. Minitab software is selected as a statistical tool for modelling and analysing the collected maintenance records. The Minitab analysis significantly determines the suitable probability distributions that best fit the norm of failures recurrence, and to assess main reliability metrics specifically, fleet availability, Time Between Failures (TBF), and Time to Repair (TTR). The expected results will be used to develop an innovative predictive maintenance plan that enhances the operational efficiency of JTC1's transportation fleet, reduces downtimes, and improves operational efficiency of JTC1.

3 Research Methodology

To achieve the objective of this research and to assess the fleet availability and reliability at JTC1, the following methodological phases are followed:

(1) Starting with data collection and maintenance records for the past five years, a comprehensive database was created for the period detailing various breakdowns, repair times, and spare parts consumed.

(2) Integrating data relevant to maintenance management and obtained from other departments, such as accounting and warehousing.

(3) Develop a statistical framework using Minitab to determine the most appropriate probability distributions.

(4) Validate the availability and accuracy of the distributions using analytical tools such as probability plots and the Anderson-Darling test.

(5) Observe the effect of vehicle brands on reliability.

(6) Identify key reliability metrics such as fleet availability, time to repair, and time between failures. Such outcomes help in the creation of a predictive maintenance approach intended to reduce vehicle downtime and increase operational efficiency for the company.

3.1 A Five-Year Analysis

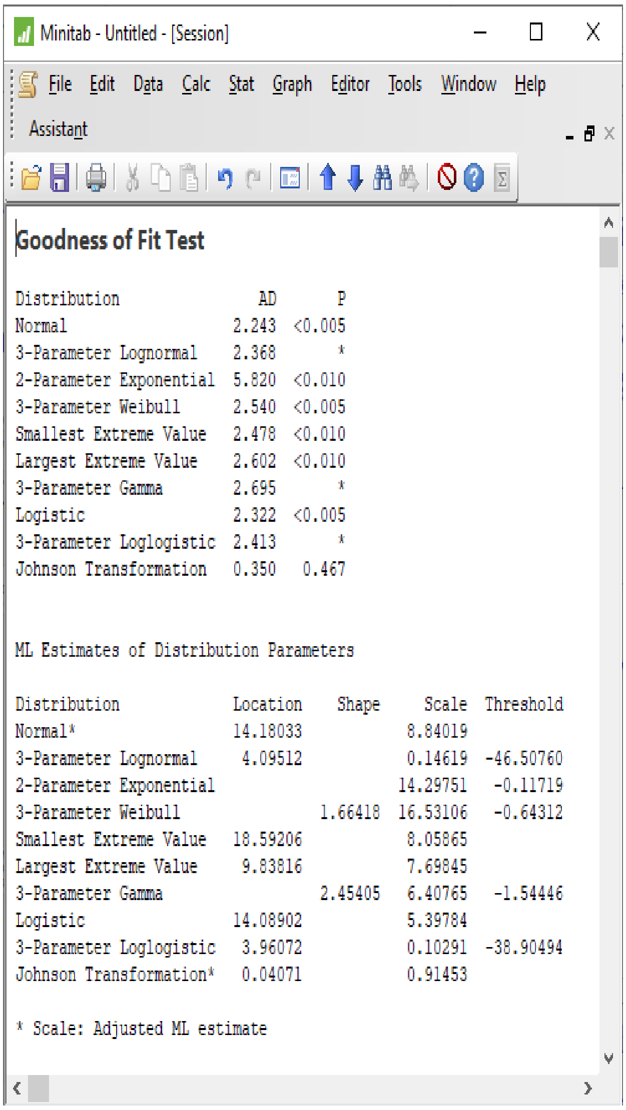
A Dataset of vehicles' failures of the JTC1 fleet over five years, focusing on 23 vehicles, is tabulated in Table 2 (Appendix). The data represents the completely active fleet of JTC1. This means that the current paper is covering the study population as a whole; therefore, there is no need for sampling.

As seen in the fourth column of Table 2 (Appendix), failure causes were categorized into five main sources: administrative, structural, preventive, mechanical, and electrical. For further analysis, Minitab 19 software is utilized. The Dataset is fed to Minitab 19 software, manipulated, and then analyzed. The obtained results provide a valuable perception of maintenance patterns, helping the enhancement of operative proficiency in the transportation sector.

Data was collected from the company's maintenance department, which maintains a maintenance record for each vehicle in paper format. These paper files document all maintenance activities needed to be performed on each vehicle. To achieve the research objectives, the contents of the records were verified, reviewed, and digitized into a format appropriate for this research.

3.2 Fleet Reliability Analysis

The analysis was achieved under the subsequent assumptions: (1) Vehicles are supposed to function only when all systems and components are serviceable. (2) Data symbolize the full working spectrum of the vehicles. (3) Failures may result from mechanical, electrical, or thermal causes. (4) TTR embraces both preventive and corrective maintenance times. (5) Vehicle utilization was evaluated in operating days. The most suitable probability distribution for the data is determined, and key reliability parameters are established. Based on the Goodness of Fit Test results from Minitab, as presented in Figure 1, the best-fitting distribution appears to be the Johnson Transformation because it has the lowest Anderson-Darling (AD) statistic (0.350). It has the highest p-value (0.467), which is greater than 0.05, indicating a good fit. Other distributions have very low p-values (< 0.05), suggesting they do not fit the data well.



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Goodness of Fit Test

Distribution	AD	P
Normal	2.243	<0.005
3-Parameter Lognormal	2.368	*
2-Parameter Exponential	5.820	<0.010
3-Parameter Weibull	2.540	<0.005
Smallest Extreme Value	2.478	<0.010
Largest Extreme Value	2.602	<0.010
3-Parameter Gamma	2.695	*
Logistic	2.322	<0.005
3-Parameter Loglogistic	2.413	*
Johnson Transformation	0.350	0.467

ML Estimates of Distribution Parameters

Distribution	Location	Shape	Scale	Threshold
Normal*	14.18033		8.84019	
3-Parameter Lognormal	4.09512		0.14619	-46.50760
2-Parameter Exponential			14.29751	-0.11719
3-Parameter Weibull		1.66418	16.53106	-0.64312
Smallest Extreme Value	18.59206		8.05865	
Largest Extreme Value	9.83816		7.69845	
3-Parameter Gamma		2.45405	6.40765	-1.54446
Logistic	14.08902		5.39784	
3-Parameter Loglogistic	3.96072		0.10291	-38.90494
Johnson Transformation*	0.04071		0.91453	

* Scale: Adjusted ML estimate

Fig. 1: Goodness-of-Fit Test Results for Vehicle Failure Data Using Minitab. "Source: created by the authors"

A graphical representation of how the Johnson Transformation for the TBF (Days) aligned with observed reliability trends is shown in the Figure 2. Using equation (1) we compute the Johnson PDF.

$$f(X) = \frac{1}{\sqrt{2\pi}} \times \frac{e^{-\frac{1}{2}\left(\lambda+\delta\ln\left(\frac{X-\gamma}{30.3219-X}\right)\right)^2}}{(X-\gamma)(\delta(30.3219-X))} \quad (1)$$

Where:
λ = 0.140953 (location parameter),
δ = 0.537517 (shape parameter),
γ = −0.0886775 (lower bound adjustment),
η = 30.3219 (upper bound).

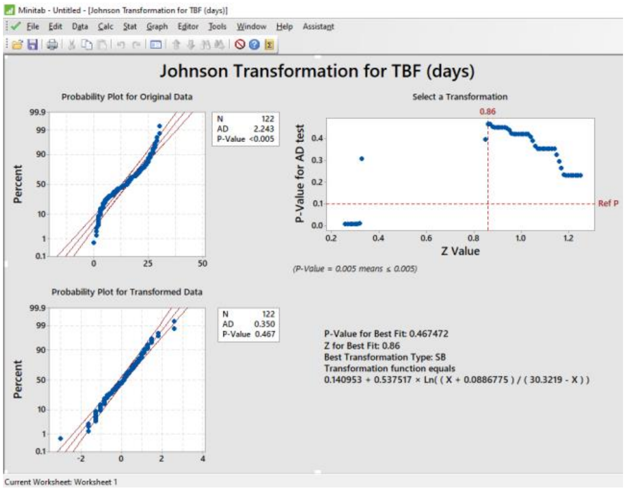


Fig. 2. Johnson Transformation for Time between Failures (TBF) Data. "Source: created by the authors"

Using equation (2), we compute the fitted CDF.

$$F(X) = \Phi\left(0.140953 + 0.537517\ln\left(\frac{X+0.0886775}{30.3219-X}\right)\right) \quad (2)$$

Where:
Φ (z) is the standard normal CDF,
X is the variable (e.g., time between failures).
Accordingly, using equation (3), we compute the **Reliability Function** R (t).

$$R(t) = 1 - \Phi\left(0.140953 + 0.537517\ln\left(\frac{t+0.0886775}{30.3219-t}\right)\right) \quad (3)$$

The **fitted formula for the average reliability** simplifies to the form shown in equation (4).

$$\bar{R} = 1 - \frac{1}{T}\int_0^T \Phi\left(0.140953 + 0.537517\ln\left(\frac{t+0.0886775}{30.3219-t}\right)\right)dt \quad (4)$$

This integral does not have a closed-form solution, but it can be numerically evaluated for a given time *T* (e.g., 30 days, 50 days), the numerical solution for the average reliability over one month (*T* = 30 days) is approximated in equation (5).

$$\bar{R} = 1 - \frac{1}{30}\int_0^{30} \Phi\left(0.140953 + 0.537517\ln\left(\frac{t+0.0886775}{30.3219-t}\right)\right)dt \quad (5)$$
$$= 1 - \frac{13.8613}{30} = 0.538$$

As an example, R (15) gives the probability that the fleet of JTC1 will survive beyond 15 days without failure = 0.4472, which is computed using equation (6)

$$R(15) = 1 - F(15) = 1 - 0.5528 = 0.4472 \tag{6}$$

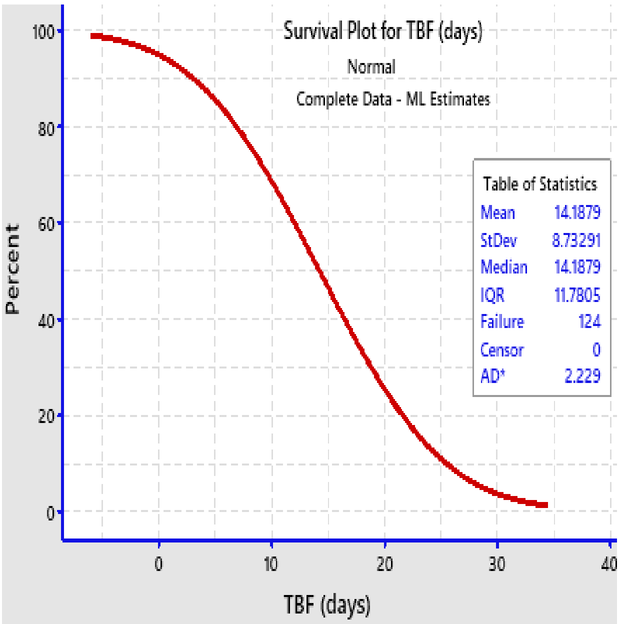


Fig. 3: Survival Function for Time between Failures. "Source: created by the authors"

The failure rate function r (t) represents the likelihood that the unit, which has been operational up to a point in time t, will fail in the next instant. This function describes how the failure rate changes over time, and the r (t) function is given by equation (7).

$$r(t) = \frac{f(t)}{R(t)} = \frac{\frac{d}{dt}F(t)}{R(t)} \tag{7}$$

$$= \frac{\phi\left(0.140953 + 0.537517 \ln\left(\frac{t+0.0886775}{30.3219-t}\right)\right) \times \frac{0.537517}{(t+0.0886775)(30.3219-t)}}{1 - \phi\left(0.140953 + 0.537517 \ln\left(\frac{t+0.0886775}{30.3219-t}\right)\right)}$$

As shown in Figure 3, the survival function for TBF exhibits a gradual decline, indicating decreasing reliability with increasing operating days. The plot of the failure rate function r (t) over time is shown in Figure 4. The shape of the curve provides that the failure rate changes dynamically over time, reflecting the system's increasing likelihood of failure, as shown in the Fig. 4 the failure rate starts low and then increases when TBF approaches to 30 days, this indicates that the system experiences *wear and aging* failures. This pattern is common in mechanical components and electronic devices that degrade due to prolonged use, leading to an increased likelihood of failure as the system approaches the end of its lifespan.

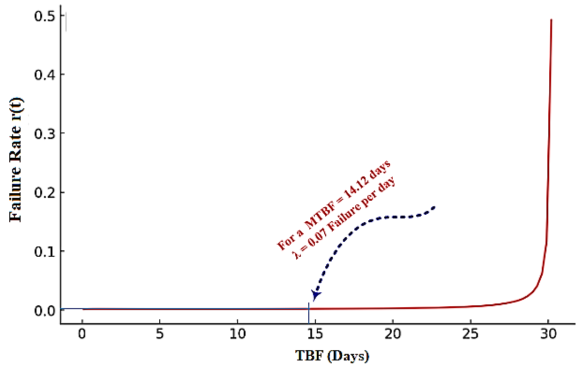
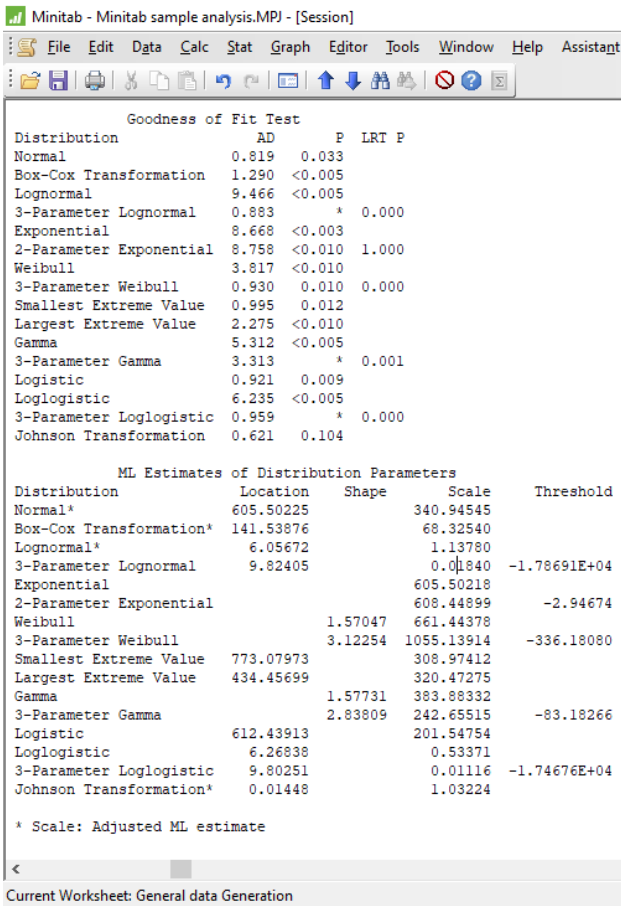


Fig.4: Failure Rate Function for Time between Failures. "Source: created by the authors"

3.3 Fleet Maintainability Analysis

For vehicle repairs, the same methodology was applied, the best-fit probability distribution for Times to Repair (TTR) data, see Table 2 (Appendix), is examined using Minitab 17. Based on the Goodness of Fit Test shown in Figure 5, the Johnson Transformation appears to be the best choice because: Lowest Anderson-Darling (AD) statistic: The AD statistic (0.621) is the lowest among all tested distributions, indicating the best fit to a normal distribution, and the highest p-value (0.104).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Goodness of Fit Test

Distribution	AD	P	LRT P
Normal	0.819	0.033	
Box-Cox Transformation	1.290	<0.005	
Lognormal	9.466	<0.005	
3-Parameter Lognormal	0.883	*	0.000
Exponential	8.668	<0.003	
2-Parameter Exponential	8.758	<0.010	1.000
Weibull	3.817	<0.010	
3-Parameter Weibull	0.930	0.010	0.000
Smallest Extreme Value	0.995	0.012	
Largest Extreme Value	2.275	<0.010	
Gamma	5.312	<0.005	
3-Parameter Gamma	3.313	*	0.001
Logistic	0.921	0.009	
Loglogistic	6.235	<0.005	
3-Parameter Loglogistic	0.959	*	0.000
Johnson Transformation	0.621	0.104	

ML Estimates of Distribution Parameters

Distribution	Location	Shape	Scale	Threshold
Normal*	605.50225		340.94545	
Box-Cox Transformation*	141.53876		68.32540	
Lognormal*	6.05672		1.13780	
3-Parameter Lognormal	9.82405		0.01840	-1.78691E+04
Exponential			605.50218	
2-Parameter Exponential			608.44899	-2.94674
Weibull		1.57047	661.44378	
3-Parameter Weibull		3.12254	1055.13914	-336.18080
Smallest Extreme Value	773.07973		308.97412	
Largest Extreme Value	434.45699		320.47275	
Gamma		1.57731	383.88332	
3-Parameter Gamma		2.83809	242.65515	-83.18266
Logistic	612.43913		201.54754	
Loglogistic	6.26838		0.53371	
3-Parameter Loglogistic	9.80251		0.01116	-1.74676E+04
Johnson Transformation*	0.01448		1.03224	

* Scale: Adjusted ML estimate

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Fig. 5: Goodness of fit test results using Minitab. “Source: created by the authors”

As shown in Figure 6, the Johnson PDF is given by equation (8)

$$f(X)=\frac{1.34377\times e^{-\frac{1}{2}\left[0.0220858+1.34377\times\ln\left(\frac{X+374.385}{1588.14-X}\right)\right]^{2}}}{\sqrt{2\pi}\times(X+374.385)(1588.14-X)} \qquad (8)$$

Where: λ=−374.385, δ=1588.14, γ=0.0232858, η=1.34377

The fitted CDF is given by equation (9)

$$F(X)=\Phi\left(0.0232858+1.34377\times\ln\left(\frac{X+374.385}{1588.14-X}\right)\right) \qquad (9)$$

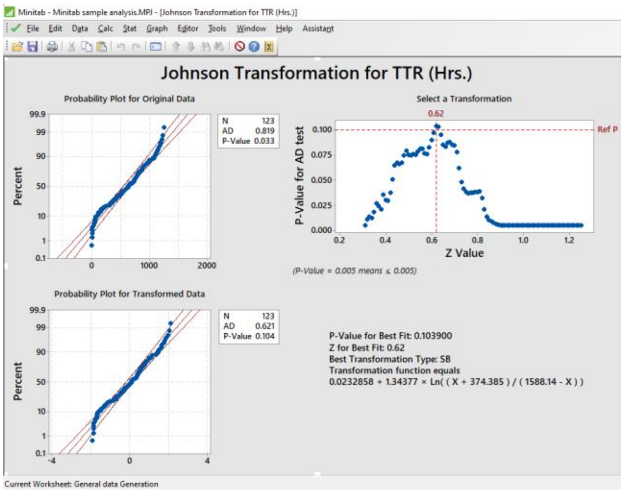

Fig. 6. Johnson Transformation fit times to repair. “Source: created by the authors”

Figure 7, shows the empirical CDF. As an example, the probability that TTR is less than or equal to 100 hours is given by the Cumulative Distribution Function (CDF) as shown by equation (10)

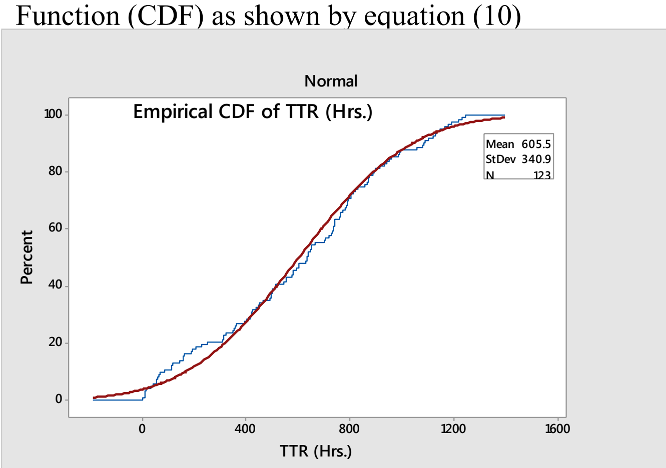

Fig. 7: Empirical probability distribution of repair times. “Source: created by the authors”

$$F(TTR\leq 100)=\Phi\left(0.0232858+1.34377\times\ln\left(\frac{100+374.385}{1588.14-100}\right)\right) \qquad (10)$$

$$=\Phi(-1.513)=6.51\%$$

Accordingly, the probability that TTR is less than or equal to 100 (≤ 100) is 6.51%. The Johnson SB distribution is continuous; the probability of a single exact value is zero. As an example, the probability that the TTR = 100 hours is computed by computing the (PDF) at 100, as shown in equation (11).

$$f(X)=\frac{1.34377\times e^{-\frac{1}{2}\left[0.0232858+1.34377\ln\left(\frac{X+374.385}{1588.14-X}\right)\right]^{2}}}{\sqrt{2\pi}(X+374.385)(1588.14-X)} \qquad (11)$$

$$\approx 2.42\times10^{-7}\ (\text{almost zero})$$

3.4 Analysis of Availability

Availability is described as the vehicle’s operational readiness; that is, it measures a vehicle’s operational readiness by minimizing downtime and extending operational periods. It is calculated using equation (12).

$$\text{Availability}=\frac{(\text{MTBF})}{(\text{MTBF+MTTR})} \qquad (12)$$

$$=\frac{(14.1897)}{(14.1897+605.5/24)}=36\%$$

This means that the overall fleet availability level is 36.%. To improve this level, two main factors influence this and require investigation: (1) Reducing Maintenance time: by performing quick repairs, this increases the vehicle’s readiness level. (2) Extending the interval Between Failures: this improves reliability.

3.5 Interpretation of Statistical Analysis

The statistical analysis results in this study contribute to a clear picture of the ongoing challenges facing the JTC1 fleet. By analysing five years of maintenance records, it became evident that the Johnson transformation provided the most accurate fit for both the time between vehicle failures (TBF) and the time required for repairs (TTR). This was confirmed by favourable

Anderson-Darling test results and high p-values, which suggest the data closely follow the modelled distribution. Reflecting natural wear and tear, results associated with TBF revealed that certain components tend to fail more frequently as the vehicles age.

The variability detected in TTR values indicates that repair times are frequently unpredictable; many issues, such as operator readiness, diagnostic and investigation of interruptions, and the inventory stock levels of related spare parts, influence variation in TTR. The general fleet availability is estimated at only 36%, revealing a considerable gap between operational needs and the performance of the present maintenance. Such outcomes mean that there is a need to improve the companies' maintenance strategy to be more predictive and proactive, which impacts data to predict failures and to decrease downtime.

The outcomes of the statistical analysis conducted in this paper pinpoint challenges and guide practical clarifications. Figures, charts, graphs, plots, etc., illustrated in this paper collectively explain the statistical behavior of failure and repair norms with the Johnson probability density function (PDF). Both the TTR and TBF illustrations show right-skewed tendencies, successfully displayed by the Johnson probability distributions, suggesting that failures and repairs norms associated with shorter times in a smaller number of circumstances bring about the tail. The results indicate that the Johnson cumulative distribution function is consistent with this pattern. The level of variation in the mean, continuing close 36%, reinforces the need for further adaptive and data-driven maintenance configuration steered by reliability indices, and emphasizes substantial structure downtime.

Such outcomes were found in similar research papers that analyse the reliability of transportation systems following the same statistical methodology of analysis. Such studies include [2], [13], [15], which reported analogous right-skewed reliability patterns and emphasized the role of data-driven maintenance in refining fleet uptime. Similarly, other studies [5], [11] examined predictive maintenance and demonstrated its effectiveness in reducing unplanned failures and repair time variability.

4 Conclusion

This paper offers a broad assessment of availability and reliability over JTC1, which is one of the primary transportation facility providers in Jordan. By examining historical maintenance statistics of five years, the paper recognises failure trends and assesses the performance of the company's maintenance practices. A strong statistical fit was observed for the repair time and breakdown data with the Johnson conversion models. The current availability level of 36% indicates the need for improved maintenance scheduling and resource allocation to enable the desired improvement, thus improving the reliability measurement of JTC1 performance. This paper demonstrates how the required reliability improvement relates to fleet efficiency and the impact of implementing a maintenance strategy that reduces unplanned downtime and improves service reliability. Based on the findings, this paper provides actionable recommendations and offers positive implications for investment in the transportation, distribution, and fleet management sectors. This paper demonstrates how reliability-engineering principles can be applied to analyze realistic transportation scenarios and how measured reliability can improve data-driven maintenance decision-making. Findings of this work provide specific practical guidelines, such as spare parts and related supplies inventory levels, designing robust and realistic maintenance schedules, and demonstrating the relationship between purchasing and JTC1 fleet reliability.

Acknowledgement:
It is optional.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Please, indicate the role and the contribution of each author:

Mohammad D. AL-Tahat: Led the conceptual design, oversaw the methodology development, and contributed to data interpretation, modeling, and the writing of core sections. Coordinated and provided technical supervision and guided the statistical analysis. *Yazan M. Y. Al-Zain*: Collected, curated, and pre-processed the maintenance datasets from JTC1. Participated and helped interpret TBF and TTR trends. *Mohammad N. S. Aladaileh*: Assisted in the literature review and background development. Conducted preliminary data exploration and helped refine the visualizations and tables.

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APPENDIX

Table 2. Vehicle failures within the JTC1 Company over five years, focusing on 23 vehicles.

Failure No.	Failure Date	TBF (days)	Failure Type	Vehicle ID	Vehicle Brands	Vehicle Model	TTR (Hrs.)
1	1-Jan-2019	0	Mechanical	Vehicle 2	Man vehicles	2001	816
2	15-Jan-2019	14	Administrative	Vehicle 18	Man vehicles	2005	879
3	12-Feb-2019	28	Body	Vehicle 19	Mercedes Alba	2008	516
4	27-Feb-2019	15	Body	Vehicle 20	Mercedes Alba	2013	720
5	25-Mar-2019	26	Body	Vehicle 3	Mercedes Alba	2013	41
6	28-Mar-2019	3	Electrical	Vehicle 3	Mercedes Alba	2013	934
7	31-Mar-2019	3	Planned Maintenance	Vehicle 6	King Long	2015	1137
8	16-Apr-2019	16	Body	Vehicle 12	King Long	2015	190
9	18-Apr-2019	2	Electrical	Vehicle 4	Man vehicles	2002	900
10	22-Apr-2019	4	Planned Maintenance	Vehicle 23	Man vehicles	2004	831
11	26-Apr-2019	4	Body	Vehicle 3	Mercedes Alba	2013	582
12	13-May-2019	17	Body	Vehicle 20	Mercedes Alba	2013	316
13	15-May-2019	2	Body	Vehicle 15	King Long	2016	55
14	9-Jun-2019	25	Electrical	Vehicle 15	King Long	2016	146
15	6-Jul-2019	27	Administrative	Vehicle 21	Man vehicles	2005	448
16	21-Jul-2019	15	Planned Maintenance	Vehicle 6	King Long	2015	417
17	25-Jul-2019	4	Mechanical	Vehicle 17	Mercedes Alba	2009	652
18	21-Aug-2019	27	Body	Vehicle 21	Man vehicles	2005	497
19	28-Aug-2019	7	Planned Maintenance	Vehicle 17	Mercedes Alba	2009	808
20	30-Aug-2019	2	Planned Maintenance	Vehicle 11	Man vehicles	2004	870
21	10-Sep-2019	11	Body	Vehicle 18	Man vehicles	2005	794
22	26-Sep-2019	16	Planned Maintenance	Vehicle 15	King Long	2016	584
23	10-Oct-2019	14	Administrative	Vehicle 14	King Long	2015	654
24	15-Oct-2019	5	Electrical	Vehicle 15	King Long	2016	1236
25	31-Oct-2019	16	Planned Maintenance	Vehicle 4	Man vehicles	2002	165
26	23-Nov-2019	23	Administrative	Vehicle 19	Mercedes Alba	2008	605
27	15-Dec-2019	22	Electrical	Vehicle 13	King Long	2016	638
28	10-Jan-2020	26	Administrative	Vehicle 10	Mercedes Alba	2010	61
29	4-Feb-2020	25	Planned Maintenance	Vehicle 17	Mercedes Alba	2009	742
30	14-Feb-2020	10	Planned Maintenance	Vehicle 10	Mercedes Alba	2010	733
31	11-Mar-2020	26	Administrative	Vehicle 1	Man vehicles	2000	64
32	13-Mar-2020	2	Body	Vehicle 17	Mercedes Alba	2009	68
33	11-Apr-2020	29	Body	Vehicle 23	Man vehicles	2004	498
34	5-May-2020	24	Mechanical	Vehicle 14	King Long	2015	315
35	27-May-2020	22	Administrative	Vehicle 3	Mercedes Alba	2013	784
36	4-Jun-2020	8	Administrative	Vehicle 15	King Long	2016	891
37	8-Jun-2020	4	Planned Maintenance	Vehicle 3	Mercedes Alba	2013	323
38	12-Jun-2020	4	Planned Maintenance	Vehicle 10	Mercedes Alba	2010	548
39	12-Jul-2020	30	Mechanical	Vehicle 1	Man vehicles	2000	361
40	3-Aug-2020	22	Planned Maintenance	Vehicle 9	Mercedes Alba	2012	557
41	24-Aug-2020	21	Planned Maintenance	Vehicle 10	Mercedes Alba	2010	825
42	30-Aug-2020	6	Electrical	Vehicle 14	King Long	2015	1180
43	4-Sep-2020	5	Administrative	Vehicle 19	Mercedes Alba	2008	799
44	17-Sep-2020	13	Mechanical	Vehicle 5	Mercedes Alba	2012	961
45	7-Oct-2020	20	Body	Vehicle 19	Mercedes Alba	2008	1167
46	15-Oct-2020	8	Electrical	Vehicle 22	Mercedes Alba	2012	1222
47	9-Nov-2020	25	Electrical	Vehicle 1	Man vehicles	2000	1062
48	20-Nov-2020	11	Body	Vehicle 19	Mercedes Alba	2008	1195
49	23-Nov-2020	3	Mechanical	Vehicle 20	Mercedes Alba	2013	467
50	18-Dec-2020	25	Administrative	Vehicle 15	King Long	2016	405
51	15-Jan-2021	28	Electrical	Vehicle 19	Mercedes Alba	2008	792
52	30-Jan-2021	15	Planned Maintenance	Vehicle 23	Man vehicles	2004	745
53	14-Feb-2021	15	Planned Maintenance	Vehicle 20	Mercedes Alba	2013	161
54	27-Feb-2021	13	Body	Vehicle 6	King Long	2015	703
55	10-Mar-2021	11	Mechanical	Vehicle 9	Mercedes Alba	2012	1250
56	27-Mar-2021	17	Planned Maintenance	Vehicle 21	Man vehicles	2005	2
57	11-Apr-2021	15	Electrical	Vehicle 6	King Long	2015	115
58	22-Apr-2021	11	Body	Vehicle 3	Mercedes Alba	2013	1084
59	11-May-2021	19	Body	Vehicle 14	King Long	2015	118
60	4-Jun-2021	24	Electrical	Vehicle 15	King Long	2016	1121

Failure No.	Failure Date	TBF (days)	Failure Type	Vehicle ID	Vehicle Brands	Vehicle Model	TTR (Hrs.)
61	1-Jul-2021	27	Electrical	Vehicle 2	Man vehicles	2001	86
62	4-Jul-2021	3	Body	Vehicle 10	Mercedes Alba	2010	996
63	9-Jul-2021	5	Body	Vehicle 10	Mercedes Alba	2010	729
64	18-Jul-2021	9	Body	Vehicle 18	Man vehicles	2005	114
65	4-Aug-2021	17	Body	Vehicle 3	Mercedes Alba	2013	311
66	9-Aug-2021	5	Mechanical	Vehicle 4	Man vehicles	2002	953
67	6-Sep-2021	28	Body	Vehicle 9	Mercedes Alba	2012	642
68	3-Oct-2021	27	Electrical	Vehicle 20	Mercedes Alba	2013	424
69	12-Oct-2021	9	Electrical	Vehicle 18	Man vehicles	2005	1103
70	6-Nov-2021	25	Planned Maintenance	Vehicle 10	Mercedes Alba	2010	1132
71	9-Nov-2021	3	Electrical	Vehicle 2	Man vehicles	2001	640
72	8-Dec-2021	29	Administrative	Vehicle 22	Mercedes Alba	2012	1149
73	15-Dec-2021	7	Body	Vehicle 13	King Long	2016	13
74	10-Jan-2022	26	Electrical	Vehicle 3	Mercedes Alba	2013	14
75	30-Jan-2022	20	Planned Maintenance	Vehicle 9	Mercedes Alba	2012	762
76	5-Feb-2022	6	Planned Maintenance	Vehicle 5	Mercedes Alba	2012	425
77	15-Feb-2022	10	Planned Maintenance	Vehicle 21	Man vehicles	2005	989
78	6-Mar-2022	19	Electrical	Vehicle 1	Man vehicles	2000	737
79	21-Mar-2022	15	Planned Maintenance	Vehicle 16	King Long	2016	554
80	11-Apr-2022	21	Electrical	Vehicle 14	King Long	2015	493
81	13-Apr-2022	2	Mechanical	Vehicle 23	Man vehicles	2004	655
82	17-Apr-2022	4	Mechanical	Vehicle 14	King Long	2015	773
83	7-May-2022	20	Administrative	Vehicle 17	Mercedes Alba	2009	768
84	8-May-2022	1	Planned Maintenance	Vehicle 11	Man vehicles	2004	745
85	19-May-2022	11	Administrative	Vehicle 17	Mercedes Alba	2009	12
86	4-Jun-2022	16	Mechanical	Vehicle 12	King Long	2015	765
87	29-Jun-2022	25	Planned Maintenance	Vehicle 21	Man vehicles	2005	595
88	4-Jul-2022	5	Mechanical	Vehicle 9	Mercedes Alba	2012	504
89	8-Jul-2022	4	Body	Vehicle 17	Mercedes Alba	2009	354
90	1-Aug-2022	24	Electrical	Vehicle 8	Man vehicles	2003	442
91	22-Aug-2022	21	Planned Maintenance	Vehicle 8	Man vehicles	2003	917
92	25-Aug-2022	3	Mechanical	Vehicle 7	King Long	2016	944
93	11-Sep-2022	17	Mechanical	Vehicle 2	Man vehicles	2001	995
94	11-Oct-2022	30	Electrical	Vehicle 7	King Long	2016	13
95	27-Oct-2022	16	Administrative	Vehicle 8	Man vehicles	2003	1086
96	5-Nov-2022	9	Planned Maintenance	Vehicle 15	King Long	2016	631
97	17-Nov-2022	12	Electrical	Vehicle 11	Man vehicles	2004	875
98	11-Dec-2022	24	Mechanical	Vehicle 18	Man vehicles	2005	210
99	24-Dec-2022	13	Mechanical	Vehicle 21	Man vehicles	2005	57
100	14-Jan-2023	21	Planned Maintenance	Vehicle 8	Man vehicles	2003	193
101	23-Jan-2023	9	Administrative	Vehicle 15	King Long	2016	737
102	30-Jan-2023	7	Body	Vehicle 20	Mercedes Alba	2013	455
103	6-Feb-2023	7	Administrative	Vehicle 14	King Long	2015	871
104	7-Feb-2023	1	Electrical	Vehicle 13	King Long	2016	35
105	20-Feb-2023	13	Electrical	Vehicle 4	Man vehicles	2002	1090
106	10-Mar-2023	18	Mechanical	Vehicle 21	Man vehicles	2005	395
107	14-Mar-2023	4	Electrical	Vehicle 21	Man vehicles	2005	503
108	6-Apr-2023	23	Mechanical	Vehicle 20	Mercedes Alba	2013	232
109	8-Apr-2023	2	Electrical	Vehicle 1	Man vehicles	2000	254
110	9-Apr-2023	1	Mechanical	Vehicle 22	Mercedes Alba	2012	668
111	19-Apr-2023	10	Mechanical	Vehicle 2	Man vehicles	2001	708
112	6-May-2023	17	Body	Vehicle 5	Mercedes Alba	2012	353
113	27-May-2023	21	Body	Vehicle 21	Man vehicles	2005	788
114	14-Jun-2023	18	Body	Vehicle 21	Man vehicles	2005	363
115	7-Jul-2023	23	Body	Vehicle 5	Mercedes Alba	2012	422
116	16-Jul-2023	9	Body	Vehicle 13	King Long	2016	808
117	5-Aug-2023	20	Administrative	Vehicle 3	Mercedes Alba	2013	158
118	24-Aug-2023	19	Planned Maintenance	Vehicle 1	Man vehicles	2000	514
119	16-Sep-2023	23	Body	Vehicle 17	Mercedes Alba	2009	860
120	18-Sep-2023	2	Planned Maintenance	Vehicle 14	King Long	2015	637
121	21-Sep-2023	3	Body	Vehicle 19	Mercedes Alba	2008	577
122	27-Sep-2023	6	Planned Maintenance	Vehicle 9	Mercedes Alba	2012	895

"Source: created by the authors

Table 3. Summary of Recent Studies on Fleet Reliability, Maintenance Strategies, and Predictive Technologies in Transportation Systems. "Source: created by the authors"

Study Title	Reference & Year	Methodology	Key Findings
Impact of Shared Mobility Fleets	[1] 2022	Analysis of regulatory policies and failure data	Policy interventions, such as taxes on externalities, could reduce traffic congestion and air pollution. Data-driven strategies and machine learning models can enhance transportation systems.
Reliability of Metro Vehicles in Poland	[2] 2019	Investigation of failure patterns in braking and door systems	Brake system issues pose safety risks, while frequent door failures suggest a design weakness that needs improvement.
Performance of Diesel Generators	[3] 2019	Study of failure rates across multiple generator brands	Failure likelihood is highest in the first 30 minutes of operation. These insights help manufacturers refine generator reliability.
Fleet Vehicle Selection for Cost Efficiency	[12] 2021	Comparison of operational reliability among different vehicle types	Vehicles classified as Type B demonstrated higher mileage before failure, making them the most cost-effective option.
Maintenance Analysis of the Dacia 1304 Utility Vehicle	[16] 2018	Application of the Weibull++8 software to evaluate repairs	Frequent mechanical and electrical failures were identified, with an average repair time of five hours.
Fleet Maintenance Management Strategies	[10] 2012	Use of DEMATEL and ANP models to analyze maintenance practices	Effective fleet management depends on balancing maintenance efficiency, transportation logistics, and environmental considerations.
Optimization of Fleet Maintenance Scheduling	[9] 2006	Ant Colony System (ACS) approach applied to scheduling problems	The ACS model proved effective in managing maintenance schedules, particularly in military aviation maintenance.
Identifying Best Practices in Fleet Management	[17] 2013	Examination of fleet maintenance processes	Key maintenance strategies were identified, improving operational efficiency.
Balancing Costs and Reliability in Fleet Operations	[13] 2018	IT-based analysis of maintenance cost-effectiveness	Implementing IT solutions improved the cost-reliability balance in fleet management.
Reliability of Firefighting and Rescue Vehicles	[15] 2023	Case study on maintenance challenges in emergency vehicles	The study pinpointed major failure areas and proposed solutions to enhance vehicle reliability.
Implementing Preventive Maintenance Strategies	[11] 2020	The Reliability-Centered Maintenance (RCM) approach is applied in a logistics company.	RCM reduced failure rates and improved overall maintenance efficiency.
Digital Twins for Predictive Maintenance	[7], [18]	Application of digital twin technology in vehicle servicing	Digital twins helped predict maintenance needs more accurately, but presented challenges in implementation.

Study Title	Reference & Year	Methodology	Key Findings
Data-Driven Maintenance for Turbochargers	[8] 2023	Predictive maintenance using a data-driven approach	Optimized maintenance scheduling for turbochargers, improving efficiency.
Predictive Quality Analysis for Vehicles	[4] 2024	Bayesian network-based analysis of vehicle failures	Used machine-learning models to assess vehicle quality and predict failures with greater accuracy.
Machine Learning for Predicting Vehicle Failures	[55]2024	Deep neural networks applied to maintenance forecasting	Improved failure prediction accuracy through AI-driven analysis.
AI-Based Engine Maintenance for Military Vehicles	[6] 2023	Application of AI models for armored vehicle maintenance	AI-driven predictive models helped anticipate and prevent engine failures.
Reliability of Train Control Systems	[19]2023	Use of the Hawkes process for reliability evaluation	Provided insights into failure patterns in train control components, improving predictive maintenance.
Spare Parts Inventory Optimization	[14] 2022	Reliability-based approach to spare parts management	Optimized parts availability, ensuring efficient fleet maintenance operations.
Machine Learning for Automotive Predictive Maintenance	[20]2021	AI-based study on fleet maintenance challenges and opportunities	Identified key challenges and potential solutions for implementing machine learning in vehicle maintenance.

“Source: [21]”