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Condition-Based Maintenance of passenger buses

Dissertation to fulfill the master's degree in Engenharia e Gestão de Ativos Físicos

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Coimbra, junho 2025

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RESUMO

As avarias mecânicas dos autocarros urbanos comprometem a eficiência da operação. Este estudo centra-se na Manutenção Baseada na Condição (CBM) de autocarros de passageiros, com foco em estratégias para reduzir falhas inesperadas, aumentar a disponibilidade dos veículos e minimizar os custos operacionais. A análise baseia-se em dados de uma frota de 53 autocarros *Autosan Sancity* M12LF que opera em condições urbanas numa cidade polaca. Estes dados incluem registos operacionais, registos de falhas e informações de manutenção, sendo utilizados para suportar a análise preditiva de falhas através de técnicas como FMECA (Análise de Modos de Falha, Efeitos e Criticidade), Análise de Pareto e Análise de Árvore de Falhas (FTA). Em paralelo, é realizada a monitorização do óleo lubrificante utilizando Análise de Componentes Principais (PCA) e Agrupamento *K-Means*, aplicados a um conjunto de dados distinto recolhido de autocarros de outros modelos em operação na Eslováquia. Este conjunto de dados complementar fornece informações adicionais sobre os padrões de degradação por meio da análise do óleo. Os resultados revelam que as falhas mais críticas derivam de um pequeno subconjunto de causas, sendo a fuga de líquido de refrigeração identificado como o principal evento topo através da Análise de Árvore de Falhas, devido ao seu impacto significativo e elevada probabilidade de ocorrência. Os indicadores de fiabilidade apontam para um MTTR (Tempo Médio para Reparação) médio da frota de 2,66 horas e um MTBF (Tempo Médio entre Falhas) de 26,55 horas, resultando numa Disponibilidade Intrínseca de 90,69%. No entanto, a Disponibilidade Operacional foi inferior, situando-se nos 78,47%, devido ao tempo prolongado de inatividade durante a manutenção. A elevada proporção de manutenções não planeadas (92,23%) evidencia a necessidade de um melhor planeamento de manutenção. A análise do óleo destaca ainda padrões de degradação bem definidos, associados às condições operacionais e à maturidade do motor. Os resultados demonstram que indicadores convencionais como a quilometragem não são totalmente fiáveis para avaliar a degradação do óleo, reforçando a necessidade de uma monitorização baseada na condição, utilizando variáveis físico-químicas e de contaminação. Os resultados evidenciam a importância da Manutenção Baseada na Condição para melhorar a fiabilidade e a eficiência operacional da frota.

Palavras-chave: Manutenção Baseada na Condição; Análise de Árvore de Falhas; FMECA; Análise de Óleo; Análise de Pareto; Análise de Componentes Principais.

ABSTRACT

Mechanical breakdown of the urban buses compromises efficient operation. This study focuses on Condition-Based Maintenance (CBM) of passenger buses, focusing on strategies to reduce unexpected failures, enhance vehicle availability, and minimize operational costs.

The study was conducted on a fleet of 53 Autosan Sancity M12LF buses operating under urban conditions in a Polish city. These data include operational records, failure logs, and maintenance information, and are used to support predictive failure analysis through techniques such as FMECA (Failure Modes, Effects and Criticality Analysis), Pareto Analysis, and Fault Tree Analysis (FTA). In parallel, lubricant oil monitoring is performed using Principal Component Analysis (PCA) and K-Means Clustering, applied to a separate dataset collected from buses of the other models operating in Slovakia. This complementary dataset provides additional insights into degradation patterns through oil analysis.

The results reveal that most critical failures stem from a small subset of causes, with coolant leakage identified as the principal top event through Fault Tree Analysis, due to its significant impact and high probability of occurrence. Reliability metrics indicate a fleet average MTTR (Mean Time to Repair) of 2.66 hours and an MTBF (Mean Time Between Failures) of 26.55 hours, resulting in an Intrinsic Availability of 90.69%. However, Operational Availability was lower, at 78.47%, due to prolonged maintenance downtime. A high proportion of unplanned maintenance (92.23%) underscores the need for improved maintenance planning. Oil analysis further highlights well-defined degradation patterns associated with operational conditions and engine maturity. The results highlight that conventional indicators like mileage are not entirely reliable for assessing oil degradation, reinforcing the need for condition-based monitoring using physicochemical and contamination variables.

The results highlight the importance of Condition-Based Maintenance to improve the fleet reliability and operational efficiency.

Keywords: Condition-Based Maintenance; Fault Tree Analysis; FMECA; Oil analysis; Pareto Analysis; Principal Component Analysis

ACKNOWLEDGMENTS

It has been a tough and changing road getting to this point, rewarding and fulfilling as well.

I would like to thank my supervisors for their constant help, support even in the most difficult times and the knowledge that they passed into me, through this work.

A huge thank you to Wojciech without whom this dissertation would never been written, for providing data, for helping me out, for being so generous with your knowledge, all of which were essential to the making of this dissertation.

Lastly, for my family and my boyfriend, I appreciate the unconditional backing, tolerance and encouragement I have received at every step of this period. Without you, this would be nothing!

And last but not least, thank you to all those who in some way contributed to this.

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SYMBOLS AND ABBREVIATIONS

AI	Artificial Intelligence
APSRTC	Andhra Pradesh State Road Transport Corporation
ANN	Artificial Neural Networks
CBM	Condition-Based Maintenance
CLR	Cumulative Logistic Regression
CNG	Compressed Natural Gas
EN	European Standard
FMEA	Failure Mode and Effect Analysis
FMECA	Failure Mode, Effect and Critically Analysis
FTA	Fault Tree Analysis
FTIR	Fourier Transform Infrared Spectroscopy
IEC	International Electrotechnical Commission
ISEC	Instituto Superior de Engenharia de Coimbra
KPI	Key Performance Indicator
LTA	Logic Tree Analysis
LVO	Low-Viscosity Oils
MCS	Minimal Cut Set
MTBF	Mean Time Between Failures
MTC	Metropolitan Transport Corporation
MTTR	Mean Time to Repair
NP	Portuguese Standard
RAM	Reliability, Maintainability, and Availability
RBD	Reliability Block Diagram

RCM	Reliability Centered Maintenance
RPN	Risk Priority Number
PCA	Principal Component Analysis
TAN	Total Acid Number
TBF	Time Between Failures
TBN	Total Base Number
TI	Technical Inspection
TTR	Time to Repair

1 INTRODUCTION

Public buses play a critical role in providing urban mobility given their considerable worth and extensive use. For proper functioning, the availability, safety, and performance of the buses must meet some standards. The failures of specific maintenance bus models geared towards the requirements of each bus are adopted and incorporated, resulting in an effective performance analysis.

The standard NP EN 13306 [1] gives a framework about maintenance terminology and system concepts. One of the various approaches discussed is Condition Based Maintenance (CBM), which allows the execution of proactive maintenance measures with the objective of alleviating and averting issues that are more serious.

As per this standard, CBM is described as a type of preventive maintenance that is grounded on the actual state of the asset and results in maintenance actions that are prompt, precise and focused towards achieving optimal results. These principles for optimizing transport company resources regarding passenger buses are fundamentally required.

Moreover, at the same time, for the bus operation to be efficient, the engine oil level and characteristics must always be monitored. The engine oil has a direct correlation with the output and service life of the engine and plays a vital role in lubricating friction surfaces, removing heat, and preventing corrosion, etc. Proactive maintenance processes depend on oil analysis and early identification of wear or contamination that allows mechanical failure to be foreseen and maintenance strategies to be optimized.

This means that when CBM is used in conjunction with engine oil diagnostics, unplanned downtime is reduced, vehicle readiness is improved, and operating costs are lowered. Oil monitoring in the context of CBM enables transport operators to dictate when maintenance occurs, to ensure a reliable fleet, while minimizing costly downtime.

However, despite the known advantages, the incorporation of oil analysis with broader reliability metrics, such as MTBF and MTTR is limited in the existing literatures especially for urban bus fleets. Fleet operators have also been experiencing increasing challenges such as higher vehicle operating costs, aging of vehicles, and random downtime events. Some authors [2] highlight the increasing complexity of fleet management, especially in dynamic environments where real-time decision-making is required. However, most methodologies reviewed tend to overlook condition monitoring tools and predictive maintenance strategies.

This study aims to bridge that gap by proposing a methodology that combines failure analysis, multivariate oil analysis, and reliability indicators, offering a structured and transferable approach to the maintenance of other bus fleets. This integration contributes to a more accurate failure prediction and more efficient maintenance planning, fostering the advancement of Condition-Based Maintenance in the public transport sector.

1.1 Objectives

The focus of this work is to develop an integrated methodology for the implementation of Condition-Based Maintenance (CBM) in bus fleets using failure analysis and reliability indicators in conjunction with lubricant oil monitoring and the application of multivariate statistical tools.

To this end, the research aims to answer a set of research questions that guide the orient methodological approach. The primary aims of the investigation are thus explicitly aimed at answering the following questions:

1. How can Fault Tree Analysis (FTA) and Failure Modes, Effects and Criticalities Analysis (FMECA) be integrated in such a way as to map failure causes and provide preventive steps in Condition-Based Maintenance (CBM)?
2. What are the critical urban passenger buses' failure modes and how do we use their identification through failure analysis for prioritization of maintenance interventions?
3. How can a joint analysis of reliability (using MTBF, MTTR) and lube oil monitoring lead to enhanced Condition Based Maintenance?
4. How can multivariate statistical analysis and failure analysis be applied together to support the anticipation of failures and optimization of maintenance in urban bus fleets?
5. How can lubricant oil analysis be well incorporated into the Condition-Based Maintenance (CBM) models to provide more accurate and timely diagnostics of the engine health?

In attempting to provide answers to these questions, the research is intended to develop a systematic and generic structure to maintenance planning, to improve the precision of failure prediction and to facilitate better decisions in the realm of Condition Based Maintenance (CBM) in the public transport sector.

1.2 Planning

The main aim of this thesis is to improve fleet maintenance strategies based on analysis of bus lifecycle data and oil analysis. The analysis starts with an exploratory data analysis about the patterns and trends that guide decision-making. Advanced methodologies, including Failure Modes, Effects, and Criticality Analysis (FMECA) and Fault Tree Analysis (FTA), are applied to identify and evaluate potential failure points.

For the quantitative measurement of fleet performance, key metrics, such as the Mean Time to Repair (MTTR), the Mean Time Between Failures (MTBF), and the Availability, are computed that provide useful information about the operational performance for the system.

Based on these analyses a predictive failure model is developed and applied to predict potential issues.

Lastly, this work will concentrate on oil analysis, using the existing data to watch for wear and diagnose potential mechanical failures.

Incorporating oil analysis into the maintenance plan, this study improves the reliability of fleet, maximizes the utilization of resources, and reduces the potential for down time.

1.3 Materials and Methods

In this work, a multidisciplinary approach employed to analyze and improve the reliability and availability of urban buses. To achieve this, various failure analysis methods from the field of maintenance engineering used, along with oil analysis techniques.

In first place, the Failure Modes, Effects, and Criticality Analysis (FMECA) method was used to determine which components of a system were critical to the function of the system and to evaluate the effects, criticality, and the possible failure mode. This analysis provides a basis for prioritizing corrective and preventative actions.

Correlation Analysis is also applied to investigate the relationship between operating variables and the performance indicators, and data about the lubricating oils use. This helps identify the factors that directly impact vehicle reliability.

Pareto Analysis applied to highlight the main contributors to failures and unplanned downtime, following the 80/20 principle, which supports the focusing of improvement efforts.

Additionally, a Cause-and-Effect Diagram (also known as Ishikawa Diagram) developed to systematically illustrate the possible causes of recurring issues, grouping them into typical categories.

Another tool to be employed is Fault Tree Analysis (FTA), which will graphically represent the combinations of failures that may lead to critical undesirable events, thus supporting a more in-depth risk analysis.

Beside qualitative tools, also quantitative indicators like Mean Time to Repair (MTTR), Mean Time Between Failures (MTBF), and Availability calculated to measure maintenance performance and equipment reliability.

For the characterization of the lubricating oil of the buses engines, PCA was applied together to the K-Means clustering algorithm. PCA was used as a technique for dimensionality reduction to convert a set of observations correlated to a smaller uncorrelated set. This allows for the detection of hidden degradation modes and the most influencing variables, which helps to interpret the data. Clustering the oil samples into distinct groups according to the above-mentioned key variables was performed with the K-Means algorithm. This step of clustering helps discover operations and anomalous events which may not be so obvious just by the analysis of the individual variables.

Lastly, a perceptron model - an elementary neural network - was used in a supervised learning setting to predict cluster membership (as determined by K-Means above).

The integration of these methodologies provides a comprehensive and robust analysis of the data, guiding strategic actions aimed at the continuous improvement of maintenance processes and fleet operation.

1.4 Structure of the Report

This report is organized to offer a complete view on Condition-Based Maintenance (CBM) in urban bus fleets, with specific emphasis on predictive maintenance schemes, failures analysis and reliability optimization.

It is structured in seven majors parts:

- Chapter 1, corresponds to the introduction, presents an overview of the study topic, highlighting the importance of CBM, defining the study's scope, and outlining the main objectives.
- The literature review, Chapter 2, provides a detailed examination of existing literature on maintenance strategies, failure prediction techniques, and reliability analysis, addressing key methodologies, such as oil analysis, fault tree analysis, and predictive models to establish a foundation for the research by identifying gaps and opportunities for improvement in CBM practices. Also discusses the concepts concerning maintenance strategies and analytical techniques, like Failure Modes, Effects and Criticality Analysis (FMECA), and the Ishikawa Diagram, which serve as basis for applied methods.
- Chapter 3 presents the data sources used that supports the research, including detailed information on the bus fleet, maintenance schedules, and the engine oil dataset that forms the basis of the case study.

- The core of this research is presented in Chapter 4, titled Case Study and Data Analysis, which focuses on the analysis of a fleet of buses operating under urban conditions and in a fleet operated in Slovakia under both urban and interurban conditions. In this chapter, a constructive collaboration of statistical methodologies, reliability engineering tools, and machine learning models is used to study the patterns of oil degradation, to discover the preference of failure, and to evaluate the operational efficacy of condition-based maintenance policies among the fleet.
- The results chapter (chapter 5) summarizes the key findings of the study, emphasizing the impact of CBM on fleet reliability and operational efficiency. Highlights trends in failure occurrence, repair time optimization, and the performance of predictive maintenance strategies and it also explores the practical implications for fleet management and maintenance planning.
- Chapter 6 discusses the implications of the results, the contributions of the study to the field, and its limitations, suggesting directions for future research.
- The last chapter provides a summary of the research findings, emphasizing the benefits of CBM implementation in bus fleets, discussing the study's contributions to the field, acknowledging its limitations, and suggesting future research directions.

This organized methodology provides logical information flow to aid the understanding of the research process and its implications to the urban bus maintenance management.

Parts of the content presented in this thesis have been proposed for publication in five scientific articles, co-authored by the author of this thesis. These manuscripts are either published, currently under review or in preparation. Each article explores specific components of the research. For the sake of transparency, several sections of this work are directly derived from these scientific articles.

2 LITERATURE REVIEW

2.1 Methodology for literature review

A literature review was conducted using academic databases, namely Google Scholar, Scopus, B-on and Science Direct. Keywords such as "bus failure analysis", "oil analysis", "diesel engine oil monitoring", "prediction models", "failure prediction" and "reliability analysis in bus fleet" were employed. After refining the search terms, approximately two hundred entries were obtained, of which approximately 40 were considered relevant to this study based on inclusion criteria, such as the year of publication, application in transportation systems, and failure analysis methodology.

The papers extracted were then analyzed to identify common themes, gaps, and trends in the literature. This involved categorizing studies based on their focus areas, such as the effect of oil analysis on early defect detection, maintenance cost reduction and fleet reliability.

2.2 Reliability, Maintainability and Availability

To ensure the required function of an asset, such as a bus, it is necessary to combine proper operation with effective repair.

To understand the elements that influence the performance and operation of the bus fleet, the Reliability, Maintainability, and Availability of the fleet is analyzed in this study. The review of these three dimensions provides insight into how failures occur, how quickly systems can be restored, and how consistently buses remain in operational condition. The aim is to identify what would most impact the overall fleet performance and operational efficiency.

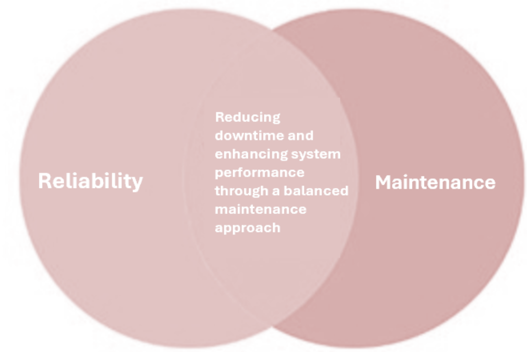

Figure 1 - The relationship between Maintenance and Reliability

Maintenance and Reliability form an interdependent parameter and both directly affect the performance of the bus fleet as presented in Figure 1. A well-designed maintenance plan improves reliability by reducing unplanned failures and maximizing operational performance. Reliability data on the other hand, enables maintenance schedules to be fine-tuned, allowing optimal use of resources and increasing the availability. It is very important to know this relationship as a base for evaluating the performance of the fleet and deciding adequate maintenance policies.

A reliable fleet implies that there are less unexpected failures, a fleet with a high maintainability means that repairs as well as inspections can be optimized, an available fleet maintains that vehicles are ready for operation whenever needed.

According to NP EN 13306, reliability is defined as "the ability of an asset to perform a required function under specified conditions, over a given period of time" [1]. Reliability is evaluated through Availability and, by consequence, using the MTBF metric, which measures the average time between two consecutive failures of an asset. A higher MTBF indicates better reliability, as the asset operates without breakdowns for longer periods.

MTBF indicates the average time between two consecutive failures of an asset, in other words, it is the time elapsed between one failure and the next.

MTBF can be calculated using Equation 1:

$$MTBF = \frac{Operating\ time\ between\ failures}{Number\ of\ failures} \tag{1}$$

The operating time between failures represents the number of hours the equipment operated without any failures. The number of failures refers to the total breakdowns that occurred during the period analyzed.

The principles of Reliability Centered Maintenance (RCM) [3] and the Bathtub Curve are key principles in maintenance management and reliability. Combined, they offer a structured framework to optimize equipment performance and extend its operational lifespan.

Figure 2 represents the failure rate of equipment from the acquisition phase (startup) to the disposal phase.

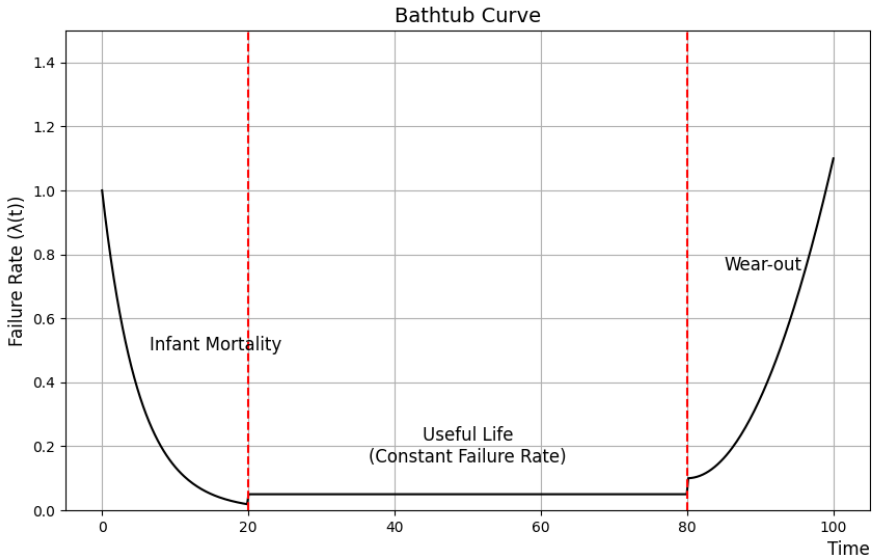

Figure 2 - Typical "Bathtub curve" representing failures rates over time

In the infant mortality phase, RCM focuses on finding and fixing design defects to ensure no early failures. In the normal life-phase, RCM uses condition-based maintenance to ensure consistent operation with minimal disruptions. Finally, during the wear-out period, RCM emphasizes more proactive replacements and large overhauls to minimize the higher risk of failures, which are expected.

The application of RCM techniques [3] is quite important to help in the development of state-based maintenance strategies by providing timely proper actions and effective interventions.

Mean Time to Repair (MTTR) measures the ability to fix a failure. An MTTR that is low suggests that repairs are effected rapidly, allowing a bus to return to operational state.

MTTR can be calculated using Equation 2:

$$MTTR = \frac{Total\ repair\ time}{Number\ of\ failures} \tag{2}$$

A low value of MTTR indicates that maintenance process are efficient and that the buses are less likely to experience excessive downtime.

Additionally, if the bus has good Maintainability, this helps to minimize MTTR. In fact, according to NP EN 13306 [1], Maintainability is defined as “the ability of an asset, under specified usage conditions, to be maintained or restored to a state in which it can perform a required function after maintenance has been carried out under specified conditions, using prescribed procedures and resources".

About the Availability, according to NP EN 13306 [1] is defined as "the ability of an asset to be in a state to perform the required function under specific conditions, at a given moment or within a defined period, assuming that the necessary external resources are provided".

Availability refers to the ability of equipment to operate as required, without unplanned interruptions.

Availability is calculated using Equation 3:

$$Availability = \frac{MTBF}{MTBF + MTTR} \qquad (3)$$

High Availability is desirable, indicating that the bus fleet operates efficiently with minimal interruptions.

2.2.1 Reliability Analysis

The analysis of Key Performance Indicators (KPIs) in bus fleets is widely discussed in the literature due to its importance in resource optimization and ensuring efficient service delivery. Most of studies are devoted to the optimal size of the reserve fleet [4], which is an important factor for ensuring operational availability while minimizing costs. These studies underscore the significance of KPIs (such as MTBF, MTTR, and Availability) which are vital for monitoring and improving the reliability of operations.

The reliability of bus fleets, however, is rather under-explored in the literature. Most studies focus on evaluating the reliability of transport services [5][6] or analyzing the conditions of bus stops [7]. Though some investigations that address comparisons between urban bus models [8], they propose simulation models [9] to assess the effects of maintenance and fleet renewal policies, and present availability analysis models [10] based on hybrid Bayesian Networks (BNs) to capture factors influencing failures or repair rates.

A recent study by Sugianto *et al.* [11] demonstrates the practical benefits of applying Reliability Centered Maintenance (RCM) in bus fleet operations. Focused on a Scania fleet in Indonesia, the authors showed that systematic reliability-based strategies significantly reduce unplanned failures and lower maintenance costs. By identifying critical components through FMEA and Logic Tree Analysis (LTA) and optimizing intervention intervals based on MTBF and operational context, the study confirmed that preventive maintenance can be more than twice cost-efficient than reactive approaches. These insights reinforce the importance of adopting structured, Reliability-Centered Models in public transport maintenance.

Govindarajulu & Rakesh [12] analyzed the reliability, availability, and maintainability of buses operated by the Andhra Pradesh State Road Transport Corporation (APSRTC). The objective was to identify bottlenecks in the vehicle subsystems that compromise reliability and propose optimal maintenance intervals to optimize operations and reduce failures. Operational data from 60 buses, including Time Between Failures (TBF) and Time to Repair (TTR), were analyzed using the Anderson-Darling test for statistical evaluation. Finally, the inherent and operational Availability was calculated based on indicators, such as MTBF and MTTR. The reliability of bus fleets, however, is rather under-explored in the literature. Results indicated that the transmission and brake controls were the major obstacles, with a high proportion of recorded failures. The MTBF of vehicles was 4,570.98 hours, MTTR was 4.92 hours, intrinsic availability was 99.88% and operational availability was 97.40%. Optimized maintenance schedules were proposed for the most critical subsystems and these have resulted in enhanced overall fleet reliability. However, it is impossible to accurately identify the bus with the lowest reliability.

Similarly, the study by Nallusamy *et al.* [13] examined the reliability of public buses operated by the Metropolitan Transport Corporation (MTC) in Chennai, India. The study examined three years of failure data (2011–2013), bucketing failures by system (engine, transmission, etc.) and using an ABC Analysis of classification of critical failures. Results indicated that engine, power transmission and running gear systems contributed 70% of the total failures observed. The corrective actions proposed involved worker training, preventive maintenance focusing and the purchase of better intensity parts. The research determined that improvements in maintenance processes could have a major impact on reliability and service interruptions.

Grimaldi's thesis [14] aimed to renew the maintenance plans of Arriva Italia by incorporating a predictive approach based on artificial intelligence and telediagnosis. The installed systems collected real-time data to estimate the remaining lifetime of mechanical parts and to schedule preventive interventions. The research revealed that the application of this technology can minimize vehicle downtimes, optimize costs and enhance operational efficiency. As a result, it is suggested to gradually replace fixed maintenance plans and adopt a predictive maintenance policy.

In addition to these studies, Macián *et al.* [15] proposed a Balanced Scorecard (BSC) for maintenance management in urban fleets, categorizing KPIs into structural, basic, and advanced to optimize operational and strategic performance. The structural indicators cover fleet structure aspects, the basics assess the execution of maintenance activities through metrics, and the advanced analyze the broader impacts of maintenance.

These studies give a holistic view of fleet maintenance activities and management strategies and the need for efficient techniques to improve operational efficiency and reduce associated costs.

Another key device for reliability analysis is Reliability Block Diagram (RBD), standardized by IEC 61078 [16].

This graphic approach displays the logical interactions between elements and systems and indicates how each one contributes to the system's reliability. RBDs are especially useful for complex systems such as vehicle fleets, allowing analysts to model configurations like series, parallel, or redundant structures. By using RBDs, it becomes easier to estimate the probability of successful operation, determine weak points, and evaluate system performance under different scenarios.

These diagrams complement tools like FMECA and FTA by providing a high-level overview of functional dependencies between components.

2.3 FMECA Analysis

Failure Mode, Effects, and Criticality Analysis (FMECA) is a structured approach, aims to define, classify, and document failure modes at system level, considering their impact on safety, performance, reliability, and maintenance. Governed by standards such as MIL-STD-1629 [17], and IEC 60812 [18], FMECA allows engineers to analyze failure modes based on both their probability of occurrence and their criticality-highlighting their capacity to create major operational or safety challenges. This prioritization is particularly useful in complex systems like public transportation fleets, in which the timely performance of maintenance is necessary to maintain operation reliability and safety.

Dzulyadain *et al.* [19] studied the use of FMECA together with Reliability-Centered Maintenance (RCM) for optimizing maintenance operations in the automotive industry. The study focuses on the identification of critical subsystems, such as braking systems, and the implementation of scheduled maintenance tasks, which resulted in a maintenance cost reduction of up to 25%. These techniques can be adapted to bus maintenance, to improve the efficient utilization of resources and minimize bus breakdown.

2.4 Ishikawa Diagram

The Ishikawa diagram also known as cause-and-effect diagram or fishbone diagram, is a visual tool to explore the potential causes of a given effect. It's a graphical method that helps identify the root causes of the problem.

Its main purpose is to clearly organize and present the potential causes of a specific problem. This detailed approach facilitates the identification of areas requiring greater attention [20], aiding in the development of more effective solutions.

The diagram is structured with a central horizontal line, known as the "head of the fish," representing the problem under analysis. Extending from this line are diagonal lines, or "bones," which represent distinct categories of potential causes.

2.5 Fault tree Analysis

Fault Tree Analysis (FTA), standardized by IEC 61025 [21], is a graphical and logical method for the identification, analysis and prevention of failures in complex systems, supporting the prioritization of maintenance efforts.

Based on FMECA that describes possible failures, their causes and effects, FTA continues to provide more detailed analyses by mapping the sequence of events that could result in a critical failure. This process makes it possible to identify Minimal Cut Sets, which represent the minimal combinations of failures that could cause the main event, thereby assisting in prioritizing preventive and corrective maintenance actions.

Fault Tree Analysis has been widely used in fault analysis in various sectors, including the automotive industry [22] and energy production [23], [24], [25]. In the field of public transport, its application is still limited but growing.

Xi *et al.* [26] developed a risk factor analysis model for urban bus operations based on FTA combined with Cumulative Logistic Regression (CLR). Using accident data from Northeast China, the study identified 16 risk factors and classified them based on structural, probability, and critical importance. The model helped to prioritize high-risk factors, including driver experience, lighting conditions, and road conditions. This approach provided practical insights for improving urban bus safety by accurately identifying and ranking risk factors.

The combined use of FMECA and FTA also demonstrates the evolution of fault analysis methodologies, particularly in complex systems such as diesel engines. Peng *et al.* [27] proposed a methodology that integrates these techniques to address limitations inherent in their individual applications. Their study focused on the combustion system of diesel engines, where the FMECA identified potential failure modes and assessed their criticality quantitatively, the FTA provided a graphical representation of logical relationships between fault causes and effects. This integrated approach was employed for the sealing system of diesel engine cylinder head focusing on the air leakage issues. According to the analysis, the ablation and deformation of the cylinder liner were determined to be the riskiest ones which can impact on performance substantially. FMECA combined with FTA, realized accurate analysis of failure modes and provided a basis of design improvement and maintenance decision making. This approach was more representative of real-word operational reality than the traditional approaches, indicating its potential for guiding technical enhancements and maintenance practices in similar complex systems.

2.6 Oil analysis

2.6.1 Classical methods

Oil analysis has been an essential tool for predicting, mitigating engine failures in buses, allowing fleet managers to implement predictive maintenance strategies. Recent studies, such as the one by Gołębiowski *et al.* [28], investigated engine oil degradation under real operating conditions of a bus fleet using classical methods like Fourier Transform Infrared Spectroscopy (FTIR) and advanced chemical analysis to evaluate critical oil parameters, including oxidation, nitration, sulforation, and soot content. These classical methods are widely used in the industry due to their precision in detecting chemical degradation of oil. The analysis revealed that oil degradation is significantly influenced by factors like frequent stops and starts, especially in urban buses.

Another classical method is the monitoring of viscosity and Total Base Number (TBN), as demonstrated in the study by Golebiowski *et al.* [29]. By measuring properties, such as viscosity at 40 °C and 100 °C, the research showed that using fixed mileage intervals for oil changes may not be efficient, and periodic monitoring of the oil's condition is crucial to ensure system reliability. These physicochemical parameters are critical for determining oil suitability and preventing damage to engine components.

Similarly, Raposo *et al.* [30] applied systematic monitoring of oil condition in a fleet of urban buses, using classical techniques to evaluate oxidation, soot, wear metals, and nitration. The study employed mathematical models, such as exponential smoothing, and statistical methods, like the t-Student distribution to predict the degradation of components like iron (Fe). These proven techniques allowed for extending the oil change intervals from 20,000 km to 25,000 km, resulting in cost savings.

Additionally, Schutz [31] also emphasized that regular oil analysis, when performed consistently, can detect internal wear and contamination, aiding in failure prediction and improving scheduled maintenance processes. Classical techniques like these are widely recognized for their reliability and applicability across different fleet types.

Rodrigues *et al.* [32] investigated multivariate analysis techniques applied to lubricating oils, showing how variations in parameters such as silicate content, sulfation and viscosity can influence lubricant performance. Their study reinforced the importance of periodic analysis in preventing mechanical failures.

Macian *et al.* [33] investigated further these results by conducting a real-world fleet test to assess the performance and degradation of low-viscosity oils in heavy-duty engines. In the study, 39 buses of diesel and CNG (Compressed Natural Gas) engines technologies were investigated, comparing four different lubricants, two of which were Low-Viscosity Oils (LVO). The findings demonstrated that LVO can deliver fuel economy gains without sacrificing engine durability. The study also noted that LVO's effectiveness is not always consistent and depends on the engine type and duty. Their results highlight the importance of rigorous assessment prior to the implementation of LVO in other fleets in order to maximize potential gains.

In this line, Lenza *et al.* [34] conducted an analysis of the use diesel engines lubricants used in urban buses working under common stop-and-go urban traffic. Through the assessment of viscosity, total base number (TBN), soot content, and the concentrations of such wear metals in the used oils, a trend of premature oil degradation attributed to frequent shut-down/starts was noticed. Statistical and multivariate techniques were used by the authors to relate lubricant status to the developing history of engine usage and maintenance. Their conclusions demonstrated the potential for regular oil analysis to extend oil change intervals, improving predictive maintenance efforts, and increasing engine reliability and operational cost savings.

2.6.2 Other approaches

In addition to classical oil analysis methods, recent studies have explored innovative approaches to enhance the efficiency of predictive maintenance. For instance, Raposo *et al.* [35] developed a condition monitoring model based on oil analysis, applying predictive models and time series to safely extend oil change intervals. Advanced statistical analysis of specific oil pollutants, such as soot, was used to predict oil degradation, increasing vehicle availability, and reducing costs more accurately.

Another innovative approach is the use of Artificial Neural Networks (ANN) and Principal Component Analysis (PCA), as demonstrated in [36]. These artificial intelligence techniques were applied to analyze variables of large maintenance datasets, such as mileage, soot, and metal content, with the aim of predicting the optimal time for oil changes. The neural networks showed high accuracy, even surpassing human expert predictions, while PCA identified the most critical variables affecting oil degradation.

Sousa [37] introduced the correlation between mechanical failures and vehicle emissions, applying a predictive model based on exhaust gas opacity and the properties of lubricant oils used. This innovative approach suggests that continuous monitoring of emissions and oil condition can improve diagnostic accuracy and further reduce maintenance costs.

Additionally, the use of alternative fuels, such as biodiesel, was investigated in [38], a study that employed atomic absorption spectroscopy and analytical ferrography to monitor oil degradation under different operating conditions. The analytical techniques demonstrated that biodiesel contamination significantly affects properties like viscosity, reinforcing the need for continuous monitoring and the application of predictive maintenance strategies.

A recent study [39] focused on the extension of the lifecycle of lubricants in internal combustion engines, which seeks to enhance engine performance and durability.

Lubricants will also break down and the tribofilm, a protective layer, will only form on the presence of Isolating pre-cursers in the oil. The evolution of these precursors, and how they relate to the formation of the tribofilm, are frequently not fully taken into account in current models. To fill this gap, the authors developed an analysis of precursors mass balance, which combines mathematical models and optimal control strategies to enhance the formation of tribofilm. The findings are indicative of the fact that lubricant useful life, system oil consumption, engine wear and system efficiency can be prolonged, reduced, and enhanced respectively, through temperature and pressure management.

These advances complement traditional methods and providing greater understanding on the prediction of oil degradation as well as improvement of engine operational performance.

2.7 Fuzzy logic

Fuzzy logic plays a crucial role in handling uncertainty in complex decision-making scenarios, offering a flexible and intuitive framework for reasoning in environments where precise data is often unavailable.

Fuzzy logic has emerged as a valuable tool in decision-making processes, particularly in maintenance planning and fault analysis, by addressing the inherent uncertainty in real-world systems. Unlike classical logic, fuzzy logic allows for degrees of truth rather than binary true/false decisions, making it well-suited for complex systems like urban bus fleets.

Recent studies have applied fuzzy logic to enhance maintenance strategies and failure prediction. Gu & Huang proposed a reliability evaluation model for diesel engines based on a fuzzy neural network [40]. The model incorporated variables such as operating conditions, failure frequency, and maintenance schedules, assigning weights based on expert opinions and historical data. This approach allowed for dynamic adjustments in maintenance planning, improving fleet reliability and reducing downtime.

Bay & Bayir integrated fuzzy logic with fault diagnosis in diesel engines. The study [41] utilized sensor data, such as vibration and temperature, to define fuzzy sets representing different engine conditions. By applying fuzzy inference rules, the system provided real-time diagnostic insights, identifying potential failures with high accuracy.

2.8 Failure prediction

Failure prediction models in public transport are fundamental to enhance fleet efficiency and reliability. These methods use historical data, advanced algorithms, and in real-time sensors to anticipate failures, as to optimize performance and reduce operational costs.

Recent advancements have introduced failure prediction models specifically tailored for urban bus fleets. A notable example is the study by Foké *et al.* [42], which presents an intelligent maintenance approach based on historical failure data and geographical information systems. This method predicts failure dates for vehicle fleets, enabling maintenance departments to efficiently allocate resources. The study utilized historical bus failure data from the Société de Transport de Montréal (STM) and weather data from Environment Canada. By employing algorithms, such as Facebook's Prophet and Uber's Simple Feed-forward and Beats, the researchers identified that 20% of buses were responsible for 80% of failures. Focusing on these unreliable components allowed for accurate predictions of future failure dates. Simulations conducted with over 250,000 data points yielded results consistent with theoretical predictions, demonstrating the effectiveness of this predictive maintenance approach in urban bus fleets.

One of the main applications is the optimization of bus replacement timing. These models [43] evaluate the ideal moment to replace or renew vehicles, considering maintenance costs, fuel consumption, inflation rates, and capitalization costs. Based on concepts such as "economic life" and "useful life", it is possible to determine the most efficient lifecycle for buses, promoting more effective financial and operational planning. Studies in this field have demonstrated significant results in cost reduction throughout the vehicles' lifecycle.

Moreover, predictive maintenance platforms have been identified as a technological system to monitor the real-time condition of vehicles. These platforms use sensors and algorithms, that they can identify latent failures before they fail which in turn can help in planning maintenance as per vehicle conditions. This helps minimize the downtime and operating costs. A notable example is the solution provided by *Stratio* [44], which integrates tools for failure monitoring and decision support, being widely used by public transport companies to increase fleet reliability.

Failure prediction also benefits from reliability and maintenance analyses in specific bus models, such as the *Mercedes Citaro O530*. Studies presented in [45] analyze failure patterns based on historical data have enabled the identification of trends and the implementation of preventive measures. These developments contribute to minimizing the unexpected failures, increasing the availability of vehicles, and allow for more effective maintenance planning.

2.9 Prediction algorithms

A literature review has revealed a significant dearth of research on failure prediction in urban buses, thus suggesting the importance of conducting more works in this area. However, related articles explore the application of prediction algorithms in adjacent fields, providing valuable insights.

However, there is a study [46] that introduces a sequential preventive maintenance model that addresses the complexity of urban bus systems. The model quantifies maintenance efficiency by evaluating the differences between actual and expected increments in failure intensity. This approach allows for the assessment of various levels of maintenance efficiency and aid in decision-making processes related to fleet management. To validate the efficiency of the proposed model in the optimization of maintenance strategies and the cost reduction, a case study is conducted in a Chinese urban bus fleet.

Another relevant study [47] studies the use of advanced AI techniques in predicting failures in critical automotive systems for enhancing vehicle reliability and safety. With the help of Artificial Neural Networks (ANNs), the study shows that predictive analytics can be used to Anti-lock Braking Systems (ABS) for enhancing accuracy of fault detection. The methodology of the study presents several benefits, including early fault detection and adaptation to changing operational conditions, which can help improve the vehicle's efficiency and safety. This approach can be transferred to the urban buses for the prediction of the maintenance and operation efficiency enhancement.

Studies such as [48] highlights how AI-driven condition monitoring and proactive scheduling can improve operational readiness and optimize maintenance interventions. This further justifies the use of structured, data-driven methodologies, such as the one described in this work, for combining oil diagnostics, failure analysis, and reliability indicators towards cost-effective and scalable maintenance practice on urban bus fleets.

2.10 Summary of literature review

Table 1 presents a comprehensive overview of key studies related to condition-based maintenance, reliability analysis, and oil diagnostics in bus fleets. It highlights the specific problems addressed, the methodologies applied, and the outcomes achieved in each study. These studies offer valuable contributions to the understanding of failure modes, reliability indicators, and data-driven maintenance strategies. They demonstrate the role of oil analysis in assessing engine health and optimizing maintenance intervals. Together, they contribute to a better understanding of how to improve fleet reliability and reduce operational costs through effective oil monitoring and analysis.

Table 1 includes the most representative studies and their relevance to oil analysis and predictive maintenance of urban fleets.

Table 1 - Main Relevant Studies Identified in the State-of-the-Art Review

Author (year)	Problem	Methods	Results

Govindarajulu *et al.* (2020) [12]	Reliability and maintainability analysis of public transport buses	MTTR, MTBF, Anderson-darling Test	Identified transmission and brake systems as main failure points; optimized maintenance intervals improved fleet availability.
Grimaldi (2022) [14]	Predictive approach for maintenance	Artificial intelligence and Telediagnosis	Gradually replace fixed maintenance plans and adopt a predictive maintenance policy.
Peng *et a*l. [27]	Diesel engine fault analysis	FTA, FMECA	Identified critical failure modes, improved design
Golebiowski *et al.* (2024) [28][29]	Engine oil degradation, optimize oil change intervals	FTIR, monitoring of viscosity and TBN	High soot levels increased oxidation and nitration; reducing the oil change interval by 7,000 km improved engine health.
Raposo *et al.* (2019) [30]	Predictive maintenance via oil analysis	Oil analysis, mathematical and statistical models	Extend oil change intervals from 20,000 km to 25,000 km; improved fleet availability and reliability.
Schutz (2022) [31]	Detecting faults and wear via oil analysis	Laboratory analysis of oil samples	Found high solid particle content, water contamination, and abnormal copper levels, indicating internal wear.
Rodrigues (2019) [32]	Influence of contaminants on lubrication	Physicochemical parameters	Demonstrates the need for continuous monitoring to assess oil degradation and contamination.
Lenza et al. (2004) [34]	Oil degradation due to urban driving conditions	Oil analysis, statistical and multivariate techniques	Identified accelerated degradation from stop-and-go cycles; showed oil analysis can optimize change intervals and enhance predictive maintenance.
Rodrigues *et al.* (2020) [36]	Optimizing oil change timing	ANN, PCA	Neural networks accurately predicted oil condition, outperforming human decisions; PCA identified 10 key variables.

This comprehensive review identifies critical methodologies and innovations for CBM in passenger buses, offering a foundation for the development of more effective maintenance strategies.

3 DATASET

The dataset used in this investigation is organized into three distinct parts. The first part includes the failure history as well as information on the fuel consumption of the urban bus fleet in Poland. The second part contains data related to the maintenance routines adopted for the same bus fleet. Finally, the third part of the dataset comprises data for the analysis of engine lubricant oil from urban and interurban buses operating in Slovakia.

3.1 Fleet and Failure Data

The first part of the study focuses on data obtained from a municipal transport fleet of 53 Autosan Sancity M12LF buses, and it is divided into two different databases: one relating to faults and the other to fuel efficiency. The summary of both datasets is presented in Table 2.

The first part of the dataset consists of the history of bus faults over the 17-month period (2023-01-01 to 2024-05-31). A total of 27 failures were recorded, with 23 of the 53 buses in the fleet suffering some kind of breakdown. The frequency of faults per bus was also calculated, indicating that approximately 50.94% of the vehicles suffered some kind of fault during the period analyzed.

The second part of the dataset is related to the fleet's fuel consumption. The consumption data is expressed in liter per 100 kilometers (liter/100 km) and was recorded over the years 2023 and 2024. Fuel consumption varied between 40.72 liter/100 km (minimum) and 49.06 liter/100 km (maximum), with an average of 44.36 liter/100 km. In addition, an average distance travelled of 122 km *per* day was observed for each bus.

Table 2 - Fleet and Failure dataset summary

Dataset	Description	Value
	Total number of buses in fleet	53
Failures database	Period under analysis of failures	2023-01-01 to 2024-05-31
	Number of failures occurred	27
	Number of buses broken	23
	Percentage of buses broken (on average)	27/53 = 50.94%
Fuel efficiency database	Min fuel consumption	40.72 liters/100 km
	Max fuel consumption	49.06 liters/100 km
	Average fuel consumption	44.36 liters/100 km
	Average daily distance	122 km

Table 3 outlines the characteristics of the 53 Autosan Sancity M12LF buses included in this study. These buses operate within the Lublin public transport system under typical urban conditions. The dataset encompasses fuel consumption, general fault occurrences, and critical failure incidents.

Table 3 - Characteristics of the buses analyzed

Average overall bus mileage [km]	Number of buses	Number of failures	Percentage of buses that failed [%]	Average daily distance [km]	Average fuel consumption per 100 km [liter]
716,963	20	11	55%	121.03	44.41
716,147	23	11	48%	120.62	44.54
748,305	10	5	50%	129.60	43.85

It is important to note that in the dataset there is a data gap for mileage between 400,000 and 600,000 km (mileage since engine replacement). This absence of samples means that no conclusions can be drawn about this mileage range. Consequently, some graphs do not display data points or information for this period, which should be considered when interpreting the results.

3.2 Planned Maintenance bus fleet data

The public transportation company adopts a preventive maintenance strategy based on a structured schedule. Maintenance routines are executed regularly to reduce the likelihood of asset failure by performing specific tasks at predefined intervals. In this context, the maintenance process is divided into four categories of maintenance sets, handled by the company's technical staff. The maintenance workflow is depicted in Figure 3.

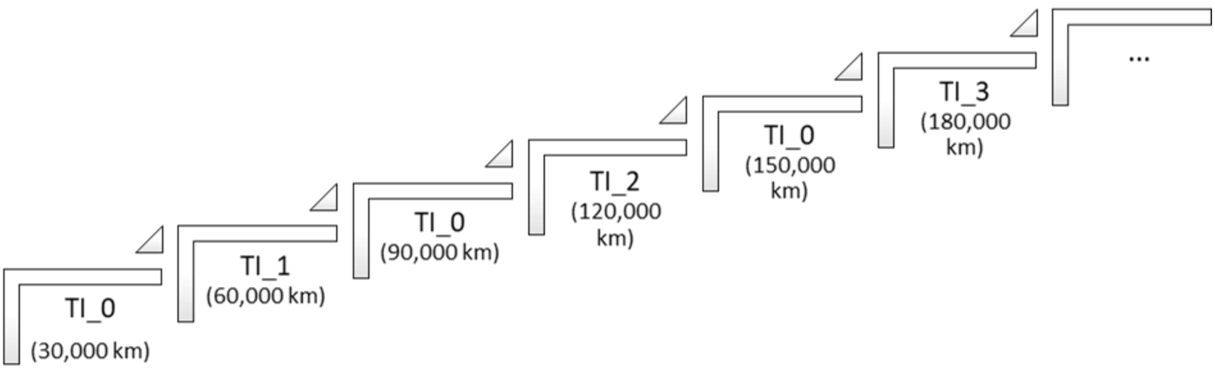

Figure 3 - Cycle of Planned Maintenance Activities in the Bus Company

The "TI" (Technical Inspection) maintenance plan involves four levels of inspections conducted at specific mileage intervals. The TI_0 plan occurs every 30,000 km and includes the inspection of lubrication points, the braking system, essential components, electrical systems, the compressed air system, engine washing, and the checking or replacement of air filters.

The TI_1, TI_2, and TI_3 plans are incremental, adding tasks to those outlined in the TI_0 plan. The TI_1 plan, conducted every 60,000 km, includes additional inspections of the suspension system, steering, air conditioning compressor, gearbox oil, and fuel filter replacement, along with checks for engine tightness. The TI_2 plan, performed every 120,000 km, extends the tasks to include brake line inspections and the replacement of axle oil and the automatic transmission oil filter. The TI_3 plan, conducted every 180,000 km, further adds the replacement of the oil filter and power steering oil, as well as the adjustment of engine valve levers.

3.3 Engine oil dataset

The dataset includes is based on oil samples collected from two different sources: buses operating in a Slovak city (using Lukoil and Urania oils) and the Polish fleet previously mentioned (using Orlen oils).

The dataset includes various samples of different types of lubricating oils used in buses. Among them are oils from brands such as Lukoil, Urania, and Orlen, with different viscosity specifications, including 15W40, 10W40, and 5W30. These viscosity grades are particularly formulated to perform in cold weather conditions, ensuring optimal fluidity at low temperatures. These lubricants are widely used in public transport fleets, providing engine protection, operational efficiency, and, in some cases, additional benefits such as fuel economy and emission reduction. Additionally, different oils are used in various bus models, including Autosan, Iveco and others.

Table 4 - Quantification of Samples by Lubricant Oil Type

Oil Type	Number of samples
Lukoil Advantg Ultra 15W40	31
Lukoil Advantg XLA 10W40	58
Urania Ecosynth 10W40	15
Lukoil Advantg Prof 5W30	9
Urania FE LS 5W30	31
Orlen Oil Platinum Extreme 10W40	21
Total	165

For each oil sample, the dataset includes specific details, such as the operator, oil type and brand, vehicle identification number, model, year of production, engine type and specifications, mileage on oil, overall vehicle mileage, sample taken date, and measurement time and date.

In addition, the dataset contains information on various essential properties that help assess oil performance and condition. These properties include oil characteristics such as viscosity at 40ºC and 100ºC, viscosity index, Total Base Number (TBN), Total Acid Number (TAN), oxidation, nitration, sulfation, phosphorus anti-wear content, remaining anti-wear additive percentage, and remaining amine antioxidant percentage.

Additionally, the dataset records pollutants such as diesel contamination, soot levels, water content, and the presence of ethylene glycol, which are crucial indicators of oil degradation and potential engine issues.

For a more detailed evaluation of oil condition and potential wear, the dataset also includes information on contaminants such as coolant leaks and the presence of metals like manganese (Mn), chromium (Cr), copper (Cu), iron (Fe), nickel (Ni), lead (Pb), tin (Sn), and titanium (Ti), which may indicate internal component wear.

Finally, the dataset contains data on additive elements, such as calcium (Ca), molybdenum (Mo), phosphorus (P), sulfur (S), and zinc (Zn), which play a crucial role in maintaining oil performance and protecting the engine.

The data presented in Table 5 provides a comprehensive overview of the performance of lubricating oils used in those buses, highlighting aspects such as wear, degradation, and contamination. The analysis reveals significant differences between lubricants in terms of oxidation, nitration, and sulfation, indicating variations in operating conditions and oil change intervals. Additionally, TAN and TBN values help assess the oil's ability to neutralize acids and maintain its effectiveness over time.

Another important aspect is the presence of contaminants such as soot, diesel, water, and ethylene glycol, which may indicate engine issues like inefficient combustion or coolant leaks. The analysis of metals, including iron, copper, and lead, also provides insights into internal engine wear, allowing for the identification of potential failures in specific components.

Finally, the depletion of essential additives, such as calcium, molybdenum, phosphorus, and zinc, suggests that the oil's protective capacity may be decreasing, particularly in high-mileage lubricants.

Table 5 presents the means and standard deviations of all parameters of the lubricating oils under analysis.

Table 5 - Statistical Analysis of Lubricating Oils: Mean and Standard Deviation of Key Properties

	Lukoil			Orlen	Urania	
	15W40	10W40	5W30	10W40	10W40	5W30
Sample data						
Model	SOR C	Solaris Urbino, SOR C	Iveco Crossway	Autosan Sancity M12LF	Iveco Urbanway 12M, Irisbus Citelis 10,5M	Iveco Crossway
Engine	Iveco SPA ITA, Fiat Auto SPA	FPT Industrial, Cummins ISB6	Iveco SPA ITA	-	Cursor 8 CNG, F2BE0642F	FPT INDUSTRIAL S.P. A

Year of production	μ = 2010		μ = 2019		μ = 2009		-		μ = 2011		μ = 2017	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
Oil properties												
Viscosity (40°C)	90.2	19.5	113.9	19.31	72.4	9.41	113.8	16.00	67.4	14.80	100.0	58.16
Viscosity (100°C)	13.5	1.5	13.7	1.15	12.7	0.44	14.8	0.47	13.3	1.23	14.4	2.71
Viscosity index	157.6	7.6	133.5	14.20	161.6	6.66	137.1	13.85	173.5	8.58	172.3	33.93
TBN (mg KOH/g)	5.7	1.8	**4.4**	1.50	**7.1**	1.01	5.4	2.11	5.6	2.02	6.4	7.30
TAN (mg KOH/g)	2.8	0.9	2.4	0.68	2.8	0.48	2.0	0.93	**6.0**	2.31	4.4	2.18
Oxidation [A/cm]	10.6	2.9	**20.7**	8.71	19.5	3.38	15.9	5.71	**25.9**	8.37	23.3	15.50
Nitration [A/cm]	15.0	4.3	21.3	7.66	**23.1**	5.32	19.5	6.94	**37.8**	18.90	23.7	16.50
Sulfation [A/cm]	15.9	4.8	15.6	4.37	18.0	4.57	21.7	6.59	19.4	7.11	12.5	9.11
Phos. Antiwear	-12.0	3.1	-13.2	2.03	-12.0	1.44	-16.9	3.37	-8.0	0.72	-9.2	11.34
Remaining Antiwear [%]	7.8	23.9	2.4	12.79	**0.0**	0.0	9.8	28.24	0.0	0.0	0.0	0.0
Remaining Amine Antiox. [%]	81.	35.0	20.9	16.61	29.1	38.42	82.5	30.00	8.0	11.0	28.8	19.88
Pollutions												
Diesel [%]	0.2	0.8	0.0	0.24	**2.2**	1.85	0.0	0.0	0.5	1.31	**1.8**	2.26
Soot [%]	**1.0**	0.7	0.5	0.28	0.4	0.23	0.5	0.34	0.1	0.13	0.8	0.36
Water [%]	0.1	0.1	0.1	0.03	0.1	0.02	0.0	0.04	0.2	0.08	0.1	0.49
Ethyl. Glycol2 [%]	0.4	0.1	0.4	0.12	**0.6**	0.08	0.3	0.12	0.3	0.19	**1.4**	3.88
Contaminants												
Coolant leaks (ppm)	18.2	14.9	11.7	5.45	16.3	11.77			19.7	9.57	**124.4**	584.75
Abrasive metals												
Content in Mn (ppm)	0.7	0.4	0.9	0.85	0.7	0.16	3.1	4.34	0.7	0.29	1.3	1.72
Content in Cr (ppm)	2.7	0.9	1.4	0.48	3.7	1.05	9.7	10.58	2.9	2.72	2.3	0.94
Content in Cu (ppm)	8.1	30.7	10.8	32.66	6.2	5.65	75.5	36.84	52.4	57.71	4.6	2.94
Content in Fe (ppm)	79.0	21.6	69.8	25.87	**91.0**	25.61	75.5	36.84	35.3	20.59	**243.3**	574.19
Content in Ni (ppm)	0.6	0.2	0.6	0.22	1.2	0.27	1.0	0.55	0.9	0.41	1.1	0.47
Content in Pb (ppm)	6.1	13.4	0.8	0.82	**14.4**	8.38	**23.6**	32.76	22.0	15.40	4.0	4.99
Content in Sn (ppm)	76.0	6.4										
Content in Ti (ppm)	0.5	0.5	0.6	0.67		11.24			0.6	0.47	0.8	2.45
Additives												
Detergent (Ca) (ppm)	1741.8	1286.6	1151.1	196.22	**5060.1**	295.15	3739.2	1067.70	1864.0	199.64	2185.7	753.44
Friction Reducer (Mo) (ppm)	369.9	22.5	**388.3**	19.62	321.9	20.15	**387.7**	22.85	366.1	17.96	363.1	24.39
Anti-wear (P) (ppm)	966.9	60.3	923.6	71.81	924.0	68.62	1077.6	989.10	698.2	117.62	687.2	106.44
Anti-wear, Antioxidant (S) (ppm)	3200.0	299.9	2671.9	243.74	2709.9	67.00	2948.5	698.97	3082.6	342.87	2590.6	375.35
Anti-wear (Zn) (ppm)	1346.5	58.6	1239.9	90.21	1341.0	99.43	1261.9	239.07	1001.7	139.23	966.1	145.36

The consolidated analysis of the lubricating oils, presented in Table 5, enables a more comprehensive comparison of different oil types and brands, including Lukoil, Urania, and Orlen. This broader view highlights significant differences in composition, degradation profiles, and potential engine implications.

Among the Lukoil oils, the 5W30 formulation stands out for its high Total Base Number (TBN 7.1), indicating a strong alkaline reserve that enhances resistance to acidification and extends the oil's protective function. However, this formulation also exhibits the highest contamination levels of diesel (2.2%) and ethylene glycol (0.6%) among the samples, which may suggest issues such as fuel leakage or coolant infiltration. Elevated concentrations of iron (91 ppm) and lead (14.4 ppm) further indicate advanced engine wear and potential component degradation.

Lukoil 10W40, in contrast, shows elevated oxidation (20.7 A/cm) and nitration (21.3 A/cm) values, pointing to accelerated chemical degradation. Despite this, it has a high molybdenum content (388.3 ppm), a friction-reducing additive that may help mitigate wear and improve mechanical efficiency under stress.

Lukoil 15W40 distinguishes itself with the highest concentrations of antioxidants and anti-wear additives, including calcium, phosphorus, sulfur, and zinc. This profile suggests that this oil variant is more resistant to degradation and offers extended protection, especially under demanding operating conditions.

Among the non-Lukoil oils, Urania 5W30 reveals critical signs of distress, with the highest iron content observed (243.3 ppm), which is indicative of significant engine wear. Additionally, the presence of 1.8% diesel and 1.4% ethylene glycol contamination raises concerns about combustion efficiency and coolant system integrity. Urania 10W40 also demonstrates substantial chemical degradation, marked by elevated oxidation (25.9 A/cm) and especially high nitration (37.8 A/cm), implying shorter oil life and reduced engine protection over time.

Meanwhile, Orlen 10W40 is notable for its elevated lead concentration (23.6 ppm), potentially signaling bearing wear or corrosion, which may compromise the lubrication of moving parts within the engine.

This analysis of this data provides valuable insights into the performance and condition of the lubricating oils across different brands and formulations. It underscores the importance of evaluating both additive preservation and contamination indicators when assessing oil health.

4 CASE STUDY AND DATA ANALYSIS

4.1 Correlation Analysis

The correlation analysis was divided into three parts, according to the nature of the data analyzed: (i) operational variables and failure occurrence, (ii) reliability and performance metrics, and (iii) oil analysis parameters. This approach aims to identify patterns of association between critical variables related to fleet performance and maintenance, contributing to the understanding of relationships between technical factors and asset degradation.

4.1.1 Operational variables and Failure Data

Table 6 presents the correlation matrix between operational variables (such as fuel consumption, average daily distance, and total mileage) and the occurrence of critical failures. Most observed correlations were weak (Pearson's $r < 0.3$), suggesting limited associations among these variables. However, two statistically significant negative correlations ($p < 0.05$) were found: between mileage since engine change and critical failures, and between repair time and mileage since engine change. This indicates that, as time passes since the last engine change, there is a slight tendency for critical faults to decrease, and buses that have been running longer since an engine change tend to require shorter repair times.

Table 6 - Correlation matrix of fuel efficiency and failures of the buses

	Overall mileage [km]	**Overall mileage when engine was changed [km]**	**Mileage since engine change [km]**	**Bus (year of production)**
01-09.2023 fuel consumption per 100 km [liter]	0.859	0.749	0.075	0.958
01-09.2023 average daily distance [liter]	0.697	0.688	0.119	0.715
09.2023-05.2024 fuel consumption per 100 km [liter]	0.855	0.766	0.057	0.961
09.2023-05.2024 average daily distance [liter]	0.677	0.697	0.015	0.702
Overall in 1.5-year fuel consumption [liter]	0.051	0.763	0.129	-0.104
Overall average daily distance [km]	0.119	0.195	-0.005	0.189

Critical failure occurred	-0.076	0.104	**-0.321**	-0.033
Repair time [hours]	0.131	0.059	**-0.134**	0.103

Additionally, overall mileage when the engine was changed exhibited a moderate positive correlation with overall fuel consumption over 1.5 years, suggesting that buses with higher mileage at the time of engine replacement tend to consume more fuel over time. Similarly, a positive correlation was found between overall mileage and repair time, indicating that buses with higher total mileage tend to have slightly longer repair times.

Finally, the bus year of production had a strong positive correlation ($r = 0.958$) with overall fuel consumption per 100 km during the period from January to September 2023, indicating that newer buses tend to have higher fuel consumption.

4.1.2 Reliability and Performance Metrics

The second stage of the analysis assessed the relationship between reliability metrics - such as Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), and Intrinsic and Operational Availability - and operational and maintenance-related variables. Figure 4 presents the corresponding correlation matrix, revealing strong relationships between some variables.

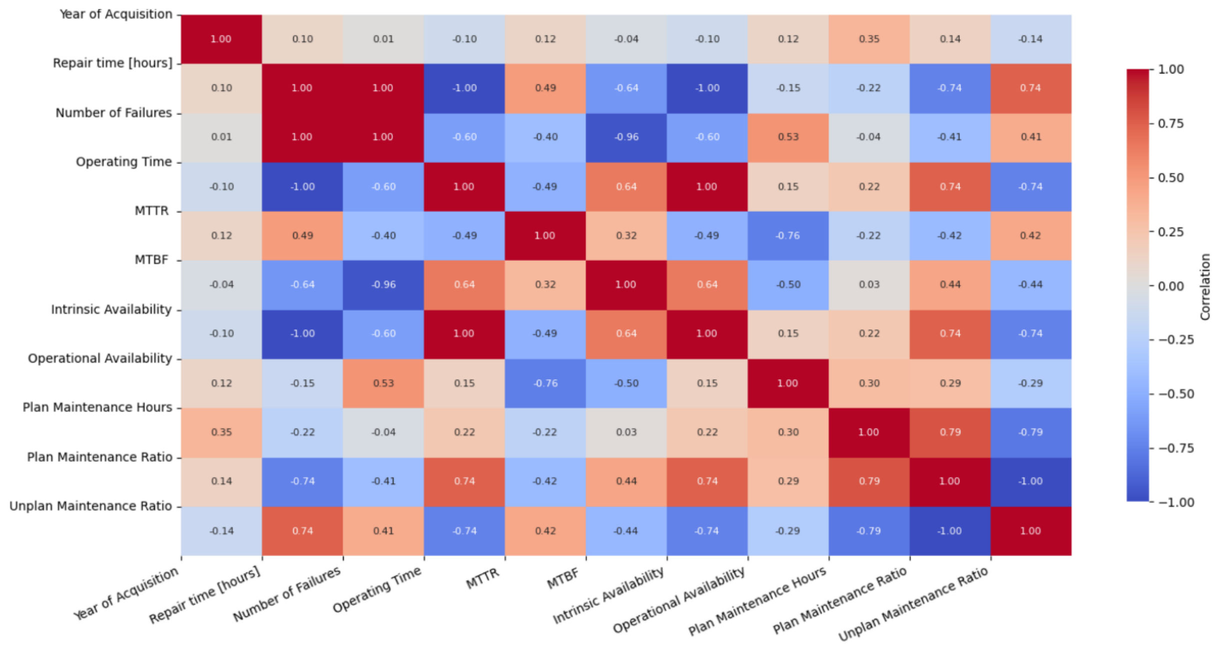

Figure 4 - Correlation matrix with metrics

A moderate negative correlation is observed between the year of acquisition of the buses and performance metrics such as Intrinsic Availability and MTBF, which is expected as wear and tear tend to affect reliability over time. Older vehicles are likely to exhibit lower availability and reliability due to an increase in failures and maintenance requirements.

The MTBF shows a moderate negative correlation of approximately 0.64 with "Repair time [h]," indicating that longer repair times tend to be associated with a lower MTBF. This relationship suggests that vehicles requiring longer repair durations may be less reliable, leading to shorter intervals between failures. While the correlation is not very strong, it reinforces the importance of optimizing repair times to improve overall reliability.

Intrinsic availability shows an inverse correlation with the number of failures, repair time, and MTTR. This demonstrates that effective maintenance and a lower failure rate contribute to higher operational availability.

Another notable observation is the relationship between planned and unplanned maintenance. A positive correlation is observed between the proportion of planned maintenance and operational availability, highlighting the importance of proactive and scheduled maintenance activities in ensuring up time. Conversely, unplanned maintenance proportions show a negative correlation with operational availability, such as unexpected failures and reactive repairs, disrupting operations and reducing performance.

4.1.3 Oil Analysis Parameters

The third stage of the correlation analysis focused on the lubricating oil analysis, aiming to evaluate associations between physicochemical oil properties and operational variables, particularly mileage. The goal was to identify degradation patterns and metal accumulation in engine oil as a function of usage, providing insight into internal component wear and its relationship with vehicle operation.

To this end, all available data on oil samples were consolidated, and a correlation matrix was generated (Figure 5). The analysis specifically examined the relationship between mileage and the concentration of wear metals in the oil, such as iron (Fe), copper (Cu), chromium (Cr), lead (Pb), nickel (Ni), and manganese (Mn).

Additionally, the behavior of additive elements - including phosphorus (P), zinc (Zn), and calcium (Ca) - was also assessed, allowing for a broader understanding of both degradation processes and additive depletion over time.

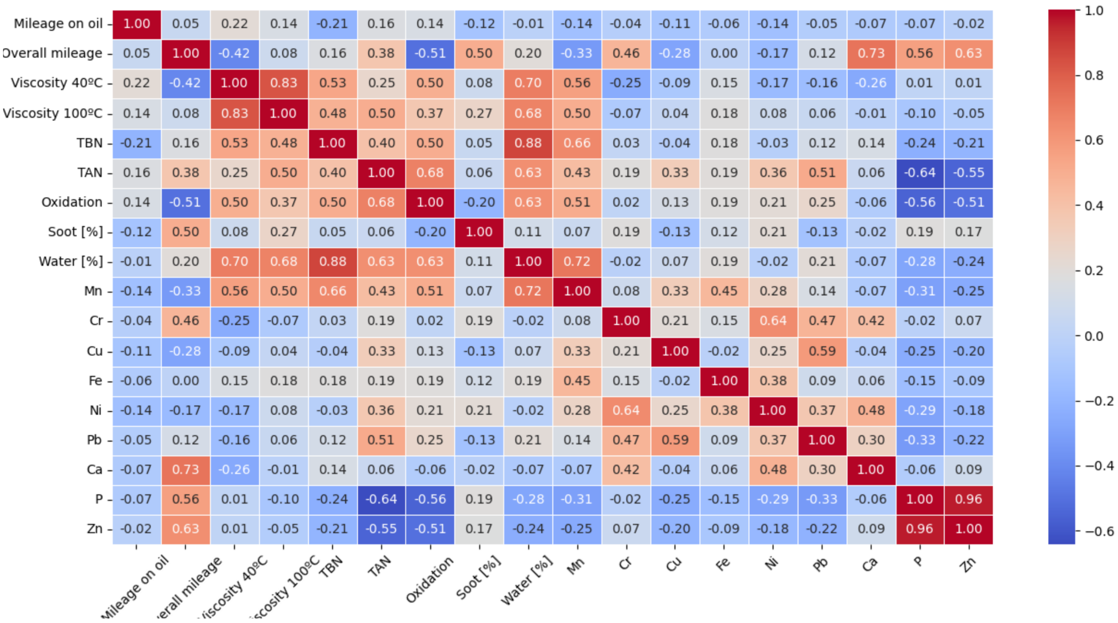

Figure 5 - Correlation Matrix between Lubricating Oil Performance Variables and Operational Indicators of the Buses

Surprisingly, the results deviated from expected patterns. In general, mileage showed weak to moderate negative correlations with most wear metals, which exhibited slight positive or near-zero correlations. This outcome contradicts the anticipated trend in which higher mileage is associated with greater concentrations of wear metals due to progressive mechanical wear.

One possible interpretation of these results is that vehicles in better mechanical condition may have extended oil change intervals. In such cases, although the mileage is higher, wear rates may be lower, leading to reduced metal concentrations in the oil. However, this does not imply that engines become more robust over time, creating a paradox that underscores the complexity of interpreting oil degradation purely through mileage.

To deepen the analysis, the correlations were also separated by oil type, as shown in Table 7. The different oil formulations - including Lukoil 15W40, 10W40, 5W30, Urania 10W40, 5W30 and Orlen 10W40 - revealed similar patterns, with minor variations in correlation strengths.

Table 7 - Correlation Coefficients Between Mileage, Wear Metals, and Oil Degradation Indicators for Different Lubricant Types

Variable Pair	**Oil type**					
	Lukoil 15W40	Lukoil 10W40	Lukoil 5W30	Urania 10W40	Urania 5W30	Orlen 10W40
Mileage on oil Vs Cr	-0.23	0.06	0.13	-0.09	-0.04	-0.11
Mileage on oil Vs Cu	-0.09	-0.12	0.32	-0.18	0.18	0.13
Mileage on oil Vs Fe	-0.14	-0.04	0.09	0.59	0.15	-0.14
Mileage on oil Vs Pb	-0.09	-0.13	0.49	-0.37	0.41	0.25
Mileage on oil Vs Ni	-0.29	-0.09	0.15	-0.26	-0.03	-0.30
Mileage on oil Vs Mn	-0.19	-0.14	0.38	-0.03	0.28	-

Mileage on oil Vs Soot [%]	-0.23	-0.08	-0.53	0.65	-0.02	-0.20
Mileage on oil Vs Water [%]	-0.07	0.09	0.16	-0.42	0.27	-0.11
Mileage on oil Vs Oxidation	-0.05	0.22	0.53	-0.31	0.30	0.39
Mileage on oil Vs Nitration	-0.05	0.35	0.44	-0.24	0.29	-0.05
Mileage on oil Vs Sulfation	-0.02	0.36	0.45	-0.20	-0.07	-0.20
Cr Vs Fe	0.62	0.64	0.62	0.41	0.35	0.79
Cr Vs Cu	0.62	0.28	0.11	0.15	0.52	-0.02
Cu Vs Pb	0.99	0.55	0.47	0.60	0.62	0.38
Fe Vs Pb	0.58	0.40	0.57	0.20	0.65	0.39
Fe Vs Ni	0.59	0.92	0.88	0.27	0.45	0.91
Ni Vs Mn	0.32	0.59	0.15	0.61	0.12	-
Soot vs. Fe	0.50	0.64	0.58	0.59	0.06	-0.02
Soot vs. Pb	0.11	0.22	0.27	-0.37	-0.12	-0.13
Water vs. Cu	0.02	0.12	-0.56	0.32	0.32	-0.26
Water vs. Pb	-0.01	0.03	-0.16	0.47	0.71	-0.13
Oxidation vs. Fe	0.47	-0.07	0.71	0.03	0.24	0.48
Zn vs. Fe	-0.28	0.23	0.60	0.83	0.09	0.01
Zn vs. Pb	-0.47	0.06	0.16	-0.34	-0.40	-0.23
Zn vs. Cu	-0.47	-0.19	-0.26	-0.19	-0.15	-0.45
P vs. Fe	-0.41	0.12	0.46	0.66	-0.05	0.70
P vs. Pb	-0.49	-0.04	0.08	-0.55	-0.54	-0.06
P vs. Cu	-0.44	-0.26	-0.17	-0.37	-0.27	-0.08

In addition to correlations with mileage, relationships among metal concentrations and degradation indicators were also examined. Strong positive correlations were found between various wear metals (e.g., Fe vs. Ni, Cu vs. Pb), suggesting that when one type of wear is present, others tend to co-occur. This pattern may reflect the simultaneous degradation of multiple engine components under certain operational or lubrication conditions.

Furthermore, associations were observed between soot content and wear metals, particularly iron and lead, indicating that oil contamination may be linked with abrasive wear. Similarly, oxidation and nitration — markers of thermal and chemical oil degradation — showed moderate to strong correlations with iron and other metals in some oil types, reinforcing the importance of monitoring these parameters as indicators of engine health.

These findings underscore the complexity of interpreting oil analysis data, which is influenced not only by operational factors such as mileage but also by maintenance practices, oil type, and engine condition. The results highlight the need for a more nuanced approach in CBM, where oil parameters are used alongside other reliability indicators to optimize maintenance schedules and extend asset life.

4.2 The Pareto Analysis

Based on the analyzed fault data, the frequency of critical bus failures was calculated. These failures necessitate immediate vehicle immobilization. Such incidents result in financial losses for the transport company and erode passenger confidence. To prevent these occurrences, regular vehicle inspections by drivers, routine technical checks, and skilled maintenance are essential. Analysis of historical repair data can also help identify recurring failure patterns.

The Pareto principle, also known as the 80/20 rule, states that 80% of the results come from only 20% of the causes. This means that achieving greater benefits or effects can be done with less resources and effort.

To identify the areas that require immediate attention and improvement, the Pareto method was used.

The purpose of the Pareto method was to identify areas of improvement that can yield the best results for the public transport company. These improvements can be corrective or preventive measures. This method can be beneficial in decision-making related to the functioning of the enterprise and can also help in solving economic problems.

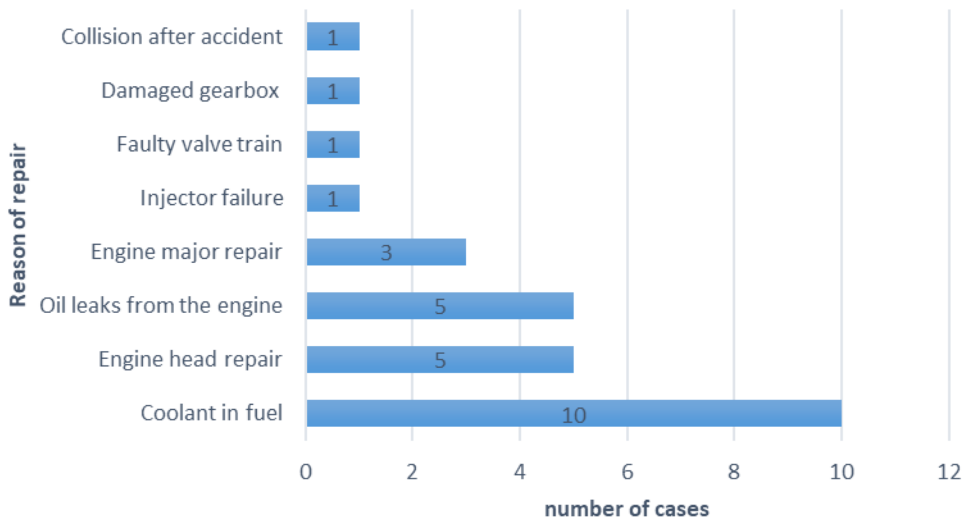

Figure 6 - Summary of critical faults in the buses analyzed

Figure 6 summarizes critical bus failures during the period analyzed. Among the fifty-three buses examined, single incidents of collision with another vehicle, gearbox failure, valve system damage, and engine power supply system failure were recorded. Additionally, three buses underwent complete engine overhauls, five experienced excessive engine oil consumption, and five required engine head replacement. The primary cause of critical bus failures was coolant contamination.

The graphical interpretation of the share of individual elements is a Pareto chart. Showing cumulative values for factors in descending order produces a Lorenz curve. Isolating three groups of parts that have different importance in the interpretation of the results is called the ABC method, and determining the group of 20% of parts that entail 80% of the results is the idea of the 20-80 rule. The list of critical failures that occurred on buses is presented in Table 8.

Table 8 - Pareto analysis: list of critical failures in buses

Nº	Reasons of repair	Number of cases	Share in reasons of occurred failures [%]	Cumulative number of cases [%]	Category
1	Coolant	10	37%	37%	A
2	Engine head repair damage	5	19%	56%	A
3	Oil leaks from the engine	5	19%	74%	A
4	Engine major repair	3	11%	85%	B
5	Collision after accident	1	4%	89%	B
6	Injector failure	1	4%	93%	C
7	Faulty valve train	1	4%	96%	C
8	Damage gearbox	1	4%	100%	C
Total		27	100%	100%	

The results of categorizing the failures dataset based on the ABC method are shown in Table 8. The Pareto chart organizes the results into three categories:

- Category A - Characterized by a condition in which approximately 20% of items result in approximately 80% of the total failures.
- Category B - Condition in which about 30% of the items results in about 15% of the results.
- Category C - Characterized a condition in which approximately 50% of the items result in approximately 5% of the result.

The ABC grouping method results are shown in Table 9. The results of empirical research indicate small deviations from these proportions, but the main idea of the 20-80 rule remains unchanged.

Table 9 - Pareto analysis: ABC method results

Category	Share in total reasons of failures [%]	Cumulative share in total number of failures [%]
A	25%	55.5%
B	37.5%	33.4%
C	37.5%	11.1%

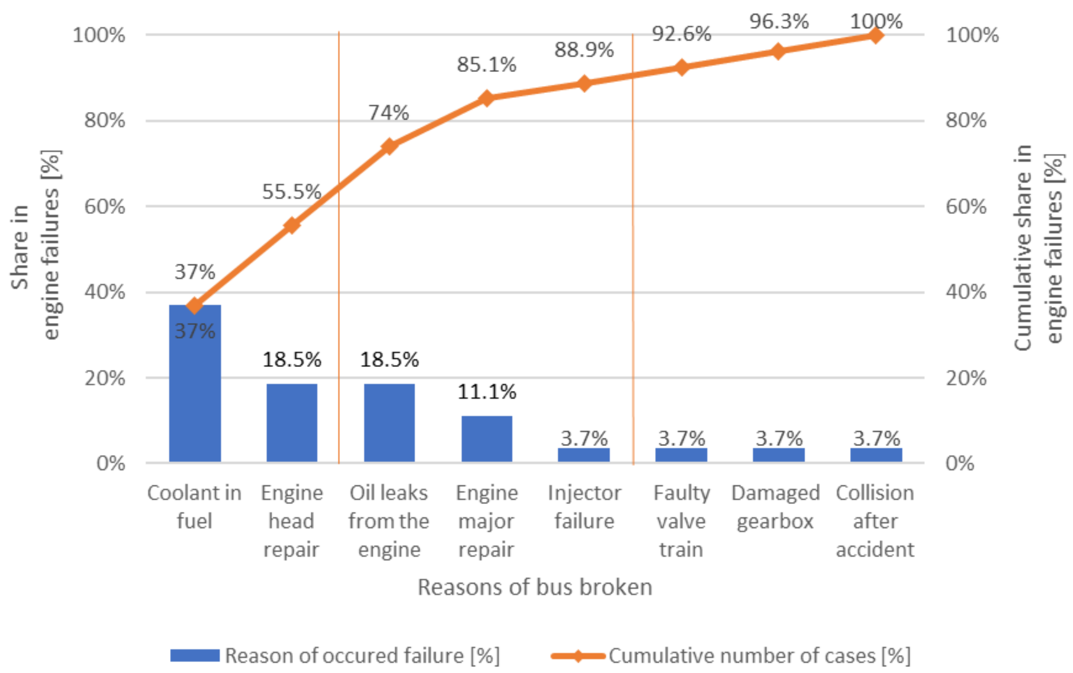

Figure 7 - Pareto chart and Lorenz curve of critical failures in buses

The Pareto chart and Lorenz curve combined in a chart are presented in Figure 7. A Pareto analysis revealed that the most significant benefit for the public transport company would be to reduce the frequency of engine failures caused by coolant leaks. These failures, often requiring engine head replacement, account for 55.5% of all critical breakdowns leading to bus immobilization.

4.3 Analysis of Fleet Performance and Maintenance Patterns

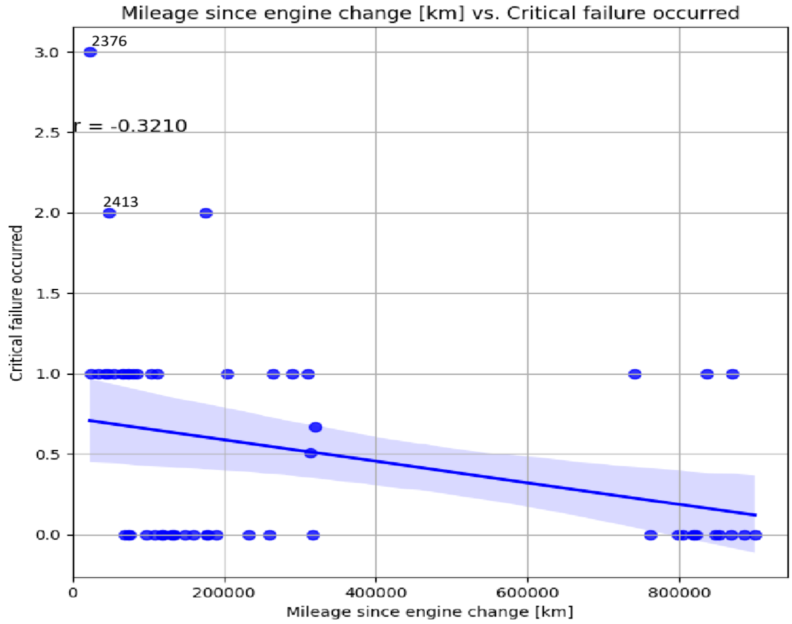

Figure 8 - Summary of the occurrence of critical failures in the buses analyzed

Figure 8 illustrates the frequency of critical bus failures. As previously mentioned, a negative correlation exists between critical failures and mileage since the last engine replacement. The graph further highlights a concentration of critical failures within the first 100,000 kilometers post-repair. Notably, buses 2376 and 2413 both experienced multiple critical failures during this period. Enhanced vehicle monitoring is recommended for this critical mileage range.

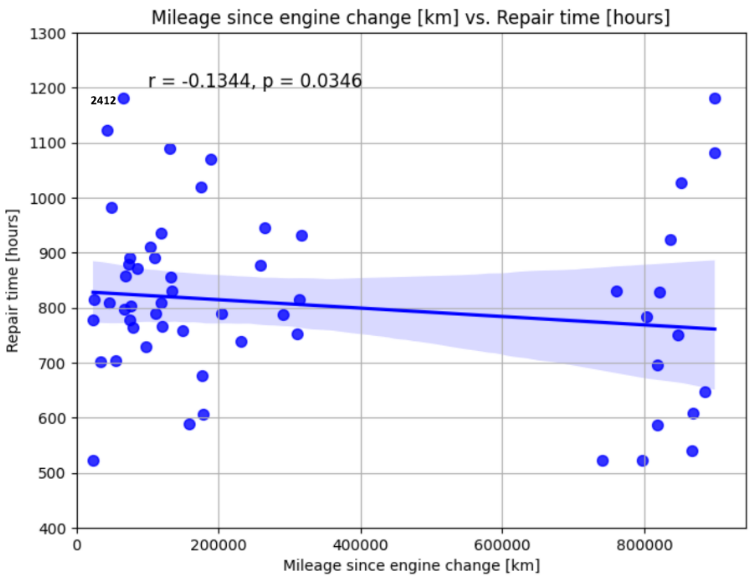

Figure 9 - Summary of repair times in the analyzed buses

Figure 9 compares repair times for individual buses against mileage since the previous critical failure. The average repair time for the entire fleet of buses analyzed over a period of 1.5 years was 816 hours. A negative correlation was found between repair time and mileage since engine replacement. Notably, 57% of the buses with under 200,000 kilometers since engine replacement had repair times shorter than the average. This is in line with the increased frequency of secondary critical failures observed in this mileage range. Bus 2412, with a gearbox failure, recorded the longest repair time at 1182 hours, 45% above the average.

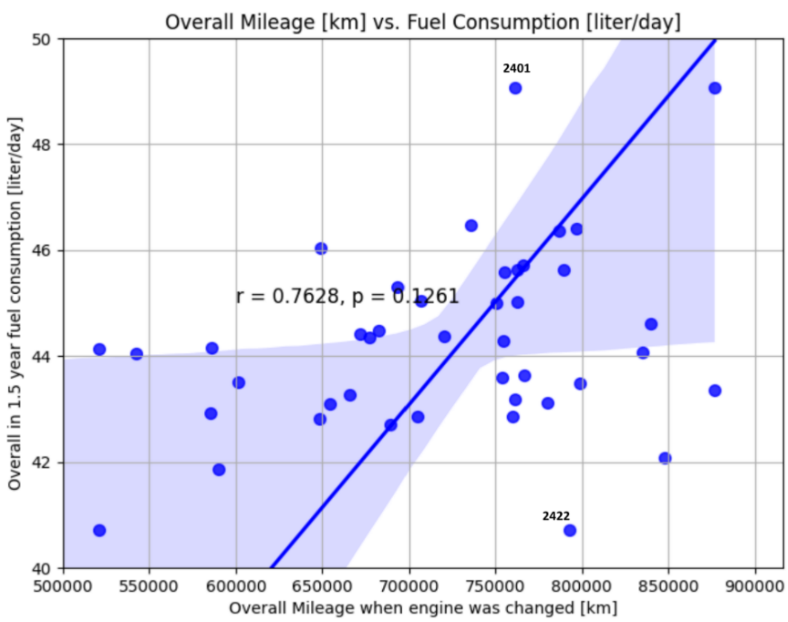

Figure 10 - Summary of fuel consumption in liters/day in the buses analyzed

From the analysis of Figure 10, it is noteworthy that the average fuel consumption was 44.36 liters for an average daily distance of 122 kilometers. A correlation between increased mileage and higher fuel consumption was observed. Bus 2401 consumed the largest amount of fuel (49.06 liters/day), 11% above average, while covering 11% more kilometers daily. A November check engine light indicated a faulty fuel filter base, potentially causing fuel leaks. The filter was replaced. Despite longer distances and no critical failures, repair time was 11% below average. Bus 2422 achieved the lowest fuel consumption of 40.72 liters, 8% below average, with 8% fewer kilometers daily. However, it suffered a critical engine failure due to excessive oil consumption in the busy winter period. A fuel filter was replaced in March. Multiple engine seal repairs linked to coolant leaks were conducted. Potentially, such repairs could prevent excessive engine overheating, thus resulting in lower fuel consumption.

4.4 FMECA Analysis

In this study, the FMECA approach is applied to analyze the critical failure modes affecting city buses, specifically Autosan Sancity M12LF models. The analysis starts by outlining the system's operational scope and examining key components, like cooling, fuel supply, and the engine. Each potential failure is evaluated using Severity (S), Frequency (F), and Detectability (D) factors to calculate a Risk Priority Number (RPN). This RPN guides the prioritization of corrective actions based on failure criticality.

Table 10 - Identification and Prioritization of Critical Failures in Urban Buses Using FMECA Analysis

Failure Group	Failures	Failure causes	Maintenance action	Number of occurrences	Probability	S	F	D	RPN
CF (Critical Failure)	Engine	Coolant in fuel, engine head repair, oil leaks from the engine	Removed / installation	27	1.23%	8	3	4	96
CL (Coolant Fluid Leakage)	Overheating, leakage of coolant	Leaks in the cooling system	Cooling system - repair	237	10.77%	8	7	5	**280**
	Leaks in the cooling system	Compression in the cooling system	Cooling system - sealing	291	13.22%	7	8	4	224
	Leaks in the cooling system	Cracked or loose thermostat housing, faulty radiator hoses	Cooling system - top up fluid	398	18.08%	7	7	5	245
FL (Fuel Leakage)	Fuel Supply system	Fuel pump malfunction, clogged fuel filter	Replace injection system	55	2.50%	8	2	6	96

	Fuel leaks	Leaking fuel lines, fuel tank damage	Fuel supply system - repair	24	1.09%	8	4	5	160
	Fuel injector issues	Fuel injector (clogged, weak)	Fuel supply system - resultant	57	2.59%	8	4	3	96
	Lack of engine power	Clogged fuel filter	Fuel filter replacement	36	1.64%	5	3	7	105
OL (Engine Oil Leakage)	Oil leakage	Loose or damaged oil filter, worn or damage turbocharger seals	Check pipes leaks and connections	51	2.32%	7	4	8	224
	Oil leakage	Oil pan gasket, engine head gasket, seals the rear of the crankshaft, camshaft seals	Engine - sealing	158	7.18%	7	6	6	252
EH (Engine heating/lack of heating)	Heating	Heat exchange failure	Check heating element	408	18.54%	5	9	2	90
CE (Check engine (red) - hot coolant)	Hot coolant	Faulty thermostat	Thermostat replacement, water cooler replacement	10	0.45%	4	2	8	64

Upon examining Table 10, it becomes evident that the most critical issues demanding close attention are associated with the cooling system. Cooling system failures, particularly those related to overheating and fluid leaks, are among the most critical, with maximum RPN values reaching 280. These failures stem from multiple causes, including system leaks, compression issues, and defects in the thermostat housing and radiator hoses. The high RPN values reflect both the severity of these failures and their frequency, with leak-related issues showing the highest probability of occurrence, up to 17.95%. Cooling system failures can cause serious engine damage due to overheating, shortening engine lifespan and resulting in costly repairs.

Engine-related failures and fuel system issues also present significant risks. Engine failures can lead to severe damage and costly repairs, while fuel system leaks pose safety hazards.

This analysis will serve as a basis for fault tree analysis.

4.5 Ishikawa Diagram

In this section, an Ishikawa diagram is used to identify and categorize the root causes leading to coolant leakage. This analysis helps visualize the interactions between different failure modes, supporting a structured approach to diagnosing and preventing critical issues.

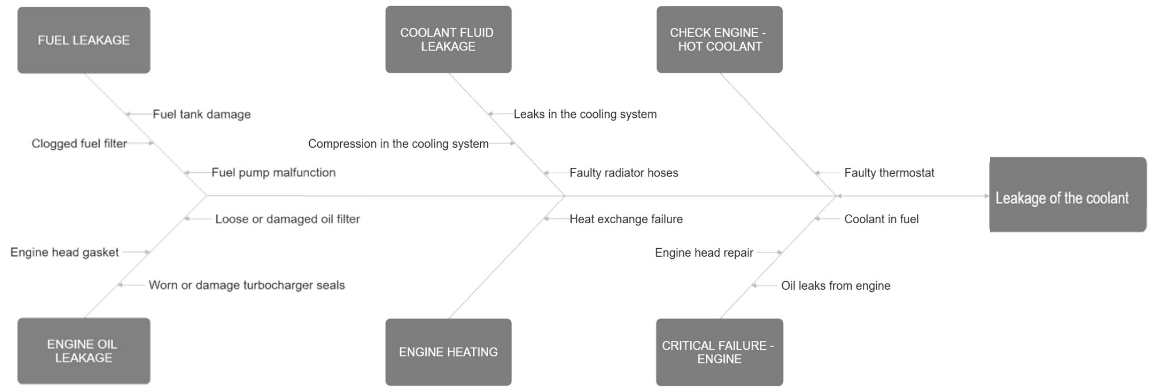

Figure 11 - Ishikawa Diagram

Based on the analysis of Figure 11, it is possible to identify several causes that directly contribute to the main event, which, in this case is the "coolant leakage”. Through the categories presented, such as "Fuel System Failure," "Cooling System Failure," and "Engine Failure," they can be observed that various component failures, such as clogged fuel filters, fuel pump malfunctions, radiator hose issues, and thermostat failures, can interact and lead to this critical event.

4.6 Fault Tree Analysis

This section applies Fault Tree Analysis (FTA) to systematically identify the root causes and failure combinations that lead to critical system issues. By mapping failure pathways, this analysis supports maintenance decision-making and enhances system reliability.

In this specific analysis, we began by identifying the top event for the fault tree, "Leakage of coolant", which was selected due to its high severity, difficulty in early detection, and potential to trigger other critical secondary failures. This event was considered a priority for monitoring and prevention, as it would necessitate complex maintenance if it occurred.

Once the top event was defined, we identified intermediate events that could contribute to this critical failure. These events were derived from the FMECA data, focusing on subsystems with failure modes that could directly or indirectly lead to coolant leakage into the fuel. For this system, intermediate events included overheating the engine, leaks in the cooling system, damage to the head gasket, engine oil leaks and compression in the cooling system. Each of these intermediate events represents a step in the potential failure path leading to the top event, providing a structured view of how various subsystems could interact to cause a critical malfunction.

Following this, they were identified basic events, which are the primary and independent causes underlying each intermediate event. The basic events included specific failures such as heat exchanger failure, faulty thermostat, worn or damaged radiator hoses, broken water pipes, excessive compression in the cooling system, loose or damaged oil filter, among others. These basic events are the root causes that, when combined, can lead to the intermediate events, and subsequently, the top event. By breaking down the failure pathways into these discrete events, we could better understand the foundational issues that require attention in maintenance planning.

With the top event, intermediate events, and basic events defined, we constructed the fault tree, which is shown in Figure 12. In this diagrammatic representation, the top event is placed at the top of the tree, with intermediate and basic events branching out below it in a hierarchical structure. Logical gates are used to show the relationships between events, specifying how combinations of basic and intermediate events can lead to the top event.

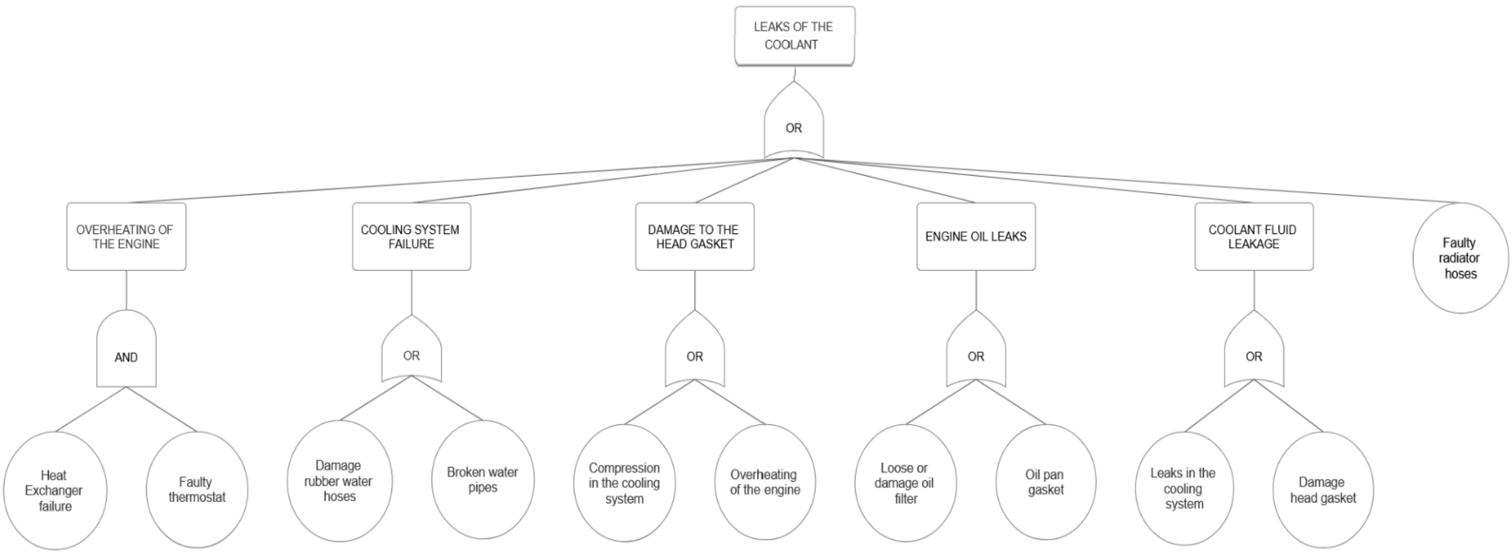

Figure 12 - Diagram of Fault Tree Analysis

Table 11 - Probabilities of the basic events associated with the fault tree

Failure Event	Probability (%)
Heat exchanger failure	18.54
Faulty thermostat	0.45

Damage rubber water hoses	2.32
Broken water pipes	2.32
Compression in the cooling system	13.22
Overheating of the engine	10.77
Loose or damage oil filter	2.32
Oil pan gasket	7.18
Leaks in the cooling system	10.77
Damage head gasket	7.18
Faulty radiator hoses	18.08

After constructing the fault tree, it is important to identify the Minimal Cut Sets (MCS). This requires knowing the probabilities of the basic events associated with the fault tree, as shown in

Table 11.

The MCS represents the smallest combinations of basic events that, if they occur, would lead to the top event. These sets are invaluable for prioritizing maintenance actions, as they pinpoint specific failures that could most directly and critically impact system performance. In this analysis, we identified the MCS to include scenarios, like engine overheating, cooling system leaks, and head gasket damage, among others. By analyzing these MCS, we calculated the probability of the top event by summing the probabilities of each MCS while accounting for overlaps to prevent double counting.

The probability of an MCS composed of multiple basic events connected by an AND gate is calculated by multiplying the probabilities of all individual basic events. This assumes that the events are statistically independent. The Equation is the 4:

$$P_{MCS} = P(E1) \times P(E2) \times \ldots \times P(E_n) \quad (4)$$

Where E_1, E_2 and E_n are the probabilities of the basic events in the MCS.

When multiple MCS are connected by an OR gate, the combined probability accounts for the union of events. This is calculated according to Equation 5:

$$P_{Top} = 1 - \sum_{i=1}^{m}(1 - P_{MCSi}) \quad (5)$$

Where P_{Top} is the probability of the top event, and P_{MCSi} represents the probability of each minimal cut set. This equation accounts for the overlapping probabilities between different MCS.

Table 12 - Contribution of each Minimal Cut Set (MCS) to the Top Event Risk

Minimal Cut Sets (MCS)	Probability (%)
MCS7	18.08 %
MCS6	17.17 %
MCS5	13.22 %
MCS4	10.77 %
MCS3	9.32 %
MCS2	4.58 %
MCS1	0.08 %

The fault tree analysis revealed that the minimal cut set "Faulty radiator hoses" has the highest probability of occurrence, at approximately 18%, representing the most critical scenario for the occurrence of the top event. This high probability indicates that the radiator hoses are more likely to experience issues compared to other basic events in the system. This conclusion is visually supported by Table 12, which clearly highlights the dominant contribution of this failure mode to the overall system risk.

Using the probabilities provided in the FMECA, we estimated the probability of the top event, "Leakage of coolant". Based on the probabilities of each MCS, the cumulative probability was approximately 54%, indicating a significant risk of coolant leakage due to the multiple failure paths that can lead to this top event. This value reflects that the system's current configuration and reliability of components allow for a high likelihood of coolant leakage, suggesting that there are critical vulnerabilities in the system that need to be addressed.

FTA allowed for a structured and thorough examination of failure paths leading to the critical event. By visually mapping these pathways and calculating the MCS, we gained a clearer understanding of how individual component failures contribute to the overall risk. This insight enables more focused and effective maintenance planning, prioritizing actions that address the most critical basic events to prevent the top event from occurring. This analysis underscores the importance of regular inspections and maintenance on the cooling system, thermostat, and oil seals, as well as prompt repairs for any detected leaks or overheating issues. Through such preventive actions, the likelihood of coolant leakage into the fuel can be reduced, enhancing the reliability and safety of the system.

4.7 Analysis of Performance and Reliability Metrics

To evaluate the performance and reliability of the fleet, Key Performance Indicators (KPIs) were used, with a focus on MTTR and MTBF. In this analysis, it is crucial to distinguish between Intrinsic Availability and Operational Availability. Intrinsic Availability represents an idealized measure of system uptime, considering only repair time and failure rates, without accounting for external factors. In contrast, Operational Availability expands this concept by incorporating real-world variables such as spare parts availability, workforce efficiency, and administrative processes, providing a more realistic assessment of fleet readiness. These KPIs are essential for understanding maintenance effectiveness, optimizing resource allocation, and maximizing fleet availability.

For this analysis, only data from the year 2023 was considered. Using a one-year period provides a clearer and more accurate view of the fleet's performance and reliability within the context of the practices and strategies adopted during that year.

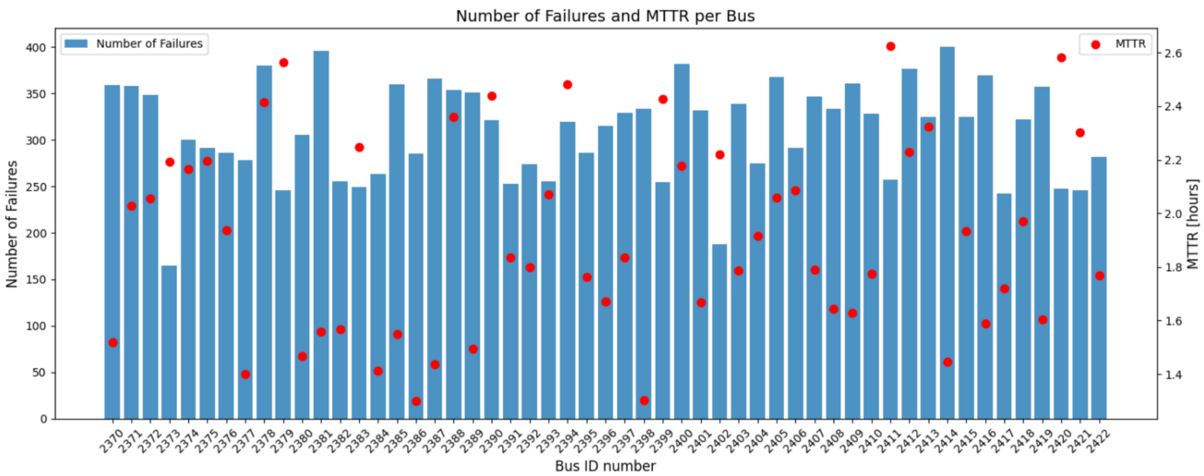

Figure 13 - MTTR and Number of Failures per Bus: Analysis of Mean Time to Repair in Relation to Failure Occurrences

Figure 13 presents the number of failures (blue bars) and the Mean Time to Repair (represented by red dots) for different buses (identified by their IDs on the X-axis). It is noticeable that the number of failures varies widely among the buses, with most showing values between 300 and 500 failures, while the MTTR predominantly ranges between 1.4 and 2.5 hours, with no obvious correlation to the number of failures. This suggests that, although some buses experience more failures, the average time to repair these failures does not increase proportionally. Therefore, the MTTR seems to be more related to the efficiency of maintenance processes rather than the frequency of failures. Variations in MTTR may also indicate differences in the complexity or severity of failures across the buses.

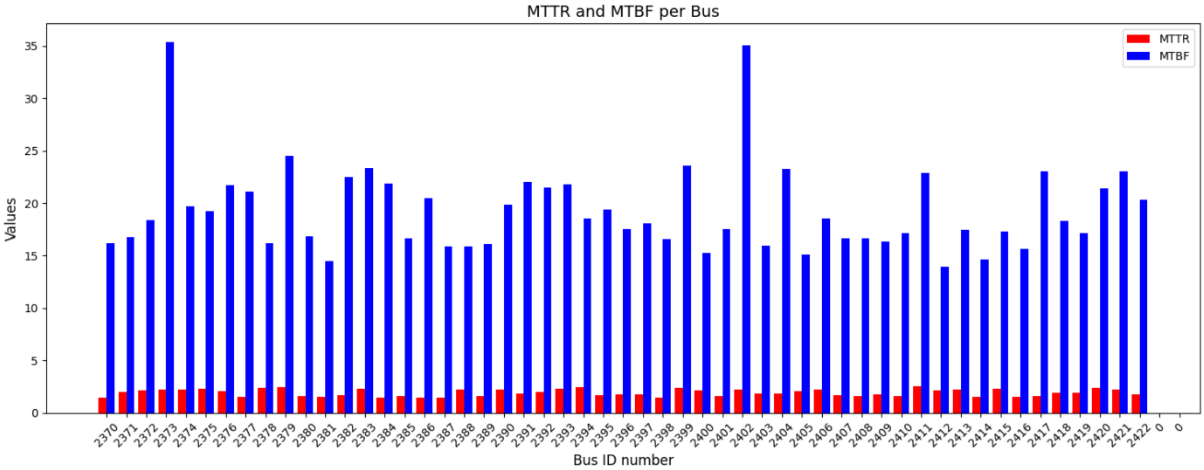

Figure 14 - MTTR and MTBF per bus

Figure 14 shows the MTTR and MTBF values for the 53 buses in the fleet. It is evident that the MTBF is significantly higher than the MTTR for all buses, which is desirable as it indicates that the average time between failures far exceeds the time required to repair them.

However, there are substantial variations in MTBF among the buses, with some showing extremely high values (such as buses with IDs 2373 and 2402), while the rest remain around the average. These differences may be related to the overall performance of the vehicles, maintenance quality, or operational use.

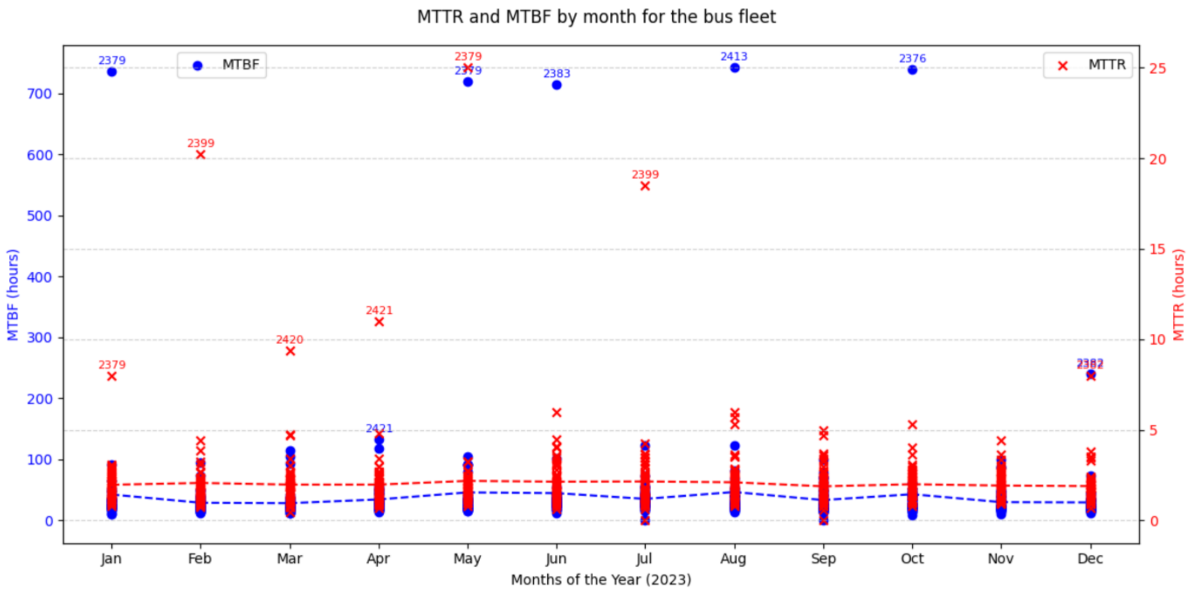

Figure 15 - Monthly Analysis of MTTR and MTBF of the Bus Fleet in 2023

A more detailed analysis, as illustrated in Figure 15, showing the monthly trends of MTTR and MTBF for the bus fleet in 2023. The image reveals that the MTBF remains relatively stable throughout the year, with minor fluctuations. However, there are outliers in certain months where some buses show significantly higher MTBF values (for example, bus ID 2376 in October and ID 2413 in August). These outliers may indicate periods of exceptional performance or a reduction in the operational load of these vehicles. On the other hand, the MTTR shows a relatively consistent trend across the months, with minimal variations. The consistency of the MTTR suggests that maintenance processes are generally efficient and not significantly influenced by seasonal fluctuations or changes in operational demand. However, the occurrence of buses with high MTTR values (e.g., bus ID 2379 in May) may indicate occasional challenges in addressing specific failures, possibly due to their complexity, parts availability, or labor limitations.

The relationship between MTTR and MTBF underscores the overall efficiency of fleet management. Despite the occasional higher MTBF values, the repair times do not show a corresponding increase, which is a positive indicator of maintenance capacity. However, the substantial variation in MTBF across buses may suggest differences in operational conditions, vehicle aging, or a greater focus on preventive maintenance.

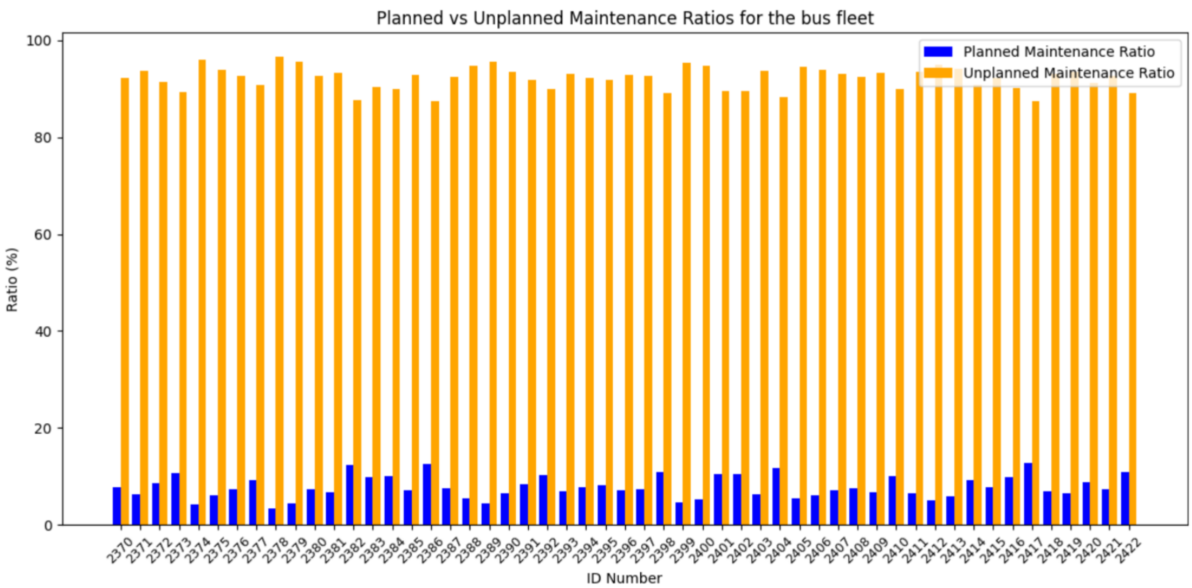

Figure 16 - Planned and unplanned maintenance ratios for the bus fleet

Figure 16 reveals that the proportion of unplanned maintenance (represented in orange) significantly exceeds planned maintenance (represented in blue) for the analyzed bus fleet. This disparity highlights a concerning pattern, indicating that a large portion of the maintenance carried out on the fleet is corrective rather than preventive.

The low proportion of planned maintenance suggests that the preventive maintenance being conducted may not be sufficiently effective. This scenario can lead to several issues, such as increased operational costs, longer vehicle downtime, and potential disruptions in transportation services.

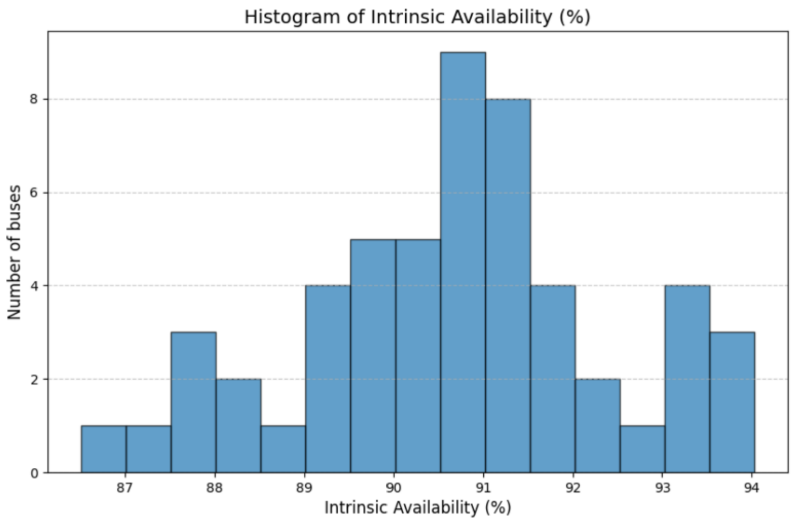

Figure 17 - Distribution of Intrinsic Availability for the bus fleet

Figure 17 shows the distribution of intrinsic Availability (%) for the bus fleet, ranging from 87% to 94%. Most buses have an availability of approximately 90% to 91%, with this interval being the most frequent (with around 9 occurrences). This indicates that the fleet generally has high reliability. However, there are fewer buses with lower availability (87%-89%) or higher availability (92%-94%), showing that the fleet's performance varies but clusters primarily in the mid-range of intrinsic availability.

An analysis of the relationship between intrinsic and operational availability is essential for evaluating the performance of the bus fleet. While intrinsic availability reflects the reliability and technical capability of the vehicles under ideal conditions, operational availability considers the impact of external factors, such as maintenance, logistics, and downtime. Figure 18 presents a comparison of these metrics for each vehicle in the fleet.

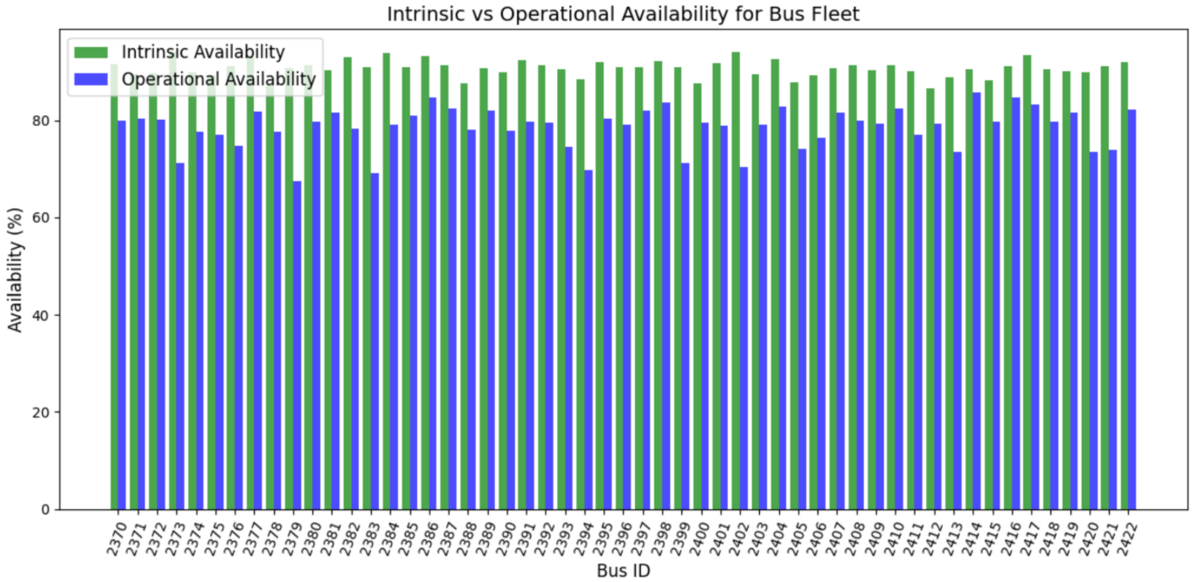

Figure 18 - Relationship Between Intrinsic and Operational Availability for the Bus Fleet

There is a significant dispersion in the values, indicating that performance varies considerably among the vehicles. A general positive trend can be observed, where vehicles with higher operational availability also tend to exhibit higher intrinsic availability, although this relationship is not uniform.

Some vehicles, such as those identified by numbers 2402, 2384, and 2382, show high intrinsic availability but are not always aligned in terms of operational availability.

Most vehicles fall within the intermediate range, with operational availability between 80% and 90% and intrinsic availability between 93% and 95%. These values can be considered representative of the typical performance of the fleet. However, some vehicles display outlier values, such as those identified by 2402 and 2378, which may indicate specific issues that resulted in higher unavailability.

A more detailed analysis of the data revealed that these two buses had critical failures related to excessive oil leaks from the engine. Additionally, bus 2402 had a 26% lower average daily distance (91 km) over the entire 1.5-year analysis period, and a 36% lower repair time compared to the average for the entire bus fleet. On the other hand, bus 2378 had a repair time 38% higher than the fleet average and an average daily distance only 2% lower (120 km).

4.8 Failure Probability Prediction Model

In order to estimate the likelihood of failure for each bus in the fleet, a predictive model was developed in Python. The objective of this model is to determine whether a given bus is likely to present a number of failures above the fleet's median. The model was developed with the objective of identifying high-risk vehicles, using key reliability indicators as predictive features.

The input features used in the model include repair time, operating time, availability, MTTR and MTBF. The output is a binary target variable named "Failure_Class", which was constructed by comparing the number of failures of each bus against the median number of failures across the fleet. Buses with a number of failures above the median were labeled as 1 (high risk), and those below or equal to the median as 0 (low risk).

The dataset was then split into a training set (70%) and a test set (30%), maintaining a representative distribution of the target classes. The predictive model was built with an input layer with five neurons (one for each feature), two hidden layers one with 64 neurons and the other with 32 neurons, and an output layer with 1 neuron with sigmoid activation (for binary classification).

The model achieved perfect classification on the test set, with no false positives or false negatives. This corresponds to a test accuracy of 100%; however, given the limited sample size (n=53), such results should be interpreted with caution due to the high risk of overfitting and lack of generalizability.

To illustrate its application, the model was used to predict the failure probability of bus ID 2382, part of the test set. The model estimated a failure probability of 0.14%, classifying it correctly as a low-risk bus. This type of prediction could be valuable in fleet maintenance planning, allowing targeted preventive actions for buses with higher predicted risk.

Nevertheless, one important limitation of this model is the small dataset size (only 53 samples). Such a limited dataset constrains the model's ability to generalize and increases the risk of overfitting. Therefore, although the preliminary results are promising, a larger dataset would be necessary to robustly validate the model's performance and ensure its applicability in real-world operational contexts.

4.9 Oil Analysis

After conducting the evaluation of fleet reliability using key performance indicators like MTTR, MTBF, and Availability, delving deeper into the issues that cause mechanical degradation and failures is necessary. Further, the engine oil condition aspect is particularly important because of its impact on component wear, thermal failure, and the failure mode progression. Failure modes can stem from obstruction of moving parts by degraded oil, including changes in viscosity, increased acidity, decreased concentration of additives, and contamination by combustion.

For these reasons, this chapter will analyze the physicochemical processes involved in the transformation of lubricating oils with respect to mileage, accumulating traces of wear, and consider supporting CBM programs. Incorporating oil analysis into a more comprehensive system of reliability enables more precise prediction of faults as well as optimization of maintenance actions on subsystems through advanced planning.

The present analysis is restricted to a single lubricant formulation - Lukoil 10W40 - selected due to its predominance in the dataset. Focusing on a single oil type ensures greater homogeneity in the data, reducing variability associated with differing additive packages and base oil compositions across brands.

The dataset under evaluation comprises a total of 58 oil samples, distributed as follows:

- 25 samples from Cummins ISB6 engines, installed in buses manufactured between 2018 and 2020.
- 20 samples from FPT INDUSTRIAL S.P.A. engines, associated with vehicles produced between 2016 and 2017.
- 12 samples from FPT INDUSTRIAL Tector engines, in buses from 2022 to 2023.
- and a single sample from an IVECO SPA ITA engine, corresponding to a bus built in 2009.

This composition reflects a diverse but well-structured sample distribution across engine types and manufacturing years, enabling the evaluation of oil degradation patterns under varied operational conditions.

4.9.1 Evolution of Oil Properties and Wear Indicators with Mileage

The continuous use of lubricants in internal combustion engines leads to progressive alterations in their physicochemical properties. These changes are primarily caused by thermal degradation, oxidation, contamination by combustion by products, and additive depletion. This subchapter aims to analyze the degradation behavior of Lukoil 10W40 engine oil as a function of mileage since the last oil change.

The following parameters were evaluated:

- Viscosity (at 40 °C and 100 °C), which reflects the oil's lubrication capacity.
- Total Base Number (TBN), indicating the oil's alkaline reserve and its capacity to neutralize acids.

- Total Acid Number (TAN), which reflects the increase in acidity due to oxidation.
- Oxidation, nitration, and sulfation, which quantify chemical degradation caused by exposure to heat and combustion gases.

Figure 19 displays the relationship between oil mileage and its viscosity measured at 40 °C and 100 °C. A moderate positive correlation is observed between mileage and viscosity at 40 °C ($r = 0.36$; $p = 0.005$), suggesting an increase in viscosity with use, potentially due to oxidation, soot contamination, and metal wear. Viscosity at 100 °C also presents a positive correlation ($r = 0.27$; $p = 0.038$), though weaker, indicating oil thickening at higher temperatures, which may impair lubrication capacity.

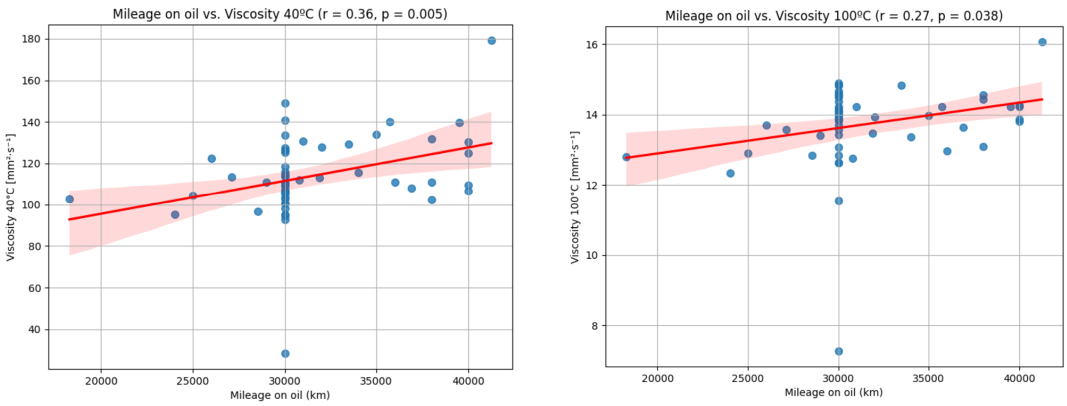

Figure 19 - Relationship between Oil Mileage and Viscosity at 40ºC and 100ºC

Figure 20 shows the relationship between oil mileage and TBN. The negative correlation ($r = -0.32$; $p = 0.015$) demonstrates that the oil's capacity to neutralize acids declines over time. This reduction is critical, as it signals a loss of corrosion protection, which may justify lubricant replacement before the TBN reaches critical levels.

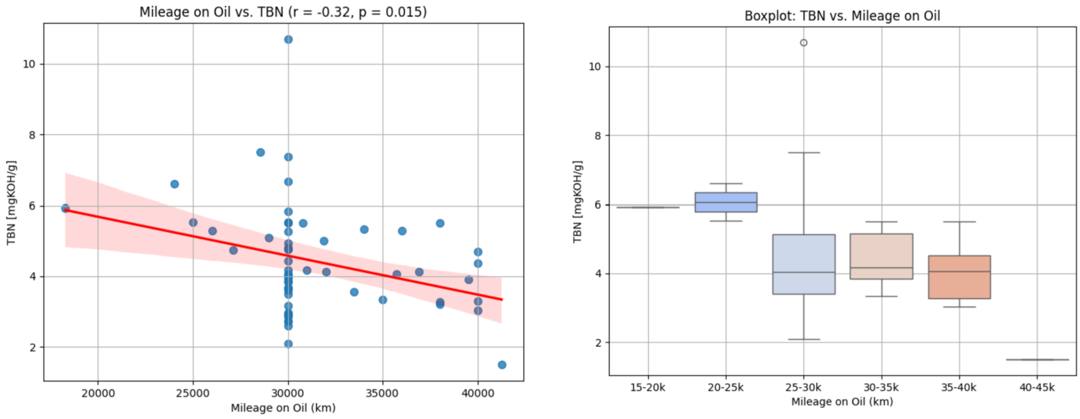

Figure 20 - Relationship between Oil Mileage and TBN

Figure 21 reveals a progressive increase in TAN with mileage, indicating the accumulation of acids in the lubricant, resulting from oxidation and contamination. This underscores the importance of continuous monitoring to prevent corrosion of internal components.

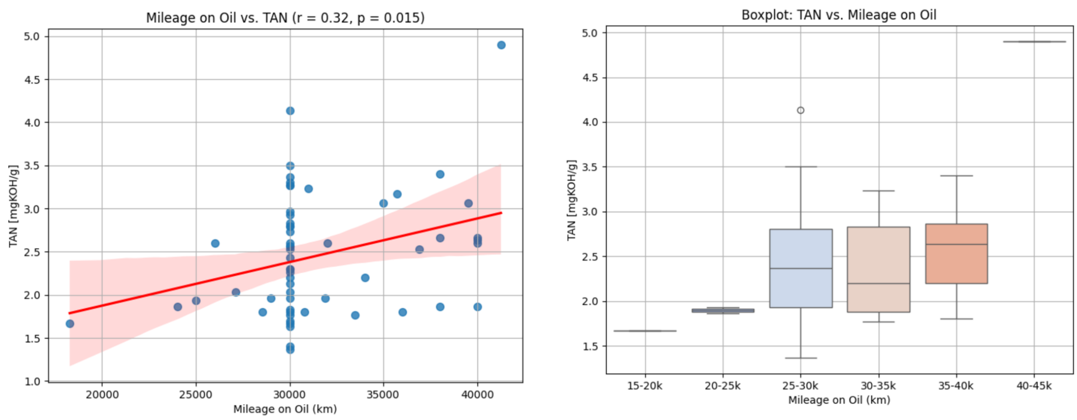

Figure 21 - Relationship between Oil mileage and TAN

Sulfation represents contamination by sulfur compounds. Figure 22 shows a moderate correlation between mileage and sulfation levels ($r = 0.36$; $p = 0.006$), indicating oil degradation caused by sulfur in fuel. Elevated sulfation can contribute to acid formation, affecting both oil stability and the corrosion resistance of metallic surfaces.

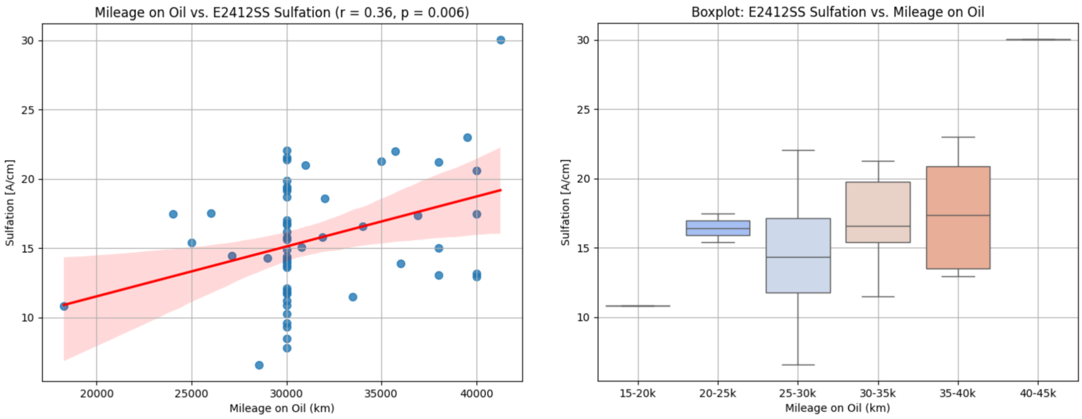

Figure 22 - Relationship between Oil Mileage and Sulfation

Nitration, caused by the interaction between oil and nitrogen oxides from combustion, exhibited a moderate correlation with mileage (r = 0.35; p = 0.007), as shown in Figure 23. This process may result in the formation of acidic compounds and harmful deposits within the engine.

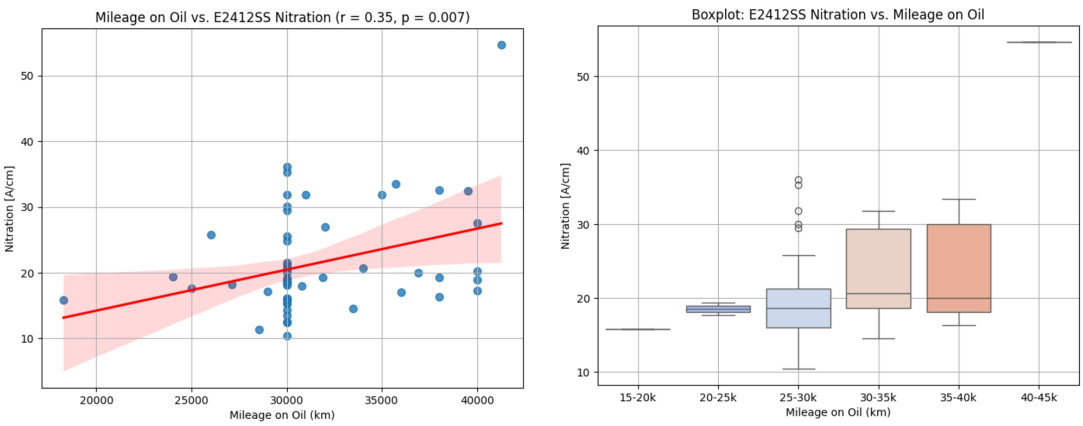

Figure 23 - Relationship between Oil Milage and Nitration

Oxidation is a natural reaction between oil, oxygen, and engine heat. Although Figure 24 suggests a weak positive correlation between mileage and oxidation levels (r = 0.22; p = 0.101), an increasing trend is observed. This may compromise the oil's viscosity and lubrication performance, even though the relationship is not statistically significant.

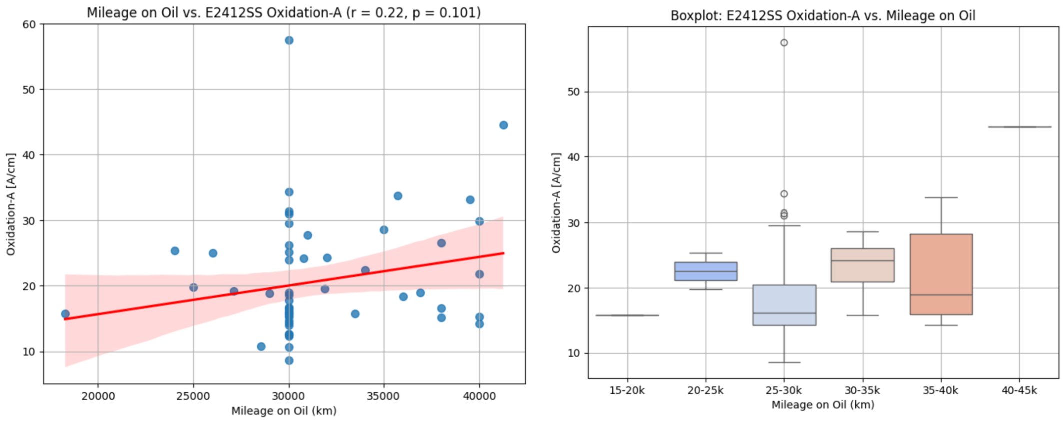

Figure 24 - Relationship between Oil Mileage and Oxidation

The results indicate a clear degradation trend of Lukoil 10W40 lubricant as mileage increases. There is a rise in TAN, sulfation, oxidation, and nitration, along with a progressive decrease in TBN - all of which are indicators of the oil's declining protective capacity. The variability observed among samples with similar mileage suggests that operational factors, such as engine type, operating conditions, and fuel quality, also significantly influence oil degradation.

These findings reinforce the importance of implementing condition-based maintenance strategies based on the actual oil condition rather than fixed mileage intervals, thereby supporting a more effective application of CBM in bus fleets.

In addition to changes in physicochemical parameters, the progressive use of engine oil is also associated with the accumulation of metallic wear particles. These elements - such as iron (Fe), copper (Cu), lead (Pb), nickel (Ni), manganese (Mn), and chromium (Cr) - are released from internal engine components due to mechanical friction, surface fatigue, and material degradation.

Figure 25 illustrates the relationship between oil mileage and iron (Fe) content. Theoretically, a positive correlation would be expected, as wear increases with engine usage. However, the dataset reveals a weak and negative correlation, contrary to this expectation. This anomaly can be largely attributed to operational factors, including oil replenishment near sampling, which dilutes metallic concentrations, and the variability in driving profiles across different buses.

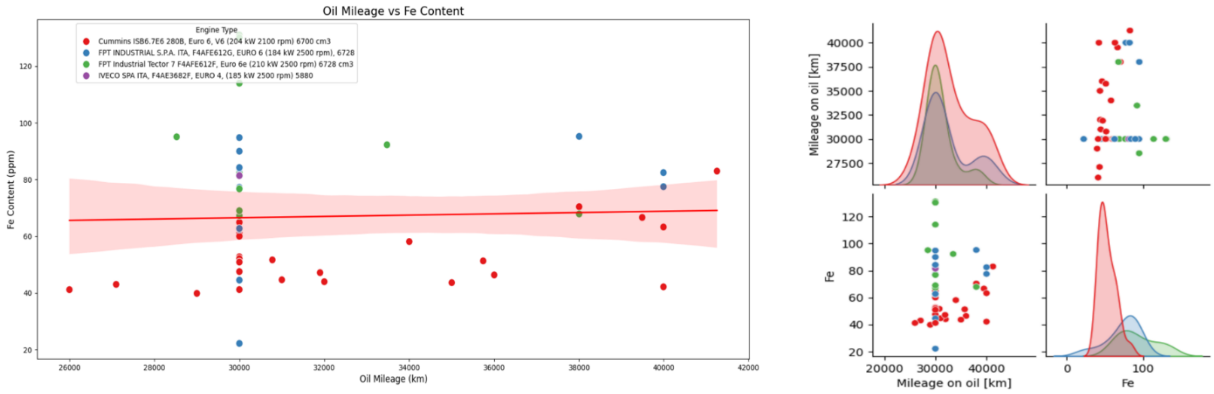

Figure 25 - Relationship between Oil Mileage and Iron (Fe) Concentration

This variability highlights a key limitation in real-world condition monitoring: wear trends are not always linearly related to oil mileage but are instead influenced by a combination of stochastic and contextual factors such as engine type, load intensity, operating temperature, and fuel quality.

Despite these limitations, tracking metal concentrations remains fundamental for CBM strategies. Abrupt increases in specific elements, or unusual ratios between them, may indicate abnormal wear mechanisms or emerging failures in particular subsystems. Therefore, combining wear metal analysis with other degradation indicators (e.g., TBN, TAN, oxidation) enhances diagnostic precision and supports targeted, condition-based maintenance interventions.

4.9.2 PCA and Clustering of Oil Variables: Loadings Analysis and Cluster Prediction via Perceptron

To deepen the data analysis and uncover underlying patterns in wear metal accumulation, Principal Component Analysis (PCA) was applied.

PCA is a statistical technique used to reduce the dimensionality of large datasets while preserving as much information as possible. It does so by transforming the original correlated variables into a new set of uncorrelated variables called principal components, which are ordered according to the amount of variance they explain in the data.

Following the PCA transformation, the K-Means clustering algorithm was used to classify oil samples into distinct groups based on their wear characteristics. This method reveals trends that may not be easily detected through traditional correlation analyses. Segmenting the data into clusters allows for the investigation of whether specific engine types or operational contexts are associated with higher wear rates, abnormal metal accumulation, or atypical degradation patterns.

The K-Means clustering was performed using the first five principal components, which together explain 71.15% of the total variance in the dataset. This means that approximately 71% of the original data variability is retained, significantly reducing complexity while maintaining most of the content. Table 13 summarizes the variance explained by each component.

Table 13 - Explained Variance by Principal Component

PCA Component	Explained Variance (%)
PC1	23.95%
PC2	19.62%
PC3	12.03%
PC4	8.08%
PC5	7.46%
Total	71.15%

The K-Means algorithm was applied with four clusters. Clustering performance was assessed using the Silhouette Score, which yielded a value of 0.4932, indicating a moderate degree of separation between groups. To better understand how well each sample fits within its assigned cluster, the Silhouette Score was also calculated individually for each cluster, as shown in Table 14.

Table 14 - Average Silhouette Score per Cluster

Cluster	Silhouette Score
Cluster 0	0.4961
Cluster 1	0.2297
Cluster 2	0.6512
Cluster 3	0.0000

Cluster 2 stands out for its strong internal cohesion (0.6512), while Cluster 0 shows a moderate structure (0.4961). In contrast, Clusters 1 and 3 show lower scores (0.2297 and 0.0000, respectively), indicating potential overlap or higher heterogeneity, possibly reflecting transitional states. The score of Cluster 3 is explained by the fact that it contains only a single sample.

Figure 26 illustrates the clustering results based on PCA components. The X-axis represents the first principal component (PC1) and the Y-axis the second (PC2). Each point corresponds to a sample, colored by cluster (0 to 3). The plot reveals clear separation between groups, indicating that the K-Means method successfully identified distinct behaviors in the reduced data.

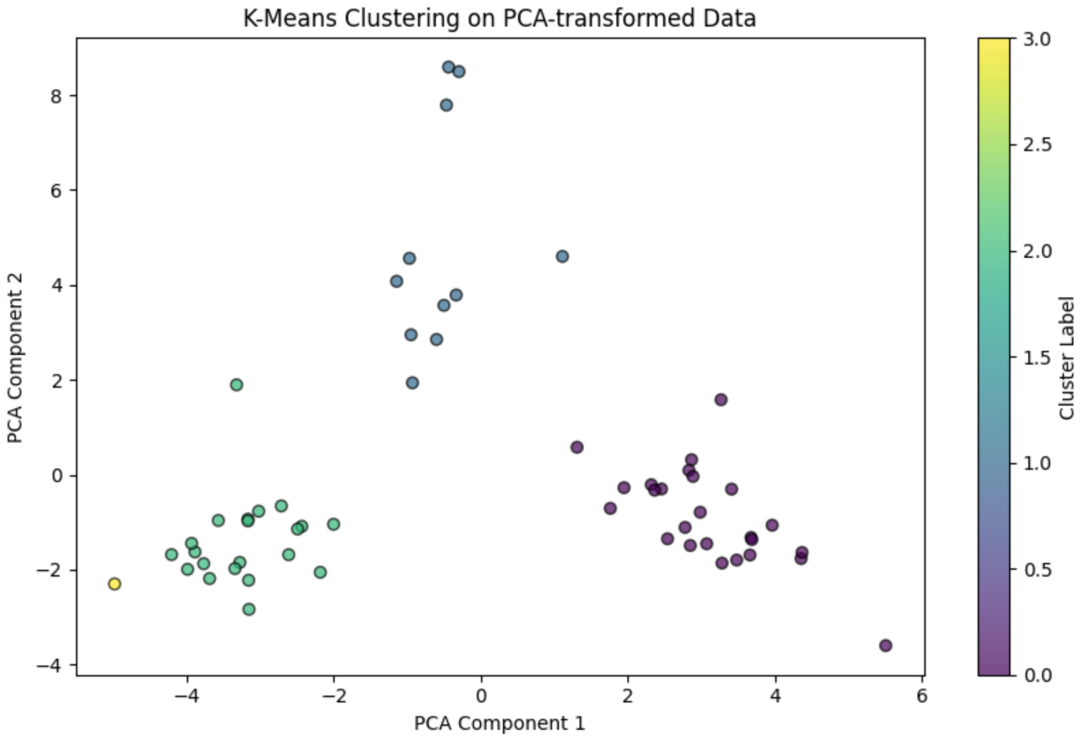

Figure 26 - Data Segmentation using K-Means after PCA Transformation

Table 15 presents the main characteristics of each cluster, including number of records, average oil mileage, total vehicle mileage, year of production of the buses, and the corresponding engine type.

Table 15 - Cluster characteristics

Cluster	Number of records	Mileage on oil (mean)	Overall mileage (mean)	Year of Production			Engine
				mean	oldest bus	newest bus	
0	25	32222.08	270413.60	2019	2018	2020	Cummins ISB6
1	11	29909.09	65138.55	2022	2022	2023	FPT Industrial Tector 7
2	21	31661.90	425443.05	2017	2016	2022	FPT Industrial S.P.A, FPT Industrial Tector 7
3	1	30000.00	759000.00	2009	2009	2009	Iveco

While no single variable fully explains the segmentation, some trends are evident. Cluster 1 includes newer vehicles (2022–2023) with low mileage and FPT Tector 7 engines. Cluster 0 consists solely of Cummins ISB6 engines in mid-aged vehicles (2018–2020). Cluster 2 is more heterogeneous, comprising various FPT engines in vehicles produced between 2016 and 2022, with higher average mileage. Cluster 3 is an outlier, representing an old Iveco vehicle from 2009 with exceptionally high total mileage.

To better comprehend the variables that underpin the formation of clusters, an in-depth examination of the PCA loadings was carried out. These loadings represent the extent to which each original variable influences the principal components, thereby highlighting those that play the most significant role in the overall data variance and, indirectly, in defining the cluster boundaries. The absolute values of the loadings for the first three principal components are shown in Figure 27 and Table 16, illustrating the strength of each variable's contribution to the respective components.

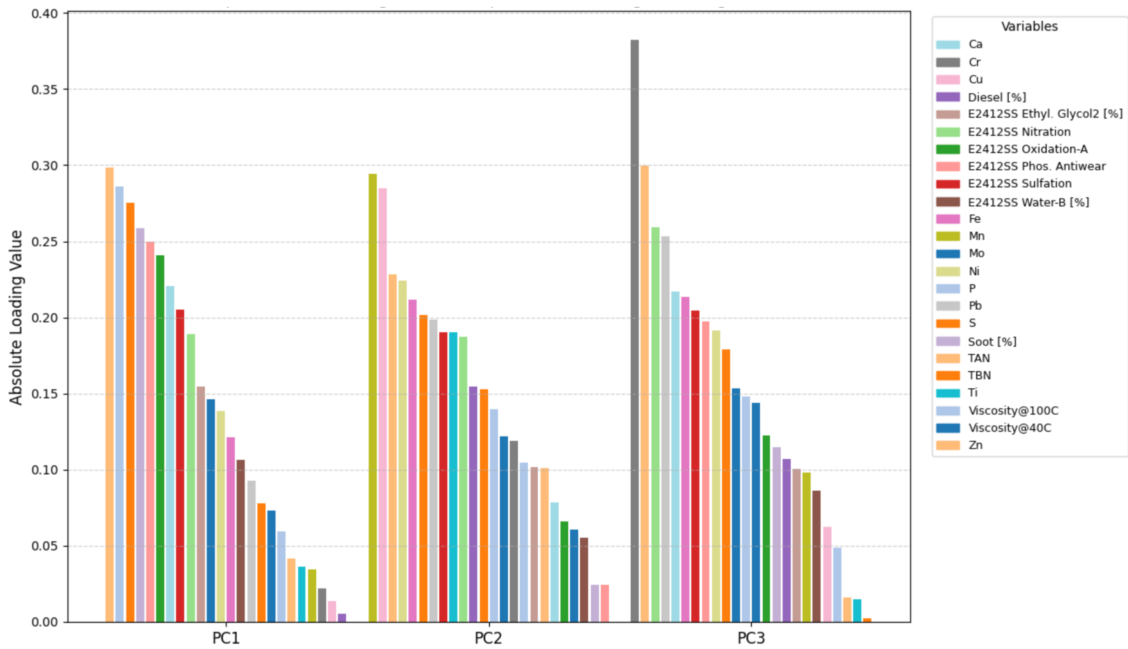

Figure 27 - Loadings of variables per Principal Component

Table 16 - Highest contributing variables to Principal Components based on Loading Values

Principal Component	Variable	Loading Value
PC1	Zn (Zinc)	0.298
	P (Phosphorus)	0.286
	S (Sulfur)	0.274
	Soot [%]	0.261
	Phos. Antiwear	0.251
PC2	Mn (Manganese)	0.296
	Cu (Copper)	0.287
	TAN	0.224
	Ni (Nickel)	0.222
	Fe (Iron)	0.211
PC3	Cr (Chromium)	0.384
	TAN	0.297
	Nitration	0.256
	Pb (Lead)	0.255
	Ca (Calcium)	0.225

The loading analysis reveals distinct patterns in how the variables influence each principal component, offering a deeper understanding of the data structure and the key factors driving cluster separation. For PC1, variables such as Zinc (Zn), Phosphorus (P), and Sulfur (S) stand out due to their association with additive depletion and wear. Soot [%] and the phosphorus-based anti-wear additive also show significant influence, as they are linked to combustion by-products and additive degradation. In the case of PC2, metallic elements, like Manganese (Mn), Copper (Cu), and Nickel (Ni) - commonly associated with component wear - carry considerable weight, along with TAN, suggesting that this component is closely related to wear processes and progressive oil degradation. Finally, PC3 is characterized by a strong contribution from Chromium (Cr), along with Lead (Pb), TAN, Nitration, and Calcium (Ca), reinforcing the interpretation of this component as representing contaminant buildup and chemical degradation. From this analysis, it becomes clear that metal content, additive levels, and degradation indicators are central elements in cluster differentiation.

Figure 28 displays the relative influence of each variable in capturing the variance structure of the dataset, calculated through the weighted sum of their loadings across the principal components. A higher score indicates a stronger role of that variable in shaping the latent patterns detected by PCA, and therefore a greater relevance to the segmentation of the data.

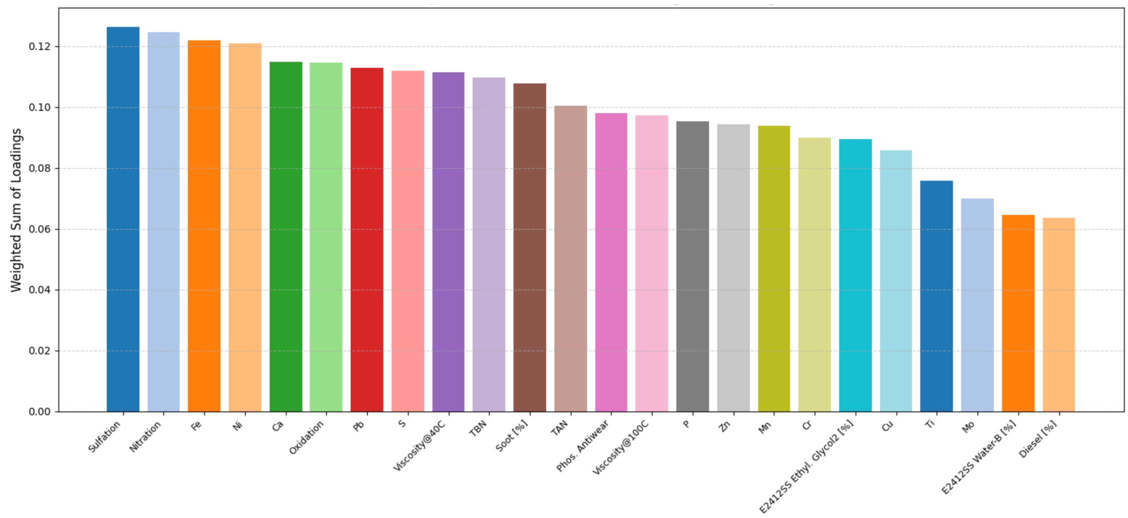

Figure 28 - Relative variable contribution in PCA (Weighted Loadings SUM)

The results suggested that sulfation, nitration, Fe (iron), Ni (nickel), Ca (calcium), and oxidation were the most influential variables, suggesting that these factors are key drivers in the variance observed across the dataset. These variables are closely related to lubricant degradation and metallic wear, reinforcing their relevance in monitoring engine health.

This supports the interpretation that the clusters mainly reflect different stages in the oil's lifecycle and degradation process, rather than variations in operating conditions.

To further dissect the internal structure of each group identified via K-Means clustering, PCA was also applied individually to each cluster. This additional step provides a clearer view of which variables predominantly account for the variance within each subgroup. Table 17 shows the percentage of variance explained by the first three components for each cluster, with total values ranging from approximately 56% to 79%.

Table 17 - Distribution of Explained Variance by Cluster

Cluster	PC1 (%)	PC2 (%)	PC3 (%)	Total Variance (%)
Cluster 0	34.12%	16.96%	10.91%	61.99%
Cluster 1	33.68%	28.94%	15.93%	78.55%
Cluster 2	25.25%	18.86%	12.21%	56.32%

By analyzing the PCA loadings within each cluster, it becomes possible to pinpoint the variables that most significantly drive internal variability. Figure 29 show cases the five variables with the highest absolute loadings for the first two components (represented by the two bars shown for each cluster), providing insights into the distinguishing features of each cluster. The presence of both positive and negative contributions in the loadings also clarifies whether a given variable enhances or counteracts the variance explained by the component.

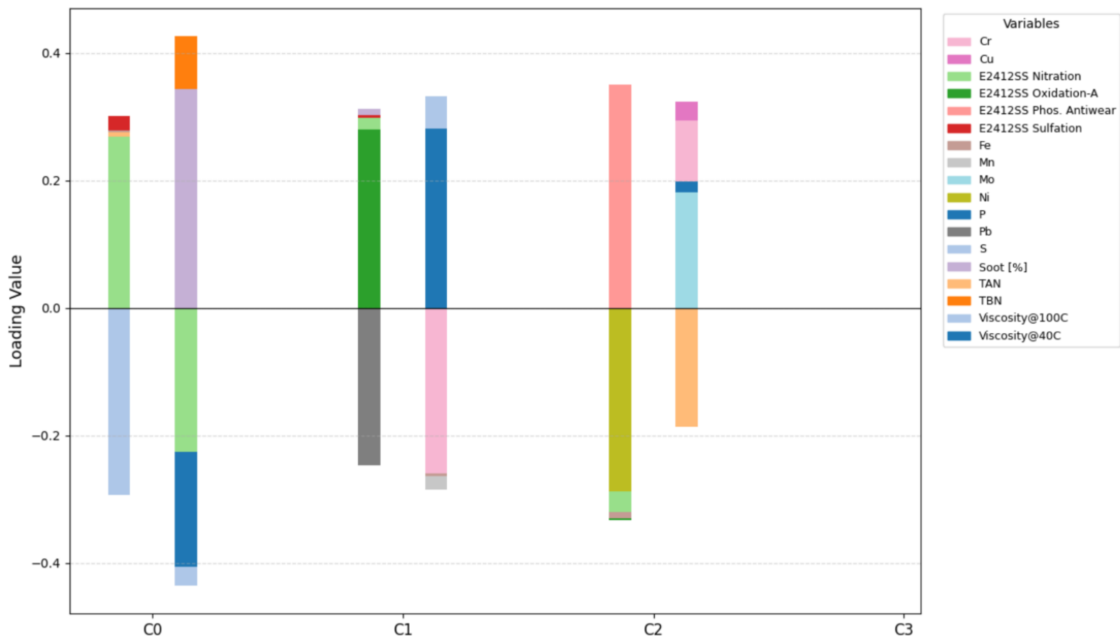

Figure 29 - Top 5 variable Loadings by Principal Component, per cluster

The loadings highlight distinct degradation patterns in each cluster. Cluster 0 is mainly influenced by additive depletion and soot buildup, indicated by variables like phosphorus, zinc, and soot, along with viscosity changes. Cluster 1 reflects chemical degradation and metallic wear, with high levels of TAN, oxidation, Cu (copper), and Ni (nickel). Cluster 2 corresponds to advanced lubricant deterioration, marked by acidification and contamination through TAN, lead, and sulfation.

After identifying the most relevant variables driving cluster separation through PCA loadings, a supervised classification method was applied to gain a clearer understanding of the criteria defining these groups. Although the combination of PCA and K-Means successfully segmented the oil samples into four distinct clusters, the interpretation of the factors behind this separation remained unclear.

By employing a perceptron, it was possible to identify the variables with the greatest weights for each cluster, highlighting the key factors that characterize and differentiate the formed groups. Figure 30 shows that.

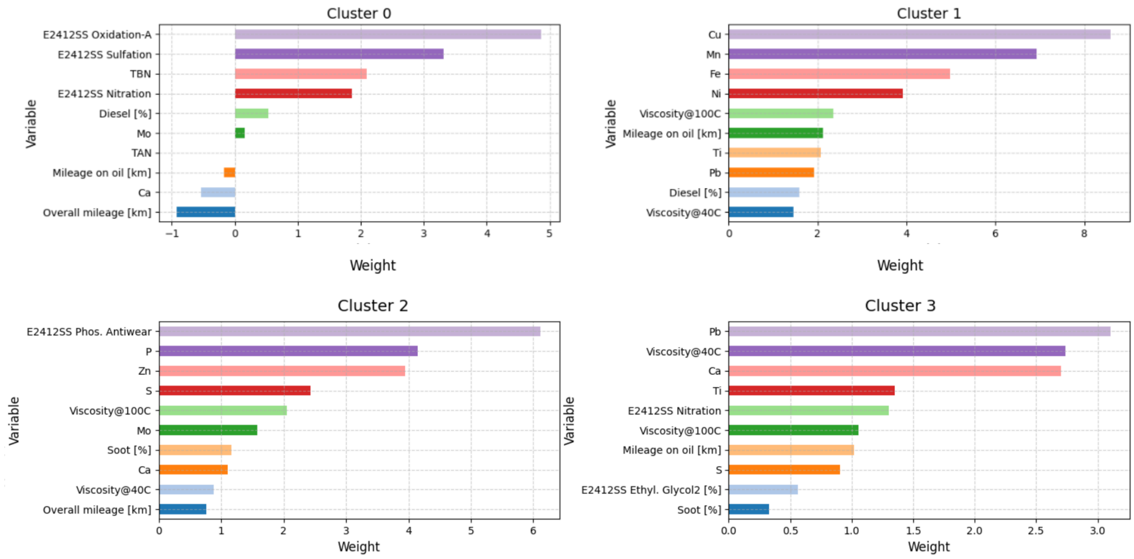

Figure 30 - Top 5 Variables per Cluster based on Perceptron Input Weights

The analysis reveals that Cluster 0 is primarily characterized by high-weight variables associated with oxidation products (Oxidation, Sulfation), followed by TBN and Nitration. This profile suggests a predominantly chemical degradation of the oil. The influence of variables such as TAN and Diesel also points to some contamination, although the main degradation mechanism appears to be oxidative wear. Notably, overall mileage shows a negative weight, indicating that this type of degradation can occur even in vehicles with relatively low mileage.

Cluster 1 is strongly influenced by wear metals, especially Copper (Cu), Manganese (Mn), Iron (Fe), and Nickel (Ni), suggesting the presence of internal mechanical faults or accelerated wear of metallic components. Viscosity at 100 °C and mileage on oil reinforce this trend, indicating physical changes in the oil due to the presence of contaminants. It is also important to highlight the significant contribution of Diesel, confirming critical fuel infiltration, which compromises the integrity of the lubricant.

In Cluster 2, variables related to the presence and preservation of additives stand out, including Phosphorus Antiwear, Zinc (Zn), Calcium (Ca), and Molybdenum (Mo). In addition, viscosity at 100 °C and low soot levels support the interpretation that this group represents oils still in good condition or at an early stage of their life cycle. The low concentration of wear metals and contaminants suggests well-maintained engines operating under favorable conditions.

Finally, Cluster 3 shows a unique combination of variables indicative of extreme and multifactorial degradation. The most prominent variables include Viscosity at 40 °C, Nitration, Ethylene Glycol, Soot, and Mileage on oil. This pattern points to a probable failure in the cooling system and accumulation of combustion by-products, leading to severe thermal degradation, possible oil emulsification, and heavy contamination.

The use of the perceptron model confirmed that each cluster presents a distinct and well-defined signature of critical variables.

The statistical analysis of Table 18 provides a clear overview of the fleet's engine health, offering a snapshot of oil degradation levels and mechanical wear across different operational contexts. By examining both the mean values and standard deviations of key parameters, it is possible to assess not only the severity of degradation in each cluster but also the internal consistency of each group's behavior.

Table 18 - Mean and Standard deviation of Oil variables per cluster

	Mean				**Standard deviation**		
Variables	Cluster 0	Cluster 1	Cluster 2	Cluster 3	Cluster 0	Cluster 1	Cluster 2
Viscosity 40ºC	**123.19**	106.49	107.86	102.63	**25.33**	12.90	5.80
Viscosity 100ºC	13.59	13.22	14.13	14.37	1.49	1.03	0.47
TBN	4.59	**5.53**	3.69	**2.6**	1.59	1.44	0.96
TAN	2.63	**1.79**	2.52	**4.13**	0.74	0.11	0.52
Oxidation	**27.13**	17.56	**14.95**	16.76	8.89	6.84	2.51
Nitration	26.55	**15.41**	18.11	**30.08**	8.81	2.46	2.78
Sulfation	18.85	**12.18**	13.55	**19.31**	3.93	3.43	2.51
Phos. Antiwear	-14.69	-13.46	-11.22	-14.28	0.79	1.01	1.92
Diesel	0	**0.16**	0	0	0	0.54	0
Soot	**0.22**	0.58	0.69	**0.89**	0.10	0.20	0.23
Water	0.05	0.06	0.08	**0.07**	0.02	0.02	0.04
Ethyl. Glycol	**0.49**	0.46	0.35	**0.25**	0.13	0.09	0.06
Fe (Iron)	**51.82**	**103.00**	73.22	81.39	11.86	**28.76**	17.14
Cu (Copper)	1.16	**49.31**	1.93	2.41	0.45	63.13	0.59
Cr (Chromium)	1.39	1.75	1.25	**3.15**	0.39	0.56	0.33
Pb (Lead)	0.35	1.65	0.56	**4.45**	0.04	1.01	0.23
Mn (Manganese)	0.55	**1.89**	0.69	0.6	0.07	1.58	0.16
Ni (Nickel)	0.46	0.89	0.65	0.7	0.10	0.20	0.16
Ti (Titanium)	0.64	0.92	0.40	0.74	0.59	0.89	0.31
Ca (Calcium)	**1046.36**	1089.88	1257.43	**2183**	47.79	51.42	157.12
Mo (Molybdenum)	385.12	384.27	**394.83**	357	15.99	12.24	10.11
P (Phosphorus)	871.99	890.15	**998.32**	993	36.57	43.66	39.17
S (Sulfur)	2514.23	2495.15	2908.79	**3438**	118.27	131.96	93.58
Zn (Zinc)	1168.15	1199.21	1337.86	**1383**	35.54	52.99	44.15

Cluster 0 is characterized by signs of chemical degradation and contamination from combustion by-products, such as elevated viscosity, oxidation, nitration, and iron content. It comprises only Cummins engines operating under urban conditions, which typically involve frequent idling and stop-start driving factors that significantly impact lubricant deterioration.

Cluster 1, composed mainly of newer FPT Industrial Tector 7 engines from 2022–2023, shows pronounced internal wear, evidenced by high levels of copper, iron, and nickel. These engines are likely still in their break-in phase, which naturally leads to increased wear metal concentrations. Additionally, this cluster includes a critical case of diesel and water contamination in one vehicle, highlighting potential infiltration issues that severely compromise oil performance.

Cluster 2 reflects more stable conditions, consisting of older engines (before 2022) that have undergone multiple oil change cycles. These samples demonstrate lower degradation levels, preservation of key additives (P, Zn, Ca, Mo), and minimal contamination - representing well-maintained systems operating under interurban conditions.

Cluster 3, although initially grouped as part of the analysis, stands apart as an outlier. It corresponds to a single older bus affected by severe contamination and oil degradation, likely caused by a known mechanical failure (oil leakage). Given its extreme values, it should not be considered representative of a broader pattern.

In summary, the segmentation reveals three operationally distinct and interpretable profiles (Clusters 0, 1, and 2), each tied to specific usage conditions and engine life stages. Cluster 3, however, represents an exceptional case that falls outside the normative operational behavior of the fleet.

5 RESULTS

This study aimed to identify failure and degradation patterns in passenger bus engines, with the overarching goal of supporting the transition from a reactive maintenance model to a Condition-Based Maintenance (CBM) strategy. The methodology combined historical fault records, operational reliability metrics, physicochemical analysis of used engine oil, and structured reliability techniques.

An exploratory analysis of fault data collected over 17 months revealed that more than half of the fleet experienced at least one critical failure, most frequently associated with the fuel system and engine cylinder head. Using Pareto analysis, it was determined that coolant leakage alone accounted for 37% of all failures, positioning it as the most critical and recurrent failure mode.

These failures were more concentrated in vehicles with less than 100,000 km since engine replacement, suggesting an early-life degradation risk not necessarily related to wear-out phenomena.

FMECA Analysis reinforced these conclusions by identifying coolant contamination as the failure mode with the highest Risk Priority Number (RPN), due to its high frequency, detectability difficulty, and severe consequences. Other critical failure modes included internal fuel system leaks and oil pressure anomalies. The FTA structured these failure modes into a logical sequence of causal events, with coolant-fuel mixture emerging as the top event. The fault tree showed a cumulative probability of approximately 45% for this failure route, confirming its centrality and potential for being a predictive trigger for maintenance interventions.

Reliability indicators were computed to quantify fleet performance: Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), Intrinsic Availability and Operational Availability. Although, average intrinsic availability ranged between 90% and 91%, variations from 87% to 94% suggest operational inconsistencies and reinforce the value of predictive tools that can reduce unexpected downtime. Maintenance records also revealed a dominance of unplanned maintenance over planned interventions, emphasizing the system's current reactivity and the pressing need for anticipatory capabilities.

In this context, the characterization of engine lubricating oil was introduced as a diagnostic tool to infer internal engine condition. This included 58 oil samples, which were tested for important degradation parameters such as viscosity (at 40°C and 100°C), TBN, TAN, oxidation, nitration, sulfation, diesel dilution, along with wear metal concentrations such as Fe, Cu, Zn, Pb, and Ni.

The results indicated moderate relationships of mileage and the chemistry deterioration of the lubricant, especially rising TAN and metal level and dropping TBN respectively. These results suggest progressive internal degradation, even before external symptoms or alarms are triggered in the vehicle.

To extract latent patterns, a Principal Component Analysis (PCA) was performed, which reduced data dimensionality while preserving the structural relationships between variables. The first two components explained a significant share of variance and were used as input for a K-Means clustering model, which identified four distinct degradation clusters.

The analysis of input weights for each cluster showed that variables such as Fe, Cu, Zn, P, S, TAN, and TBN were the most discriminating. Each cluster corresponded to a different degradation signature: for instance, one group showed high concentrations of Fe and Cu, indicating mechanical wear, while another exhibited low TBN and high TAN and oxidation values, consistent with chemical depletion and acidification.

6 DISCUSSION

6.1 Main Contributions

This study presents an in-depth analysis of Condition-Based Maintenance (CBM) in passenger buses, offering a perspective that differs from existing approaches in the literature. Rather than immediately proposing predictive models or decision support systems, the research focuses on the exploratory and descriptive analysis of real-world operational data collected from two active urban bus fleets.

The main contribution of this work lies in its empirical approach, which enables the identification of failure patterns, maintenance cycles, and vehicle behavior under real operational conditions. Based on real operation and maintenance data, this study offers valuable insight to the effectiveness of currently used CBM strategies and highlights areas for improvement grounded from a real experience.

In addition, the identification of relevant variables and operational situations associated with failures and maintenance actions allows to focus on specifically high-interest factors for predictive purposes. The proposed methodology can potentially also serve as a practical reference for public transport operators in rolling out or optimization CBM strategies, in solid support of empirical evidence and adjusted to the operational environment.

In addition to the technical and methodological contributions presented, this research has resulted in the submission of four scientific articles to international journals and one article to a national journal, demonstrating the academic relevance and impact of the work. These articles delve into specific aspects of the study, such as failure analysis, the application of statistical techniques, and the evaluation of lubricant oil degradation, thereby expanding the dissemination of the generated knowledge and contributing to the advancement of Condition-Based Maintenance in urban transport fleets.

The submitted articles, all authored by the author of this thesis, Luís Melo Margalho, Wojciech Gołębiowski, Mateus Mendes and José Manuel Torres Farinha, are as follows:

- Article 1: "Assessment of Critical Failures of City Buses using Fault Tree Analysis" submitted to an international journal, focusing on the identification and evaluation of critical failure modes in urban buses using Fault Tree Analysis.
- Article 2: "The influence of Maintenance on the Reliability and Performance of a municipal bus fleet" submitted to another international journal, presenting a statistical analysis of maintenance data and reliability metrics to assess the operational performance of the fleet.

- Article 3: "Condition Monitoring of an Urban Fleet based on Oil Analysis" submitted to yet another international journal, addressing the use of physicochemical and contamination indicators in lubricant oil to monitor engine condition and degradation processes under real-world conditions.

In addition to these, two more articles are currently in preparation: one intended for presentation at an international conference and another for submission to a national journal.

6.2 Limitations and Future Work

Despite the contributions made, this study also presents several important limitations. The most significant of these is to rely on the use of only real operational data. Although this brings more realism and practical relevance, this also brings the issues of quality, consistency and comprehensiveness of the data. The natural heterogeneity of the data and possibility of missing and recording errors could affect the accuracy of some analyses.

As future work, it is proposed to continue this research by developing machine learning models for failure prediction and decision support in maintenance planning.

Based on the observations and trends discovered in this first stage, further work will explore supervised and unsupervised learning algorithms capable of anticipating failures based on operational signals and maintenance history. The intended result is to move towards more efficient predictive maintenance practices, with lower operating costs, higher fleet availability and improved safety for passenger transport.

7 CONCLUSION

The implementation of Condition-Based Maintenance (CBM) in urban bus fleets is an innovative approach to the maintenance of urban bus fleets, which optimizes the operational efficiency, improves reliability of buses and cuts the associated maintenance costs. Using methods such as FMECA, Fault Tree Analysis, and predictive failure models, this study shows how historical data analysis can identify critical failure points, guide the prioritization of preventive actions, and extend the lifespan of assets.

The results emphasize interventions in the critical subsystems (cooling and engine) needing focused improvement to decrease downtime and increase fleet availability. In addition, the research fills the gap in literature for Condition-Based Maintenance in urban fleets, providing templates that can be replicated in other settings. These findings not only enhance the effectiveness of maintenance but also establish a realistic, sustainable perspective for other transportation systems that aim to enhance operational efficiency.

This study shows how the incorporation of techniques like Fault Tree Analysis (FTA), Failure Modes, Effects, and Criticality Analysis (FMECA), reliability metrics (MTBF, MTTR and Availability), and lubricant oil analysis gives a methodology for the implementation of Condition-Based Maintenance for a business of bus fleet services. The research questions proposed in the introduction were solved by identifying both the most relevant failure modes related to the cooling and engine systems, making it possible to have a better assignment of maintenance resources. Use of statistical data analysis in combination with analysis of failure data has enabled the early identification of anomalies, and oil monitoring has realized more accurate engine condition diagnostics. In general, such integrated approach could potentially have been used to predict failures, enhance operational efficiency, minimize the unanticipated outages, and it might also contribute in the sustainability of public transportation.

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ATTACHMENTS

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