DEVELOPMENT OF RELIABILITY-BASED MAINTENANCE POLICIES
FOR HAUL TRUCKS IN A SURFACE MINE

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ABSTRACT

DEVELOPMENT OF RELIABILITY-BASED MAINTENANCE POLICIES FOR HAUL TRUCKS IN A SURFACE MINE

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The growing production market and the resultant increase in raw material requirements create pressure on mining companies to achieve production at a higher rate by keeping unit operating costs manageable. It is recognized that the performance of mining machinery, maintenance downtime profiles, and operating cost variations are the main parameters effective in the sustainability of machinery fleets. On this basis, developing robust and up-to-date maintenance policies regarding operation dynamics and fleet machinery configuration is vital for mining production.

A maintenance policy embodies various work packages such as corrective repair, corrective replacement, preventive replacement, on-condition maintenance, and regular inspections. Which packages need to be included in the maintenance policy for which components depend on repairability or replacement conditions of components and the expected financial benefits of each decision. Moreover, reliability and maintainability behaviors of system components are highly effective in the decision-making process since a maintenance policy should provide a balance between over-maintenance and under-maintenance.

This study intends to develop reliability-based maintenance policies using fault tree analysis for a truck fleet, including six trucks operated in a surface coal mine in

Türkiye. Seven maintenance policies for improving reliability were evaluated and compared according to their contributions to operating cost and fleet availability. The policy contents generated an availability variation between 59% and 66%.

Keywords: Fault Tree Analysis, Mining, Haul Truck, Reliability, Maintenance Policy

ÖZ

BİR AÇIK OCAK İŞLETMESİNDE KULLANILAN TAŞIMA KAMYONLARI İÇİN GÜVENİLİRLİK TABANLI BAKIM VE ONARIM POLİTİKALARI GELİŞTİRİLMESİ

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Eylül 2022, 102 sayfa

Büyüyen üretim pazarı ve buna bağlı olarak hammadde gereksinimlerindeki artış, madencilik şirketlerine birim işletme maliyetlerini kontrol altında tutarak daha yüksek oranda üretim gerçekleştirme baskısı yaratmaktadır. Maden makine performansları, bakım süreleri ve işletme maliyetlerindeki değişimler, makine filolarının operasyonel sürdürülebilirliğine en çok etki eden parametrelerdir. Buna göre, üretim dinamikleri ve filoda yer alan makinelerin konfigürasyonu dikkate alınarak güçlü ve güncel bakım-onarım politikalarının geliştirilmesi, madencilik üretimi için hayati öneme sahiptir.

Bir bakım-onarım politikası; düzeltici onarım, düzeltici değişim, önleyici değişim, şartlı bakım ve düzenli denetimler gibi çeşitli iş paketlerini bünyesinde barındırabilir. Hangi bakım-onarım paketinin politikaya dahil edilmesi gerektiği, bileşenlerin tamir edilebilirlik veya değişim koşullarına ve her bir kararın beklenen finansal etkisine bağlı olarak değişebilmektedir. Aynı zamanda, bir bakım-onarım politikasının aşırı bakım ve yetersiz bakım arasında bir denge teşkil etmesi gerektiğinden, sistemdeki bileşenlerin güvenilirlik ve onarılabilirlik davranışları karar vermede oldukça etkilidir.

Bu tez çalışması, Türkiye'de bir yerüstü kömür madeni işletmesinde kullanılan altı adet kamyondan oluşan kamyon filosu için hata ağacı analizi kullanarak güvenilirlik tabanlı bakım-onarım politikaları geliştirmeyi amaçlamaktadır. Filo güvenilirliğini artırmak için yedi farklı bakım-onarım politikası karşılaştırmalı olarak değerlendirilmiştir. Bu politikaların, işletme maliyeti ve filo kullanılabilirliğine etkileri tartışılmıştır. Farklı bakım-onarım politikalarının, kullanılabilirlik oranında %59 ile %66 arasında değişen bir etki yarattığı gözlenmiştir.

Anahtar Kelimeler: Hata Ağacı Analizi, Madencilik, Nakliye Kamyonu, Güvenilirlik, Bakım Politikası

To My Family

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CHAPTER 1

INTRODUCTION

1.1 Background

Mining is a machine-intensive sector that intends to extract economically-feasible mineral reserves using different mining techniques and equipment fleets characterized according to the exploitation method. The most popular surface mining technique, open-pit mining, heavily uses truck and shovel dispatching systems to extract and haul ore and waste materials. Selecting shovels or excavators should be performed regarding annual production targets, while trucks should be appropriately matched in a way that production of excavating equipment should not be interrupted. Therefore, the number and capacity of specific types of trucks (truck fleet configuration), availability and maintainability aspects, operator efficiency, and cycle time are crucial parameters for the effective scheduling of periodic production.

At this point, trucks in a mining area must be monitored attentively regarding their operability and operating cost values. Many periodic mining reports show that trucks can contribute to more than half of the operating cost in an open pit since their consumables, like fuel, tires, lubricating oil, and other spare parts, are used frequently and add to the production cost by a remarkable amount. In addition, trucks do not only cause direct costs but also lead to unexpected revisions in the production schedule in case of maintenance downtimes during operation. Increasing occurrence frequency of failure modes, especially in complex components of a truck, may cause deterioration in their operating mechanisms resulting in a jump in unexpected downtimes. Therefore, the characterization of truck components and sub-systems by considering their up-to-date conditions is critical for robust production and maintenance plans. In this way, different system components can be maintained in a combination of varying maintenance work packages to improve system reliability.

The current thesis study intends to characterize the mining truck employed in an open-pit mine to gain insight into their uptime and downtime profiles so that an optimal balance in preventive and corrective work packages of maintenance policies can be developed.

1.2 Problem Statement

Mining equipment should be operated at high capacities in demanding working environments. Since mining production highly relies on the operability of these types of machinery, their uptime and downtime characterizations become crucial in building up robust work schedules so as not to cause any interruption in production. At this point, mining production is generally evaluated under two primary operations: excavation and haulage operations. Most of the main operations in surface mines are performed using truck and shovel/excavator dispatching systems. Proper planning of these operations requires an attentive maintenance policy for trucks and excavators due to their direct impact on production compared to auxiliary operation equipment such as graders, dozers, loaders, and water trucks since any delay in auxiliary equipment can be compensated in a way not to interrupt production. It is expected that improper determination of reliability and maintainability behaviors of trucks leads to an observable increase in operating cost and production loss due to a drop in equipment reliability and a jump in maintenance durations

1.3 Objectives and Scopes of the Study

This study aims to characterize the reliability and maintainability behavior of trucks operating in a surface coal mine and offer multiple reliability-centered maintenance policies for the fleet. The study entails achieving the sub-objectives below:

i. Decomposition of a truck system into its functional sub-systems,
ii. Preprocessing of uptime and maintenance downtime data to obtain reliability and maintainability functions of truck subsystems,
iii. Developing a fault tree diagram for the truck fleet for assessment of system reliability and the weakest chains in the reliability variation,
iv. Introducing different maintenance work packages into the fault tree simulation environment and observing the changes in total maintenance cost and system availability for each maintenance policy.

A fleet including six trucks employed for joint production in a surface coal mine was considered under the study’s scope. Four years of dataset covering the records with detailed expressions on maintenance activities were utilized in the analyses.

1.4 Research Methodology

The main research methodology steps are given as follows:

i. Decomposition of systems: Trucks in the fleet are evaluated using maintenance records, expert opinions, and machinery catalogs. Sub-systems and components to be analyzed are determined so that each sub-system embodies functionally-related components.
ii. Preprocessing of maintenance data: Each downtime and uptime record is classified into related subsystems, and the time-dependent behavior of each dataset is discussed with time series and data trend analysis.
iii. Determination of Parametric Values for Reliability and Maintainability Functions: Each subsystem's perfect and imperfect maintenance profiles and their deterioration levels are evaluated to determine their reliability (time between failures, TBF) and maintainability (time to repair, TTR) functions.

iv. System Reliability Estimation with Fault Tree Analysis: System and sub-system configurations holding different dependencies are developed in a fault tree analysis environment so that contribution of each element to system reliability in time can be evaluated.

v. Development of Reliability-Centered Maintenance Approaches: Using the stochastic uptime and downtime dependencies in the fleet, various maintenance policies covering different combinations of corrective repair, preventive inspections, and preventive component replacement work packages for changeable maintenance effectiveness levels are simulated in the fault tree environment. In this way, how the total maintenance cost and fleet availability are affected could be monitored by revealing the individual effects of each subsystem on the fleet performance.

1.5 Expected Contributions of This Thesis

The wear and tear of equipment components in time and the increasing frequency of corrective maintenance requirements can cause issues in operation planning in mining areas. Therefore, system and sub-system behaviors require continuous monitoring and performance evaluation to develop a proper task allocation for equipment. The methodology presented in this thesis study can be used to understand the top-to-bottom characterization of mining equipment. In this way, deterioration levels of components and the weakest chains in system reliability can be detected, and specific and effective maintenance policies can be built up.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This thesis study presents a systematical methodology for evaluating the system reliability of a truck fleet using fault tree analysis and offers different reliability-centered maintenance policies that can contribute to the system's operability. Accordingly, this section presents some background information on reliability and maintenance concepts and their applications in the mining industry. At this point, system reliability analysis is discussed in Section 2.2 with a theoretical part and a common implementation method integrating into the maintenance concept. Section 2.3 presents the related works previously completed for mining systems, and Section 2.4 briefly summarizes the current literature chapter.

2.2 System Reliability Analysis

This section discusses the reliability concept and its relationship with maintenance decisions to provide background knowledge for the analyses performed under the scope of this thesis study. The primary objective of a system reliability analysis is to obtain a failure distribution of the entire system utilizing the failure distributions of its components. The effect of stochastic component behavior on system operability can be observed briefly in Figure 2.1. Since each component and related failure modes generally occur in highly random intervals, system uptime behavior is also randomized. Therefore, understanding the probabilistic approach to system operating and downtime profiles is crucial when developing maintenance policies.

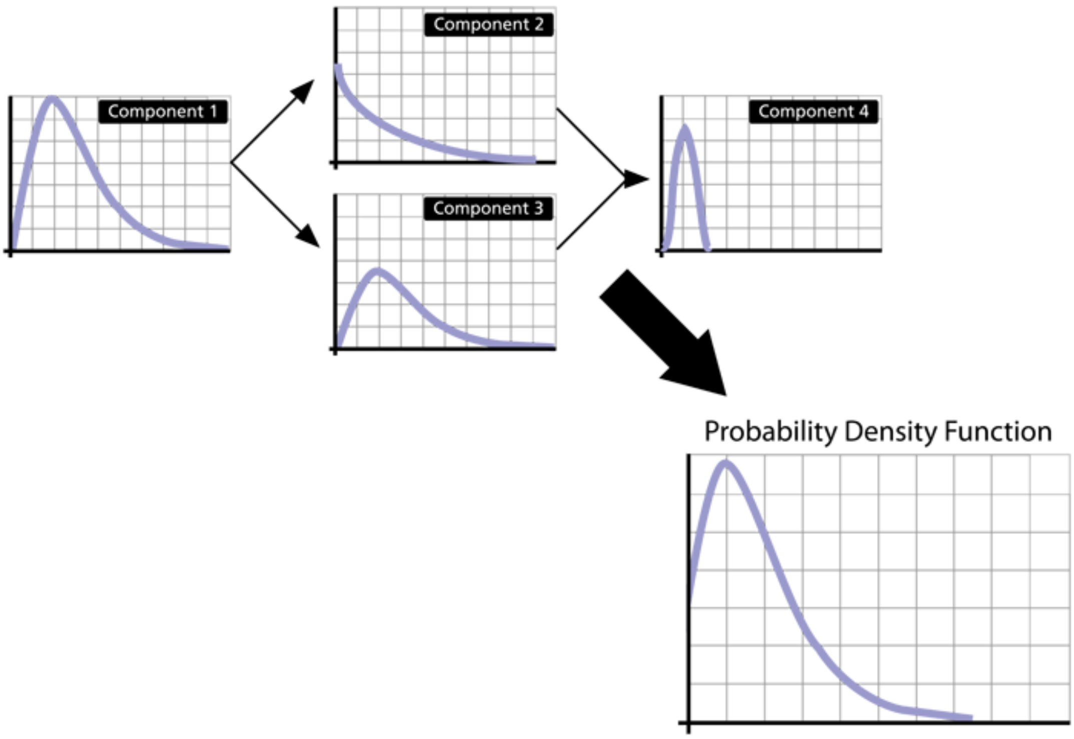


Figure 2.1 System Reliability Analysis Workflow (House, 2012)

2.2.1 Reliability Concept

Reliability refers to the probability that an item will perform a required function under stated conditions for a stated period. A more recent definition of reliability in ISO 8402 Standard and British Standard BS 4778 states that reliability can be expressed as the ability of an item to perform a required function under given environmental and operational conditions and for a stated period. The term item presents any component, sub-system, or system considered to be analyzed. A required function may be a single function or a combination of functions considered when discussing whether the item is sustaining its functionality or not. At this point, all technical items (components, sub-systems, systems) are designed to perform one or more (required) functions. These functions can be classified as passive or active. Assessing an item's reliability requires specifying the functions and dependencies between the functions within the system boundary. In brief, all defined functions of an item should be satisfied for a specified period in actual applications, not just in initial factory performance or quality specifications (Rausand & Høyland, 2004).

Reliability requires the estimation of the probability values in the intended period. Probability can be defined as the ratio of the number of times we can expect an event to occur to the number of times the trials commenced. The time between intervals of consecutive failures for specific failure modes can be used to define the probability functions of the target items (US Department of Defense, 2003). Here, the probability value for any observation period should be between zero and one. A probability value of 1.0 (100%) shows that it is unlikely to have a failure for the item at a given time since the probability density function is developed from previous failure times much higher than the observation time. On the other hand, if the reliability drops to 0.0 (0%), there is a strong indicator of item failure for the observation time. The rate of reliability variation in time is one of the customer satisfaction measures. If failure occurrences are not below tolerable levels under operation conditions, then satisfactory performance cannot be ensured.

There are three evaluation stages of reliability: design, inherent, and field reliability (Murthy *et al*., 2008). Design reliability is the predicted reliability of the product at the end of the design and development phases. The predictions rely on previous implementation experiences of similar products, testing of the product or expert opinions. Product reliability differs from design reliability due to quality variations of not satisfying design specifications in the production stage and/or having errors in the assembly process. After the production stage, reliability is referred to as the inherent reliability of the product. On the other hand, field reliability or actual reliability is estimated from recorded failures and malfunctions experienced in actual implementations. A product in use may expose to multiple deterioration phases of failure. Therefore, actual reliability can show a remarkable variation from product reliability estimations in catalogs if reliability changes depending on usage intensity, working environment, and human errors are not considered well in the design phase.

System reliability has become crucial, especially for engineering systems used in production industries. These systems are getting more complex with the integrating of different technologies and require high production capacity under certain schedules. The reliability concept helps designers and product users maintain system operability above intended levels in prescribed observation periods. In this way, overall direct and indirect financial consequences of operating the system can be reduced as well as satisfying target availability levels. An operating system is expected to have three stages of hazard rate behavior: burn-in, useful life, and wear-out, as illustrated in Figure 2.2.

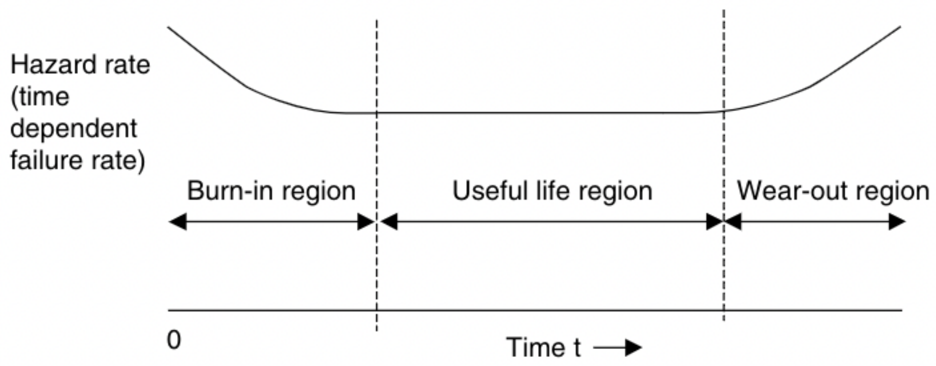


Figure 2.2 Bathtub hazard rate curve (Dhillon, 2008)

A product is expected to have high failure frequencies due to some factors, such as human errors, low-quality parts, bad quality control measures, wrong installation techniques, improper usage, and a poor transportation environment. Once the product usage is comprehended well with minimized usage errors in time, the hazard (failure) rate tends to reduce and comes into balance. This initial period is called a burn-in period. On the other hand, the failures occur randomly with expected frequencies in a useful life period with a constant hazard rate. The useful life period of a product is also used to evaluate its warranty period. Last, the hazard rate shows an ascending trend after a while due to the aging of items mainly caused by poor maintenance, wear and tear of parts, corrosion, and wrong practices.

2.2.2 Reliability Assessment Methods

There are various methods used in the assessment of system reliability, called failure mode and effects analysis (FMEA), Failure Mode, Effects & Criticality Analysis (FMECA), fault tree analysis (FTA), reliability block diagram (RBD), network reduction method, Markov method and decomposition method (Dhillon, 2004).

FMEA is one of the common reliability assessment methods and offers the analysis of potential failure modes of each system component and their effects on the system and its sub-system performance. FMEA can be used in bottom-to-top structure by detailing system decomposition and performance effects among different system levels and highlighting the weakest points in system reliability. Therefore, designers or product users can improve system performance by concentrating more on these points. On the other hand, FMECA presents a quantitative evaluation in contrast to FMEA by including the criticality of failure modes with their occurrence probabilities. In addition, fault tree analysis (FTA) discusses system reliability with a top-to-bottom approach by examining failure modes and their triggering factors with branching called fault trees. The implementation type of RBD is close to FTA. However, it analyzes the survival probability of systems and sub-systems, not failure probabilities. Besides, Markov Method uses a set of differential equations to analyze repairable and non-repairable systems with these subsequent assumptions; the transitional probability from a state to the following one in the finite time interval Δt is given by $\lambda \Delta t$, where λ is transition rate (e. g., failure or repair rate) correlated with Markov states, the probability of more than one transition incidence in a finite time interval Δt from a state to the following one is negligible, and finally, all incidences are independent of each other.

Development of reliability assessment methods was motivated especially following World War Two since technological improvements and production rates have shown a remarkable upward trend requiring highly reliable machines. At this point, FMEA was developed by NASA (National Aeronautics and Space Administration) in the 1960s for the Apollo project in the USA (Bertsche, 2008). Then, this method became one of the standard procedures applied in aerospace and aeronautical engineering applications. Following successful applications in the aerospace industry, the FMEA method gained attention in the nuclear and automotive sectors of its systematical structure in determining failure modes for systems, sub-systems, and components. Its implementation allows the usage of a detailed risk assessment to optimize system dynamics and eliminate failure-prone zones as early as possible. FMEA is frequently utilized in the development and planning phases of new products. In addition to the criticality factors referring to failure mode occurrence probabilities, FMEA turns to FMECA to provide a quantitative assessment of system performance risks.

FMEA is currently used in different production industries. A sample evaluation of failure risks for individual belt conveyor components using FMEA can be viewed in Burduk *et al.* (2020). The study embedded the method into many quality management methods and standards, such as ISO 9001 and ISO 31000. A risk priority number (RPN) was used to rate risk priorities based on records and expert experience. The following parameters were addressed in the evaluation of the belt conveyor:

- Potential defects for individual elements included in the construction of the belt conveyor,
- Their occurrence probabilities (P),
- The degree of hazard (Z), determining the magnitude of the effects that arise after a defect occurrence during the production process and the use of the product,
- Traceability (T), determining the possibility of detecting a potential defect.

RPN values of potential failure modes in the study were calculated using indicator ratings, as shown in Figure 2.3. These values should be determined by people experienced in the usage and maintenance of systems. Hazard level, occurrence probability, and detection values were determined for the belt conveyor to obtain individual RPN scores (Equation 1).

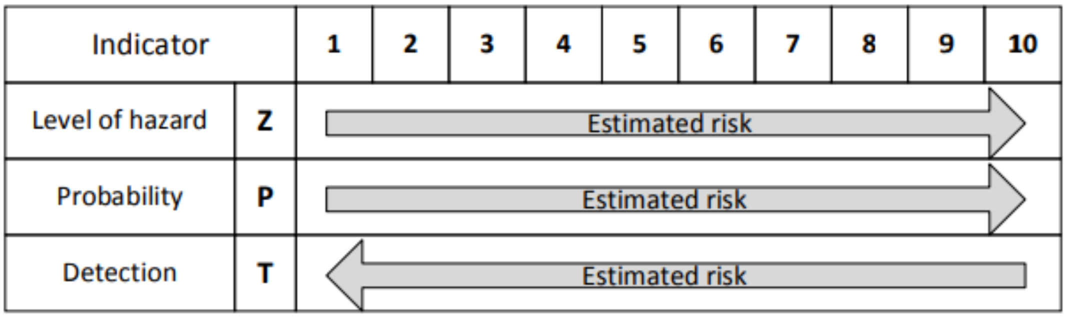


Figure 2.3 Estimated Risk Values (Wolfgang and Klaus, 2007)

$$\text{RPN} = (\text{Z}) \times (\text{P}) \times (\text{T}) \tag{1}$$

Palei *et al.* (2020) employed another method for assessing reliability. Failures of a shovel and its sub-systems were monitored in the study. First, serial correlation and trend tests were utilized to prepare the data for analysis. It ensured that all the input data for the next step had no anomaly behavior. Then, Kolmogorov-Smirnov (K-S) Test was conducted to find the best-fit distribution for the dataset. Finally, an isograph reliability workbench was utilized to determine the reliability of each machine.

On the other hand, Fault Tree Analysis (FTA) uses multiple fault trees to identify internal and external causes contributing to system or sub-system failure probabilities (Bertsche, 2008). These causes can lead to a pre-defined product failure state (mostly a fault state) in case their occurrences are individually or in combination with other causes. In this way, FTA defines the system behavior regarding certain events (and/or faults). This method was first developed in Bell Laboratories in 1962 by the motivation of the USA Air Force and then used by Boeing Company. The commercial aerospace sector started to use fault trees in the late 1960s as a standard procedure, and then the nuclear industry embedded the method into its risk assessment in the 1970s. Currently, FTA is one of the most common systems risk assessment techniques, especially for critical technology sectors such as aerospace, nuclear, automotive, communication, and robotics. FTA allows qualitative and quantitative assessments in product design and implementation phases.

Fault trees require the identification of dependencies in a system using different symbols in a systematical structure (Figure 2.4). On this basis, various gates are integrated into a network illustration and express the configuration of components in a system or sub-system. Transfer input and output symbols can be used to allow transferring between the fault trees. Standard inputs define the system elements to be analyzed. In a fault tree, inputs are combined using gates that determine different functional dependencies in the system boundary. Here, AND gate refers to series dependency where system or subsystem failure can occur if all the components covered are failed simultaneously. OR gate shows parallel dependency where any sub-event failure can damage system or subsystem reliability. NOT symbol develops a negation dependency between multiple events. These symbols can be examined in Figure 2.4.

Constructing a fault tree requires a preliminary evaluation of dependencies between components in a system. At this point, interactions between components and the correlation between component-failure and system reliability should be presented in a deductive structure. After developing system configuration with component dependencies, each component should be branched into its potential failure modes. These failure modes are generally quantified using proper distribution functions, and the resultant failure mode behavior determines component reliability (Figure 2.5).

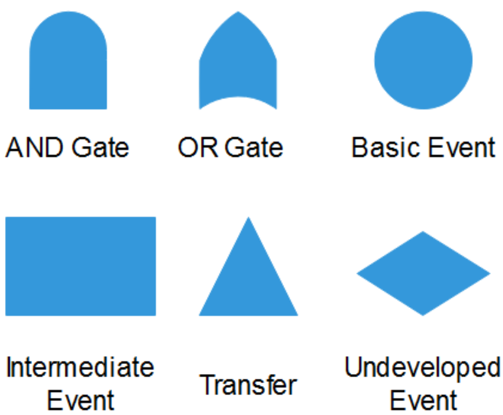


Figure 2.4 Fault Tree Analysis Symbols (Lynch, 2021)

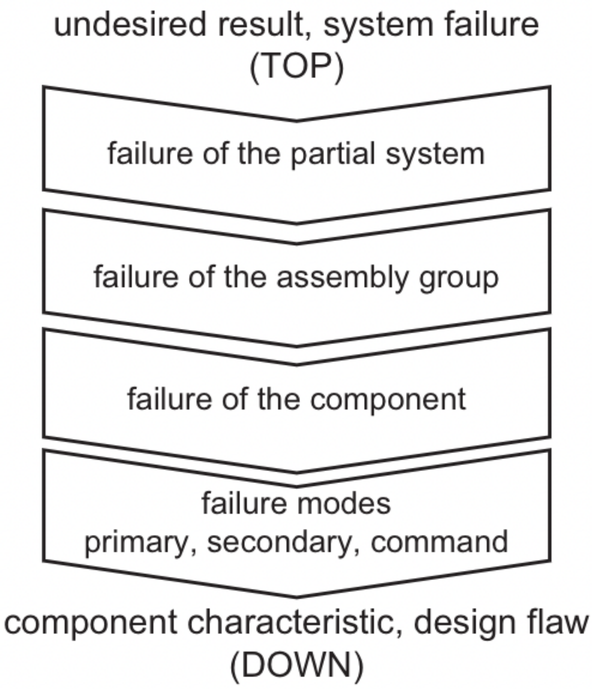


Figure 2.5 Procedure and Structure of a Fault Tree

Another reliability assessment method is Markov chains using several states that can be experienced in a system and the transitions between these states. Markov chain is a stochastic process holding random components (Stapelberg, 2009). The random variable used in the process, X(t), denotes the state of the process at time t. All possible states in their collection are called the state space and are noted by X. The state space X is either finite or countable infinite. However, in most reliability applications, the state space will be finite. These states will resemble the real states of a system. X is taken to be {0, 1, 2, . . ., r), unless it is stated otherwise, and such that X contains r + 1 different state. The time may be discrete, taking values in (0, 1, 2, . . .}, or continuous. A continuous-time Markov chain is also called a Markov process. When the time is discrete, the time is presented by n and the discrete-time Markov chain by (X_n, n = 0, 1, 2, ...). Illustration of the transitions in a Markov chain can be viewed in Figure 2.6.

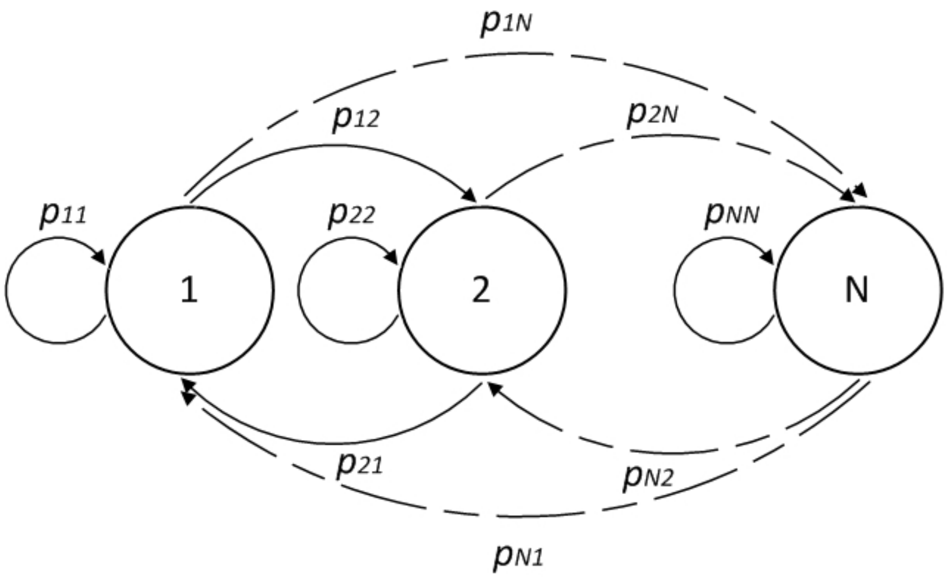


Figure 2.6 Markov Chain Transitions (Tarek et al., 2018)

2.2.3 Reliability and Maintenance

Maintenance policies should consider multiple physical assets to be maintained differently depending on their design complexities and maintenance requirements. Maintenance activities can be divided into two main groups (Ben-Daya *et al*., 2016): Preventive maintenance (PM) and corrective maintenance (CM). Equipment failures and resultant downtimes experienced in a production area affect not only the occupational health and safety aspects but also the productivity and availability of operating systems and maintenance costs. Various alternative approaches have recently been developed to improve maintenance activities and equipment performance. One of these approaches is called reliability-centered maintenance (RCM).

Previously, maintenance was performed correctively when a machine component failed. Later on, for the improvement of system availability, equipment life, and profits, maintenance policies started to include preventive measures in addition to corrective maintenance tasks in the late 1960s. With the growth of mechanization and automation, additional concerns were raised alongside safety and environmental issues. Therefore, reliability was started to be integrated into maintenance policies frequently to ensure system safety and operations most economically and efficiently.

Kobbacy & Murthy (2008) proclaimed that reliability-centered maintenance was first developed for the aircraft industry as a 'systematic approach for identifying effective and efficient preventive maintenance tasks for items in accordance with a specific set of procedures and for establishing intervals between maintenance tasks.' and later has been adapted to numerous other industries. RCM allows determining the optimal type of preventative maintenance in a structured and traceable way. The main steps of RCM are given as follows:

i. Preparation
ii. System Selection and Definition
iii. Functional Failure Analysis (FFA)
iv. Critical Item Selection
v. Data Collection and Analysis
vi. Failure Mode, Effects and Criticality Analysis
vii. Selection of Maintenance Actions
viii. Determination of Maintenance Intervals
ix. Preventive Maintenance-Comparison Analysis
x. Treatment of Non-critical Items
xi. Implementation

The idea that combines reliability and maintenance concepts is RCM or reliability-centered maintenance. RCM was first developed in the 1960s for the jumbo jet Boeing 747 since it required almost three times of maintenance compared to older generation planes, and the maintenance needed to be performed attentively. Then, this method was adapted by US Military for its aircraft. In the following years, it started to be used in the nuclear energy field, where high safety standards should be ensured. Finally, some other large-scale production industries included RCM applications in their maintenance policies. RCM policies effectively define preventive and corrective maintenance work packages regarding system elements' stochastic deterioration and failure behaviors.

Preventive maintenance aims to preserve the equipment by asking, "what can be done before failure?" Consider two identical air-operated valves in a nuclear power plant as a sample case. One regulates the water flow to the main heat exchangers that provide the proper balance of steam flow to a turbine-generator set. On the other hand, the other regulates service water flow to the plant facilities (e.g., cafeteria, lavatories, shops, etc.). Preserving the equipment type of maintenance would mean that both valves receive the same PM actions, such that this approach cannot be acceptable. Failure in the heat exchanger can result in catastrophic conditions, while the other can only cause an operationally unimportant condition. Therefore, treatment and recovery of failure modes should be motivated by operational effect and occurrence rates of failure modes that can be achieved by s RCM approach.

RCM has four main distinguishing features that differ from regular maintenance practices. The first and most important one is to preserve the functions of critical system elements before exposure to crucial failures so that overall system output and safety can be ensured. Therefore, interruptions in system element functions and their effects on overall system output should be addressed in detail by defining operational dependencies and prioritizing maintenance activities for each system element. The second objective of RCM is to prevent the loss of function or functional failure by taking required preventive maintenance actions. The third objective is systematically allocating budgets and resources according to priority rankings. The final objective is to ensure that each potential PM task is applicable and effective. An applicable task means that if it is performed, regardless of cost, it will accomplish one of the followings: Preventing or mitigating failures, detecting the beginning of failure, or noticing a hidden loss. Applicability of tasks should be evaluated in terms of their effectiveness in financial benefits and practicality.

2.3 Reliability and Maintenance Studies in Mining

Maintenance procedures should enhance the systems' functionality and dependability. However, there can be high-cost flow associated with dependability improvement and financial and technical constraints. As a result, there is a trade-off between system deterioration and the financial effects of maintenance actions. According to the unit value of production and the system's function in production, a maintenance strategy should be created to maintain the system's reliability above the desired level. Over-rated preventive work packages may result in higher system unavailability due to redundant preventive maintenance downtimes and additional investment expenses. In this context, some of the recent literature studies related to mining equipment reliability and maintenance are discussed in this chapter.

Barabady (2005) conducted a reliability analysis for the crushing plants to develop maintenance implementation intervals. The study decomposed the plant into subsystems, and maintenance records were classified accordingly. Then, these records were used to determine the time between failures (TBF) and time to repair (TTR) distribution functions. Finally, using the obtained results, maintenance intervals could be adjusted accordingly to get the desired reliability of the crusher systems, starting with 75% reliability to be later adapted to achieve 90% reliability.

In addition, Vayenas and Wu (2009) concentrated on maintenance analysis of load-haul-dump (LHD) vehicles used frequently in underground mines. The methodology used in this study was probability distribution modeling techniques. It was assumed that there were no failures during a shift if there were no data and that the machinery's stand-by times were registered separately. It was concluded that preventative maintenance takes a long time and does not contribute to availability improvement. Moreover, Bugaric & Tanasijevic (2012) analyzed the effect of rubber belt failures on production costs by fitting distributions of gradual and sudden failures to predict the equipment will break. On the other hand, Hoseinie *et al.* (2012) studied the reliability of cable drum shearers using the power law process model to achieve high productivity with smooth machinery function. The study model shows the failure numbers grow cumulatively, and after modifying the preventative maintenance intervals, the drum shearer performs appropriately for a longer time.

Additionally, Palei *et al.* (2012) proposed a preventative maintenance strategy for a dragline used in the opencast coal mining site. Failure mode effects analysis (FMEA) with real operational data was used to analyze the failure rates of components. The failure time behaviors of the dragline components were expressed by the Weibull distribution. This study showed that dragline downtime could be reduced by 231 hours a year by integrating a more effective maintenance policy. Gustafson *et al.* (2013) analyzed the reliability of LHDs using fault tree analysis. Semi-automatic and manual types of equipment were evaluated, decomposing LHDs into subsystems. The environment that benefits from using automation was detected to be the main issue that causes the failures in LHDs. This analysis of LHD automation in an underground mine revealed the importance of preventative maintenance to keep idle times as low as possible. Demirel et al. (2013) used trend tests and fault tree analysis to investigate the system reliability of draglines. Morad *et al.* (2014) investigated an equipment fleet employed in a copper mine and tried to improve fleet productivity using reliability-based maintenance approaches such as Markov chain, GRP, PLP, and RP. Monitoring the wheels as the most critical components and developing a more effective spare part inventory policy were observed to improve productivity with decreased operating costs.

Moreover, Barberá *et al.* (2014) conducted a case study in the mining industry with a graphical analysis for maintenance management (GAMM) for two slurry pumps having high failure rates. GAMM method's graphics have shown and characterized these slurry pumps' issues. The method improved maintenance practices and strategies by decreasing peak loads and malpractice. Kovacevic *et al*. (2016) provided a two-step method for analyzing the aspects and factors influencing human errors during the maintenance activity of mining machines. The group fuzzy analytic hierarchy process and cause-effect analysis are both included in the developed methodology. The analysis's findings indicated that the most critical factors are work organization and instructions, individual training and characteristics, work experience, and equipment specifications. Gölbaşı and Demirel (2017) developed a simulation algorithm to optimize inspection intervals. Typically, these inspections are performed regularly to detect hidden or apparent failures and to preventively maintain components with approaching failure. The model can introduce multiple series-parallel systems with random lifetime and repair time behaviors. The developed algorithm was applied for two draglines decomposed into subsystems and different failure modes. Besides, Jonsson *et al.* (2018) examined digitalized condition-based maintenance data for machines operating in an iron ore mine. Two complementary work practices, which are digital representation and digital mediation, were investigated in the study. Pandey et al. (2018) combined various methods for evaluating critical sub-systems of a dragline and presented a critical review of the planned maintenance program. Balaraju *et al.* (2020) used RBD (reliability block diagram) method to evaluate the performance of load haul dumper machinery (LHD) used in underground mining operations to preserve equipment life. An LHD can be exposed to tough working environments resulting in unexpected maintenance breakdowns. This study examined the expected failure modes of the LHDs using Kolmogorov–Smirnov (K-S) best-fit distribution analysis. Then the subsystem and system reliabilities were evaluated. In addition, Burduk *et al.* (2020) used FMEA analysis to assess the reliability of a belt conveyor system used in a copper mine.

Many studies were performed about the reliability concept in the mining industry, where its cash flow depends heavily on machines operating in challenging working environments. Any delays caused by breakdowns can lead to an observable amount of production loss. Therefore, reliability and maintenance aspects must be examined jointly. In some cases, risk factors, including operational history, equipment design, available conditions of the work environment, and material qualities, can also be considered for a broad evaluation (Agrawal, 2019). At this point, reliability analysis is vital to evaluate machine performance and the frequency of failures. This analysis can better plan maintenance activities on a priority basis so that the machines can be kept in the operational state for longer (Agrawal, 2019). Previous annual reports showed that maintenance-related expenses could be about 40 to 50% of all equipment operating costs in mining. This also equates to 20 to 35% of the total operating cost in a mine (Unger and Conway, 1994). Therefore, alternative maintenance policies should be investigated attentively regarding their positive and negative contributions to operating costs and production losses.

CHAPTER 3

PREPROCESSING OF THE DATA

3.1 Introduction

The dataset utilized in the current study requires a preprocessing stage for evaluating subsystems and components within the system and determining the time-dependent behaviors of the individual datasets. Accordingly, Section 3.2 will mention how the system is decomposed into its sub-elements considering functionally similar components. On the other hand, data preprocessing stages and parametric estimations of lifetime and downtime functions will be discussed in Sections 3.3 and 3.4.

3.2 System Decomposition

In the current study, reliability (lifetime) and maintainability (downtime) assessments of system components and iterative maintenance policy models were accomplished using maintenance records of mining trucks employed in an open pit coal mine in Türkiye. The maintenance records mainly comprise the start and finish dates and hours of failure modes of seven different Komatsu 785-type trucks with five different subsystems each and the short descriptions of failure modes in an observation period between 2015 and 2019. As illustrated in Figure 3.1, a mining truck can be decomposed into five main subsystems: Hydraulics, Body and Frame, Electrical, Drivetrain, and Tires. At this point, the Body and Frame subsystem covers the chassis holding engine, drivetrain, suspension, wheels, damper, and driver’s cab. On the other hand, the Electrical subsystem consists of all the required electrical components, including battery, lights, alternator, and transmission cables. In addition, Engine and Gearbox are classified under the Drivetrain subsystem. The hydraulics subsystem covers hydraulic components mainly related to steering, braking, damper lifting, and other systems where hydraulic fluids are used. Lastly, the Tire subsystem includes four rear tires and two front tires for each truck, including punctures. Detailed branching of subsystems according to failure-prone components is given in Figure 3.2.

Figure 3.1 Komatsu HD 785 Sub-system Schematic View

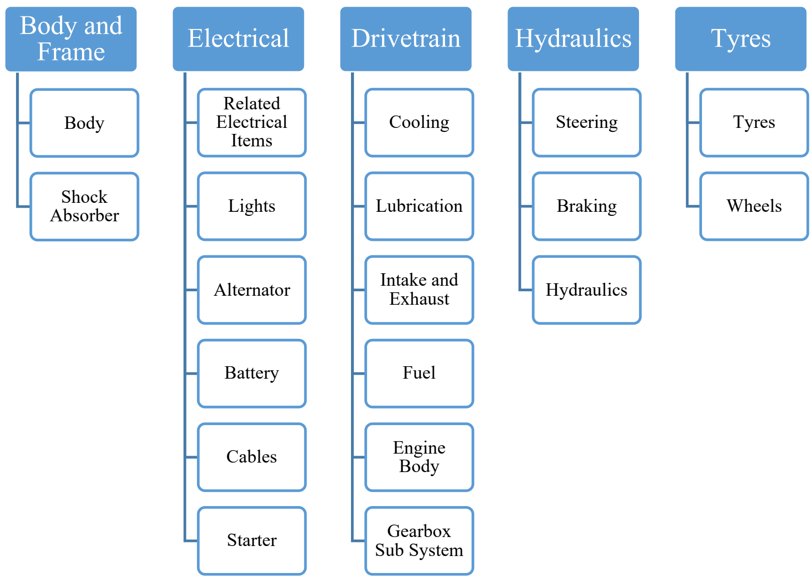


Figure 3.2 Sub-Systems and Failure-Prone Components of a Truck

Pareto charts of failure distributions in terms of failure numbers and downtime durations are shown in Figure 3.3 for Truck ID321. Among these seven trucks, Truck ID 323 is seen to be the truck experiencing the highest failure-based downtime, where Truck ID 327 shows the least total downtime at the observation time. In addition, there were 611 failures in total during the 4-years of observation.

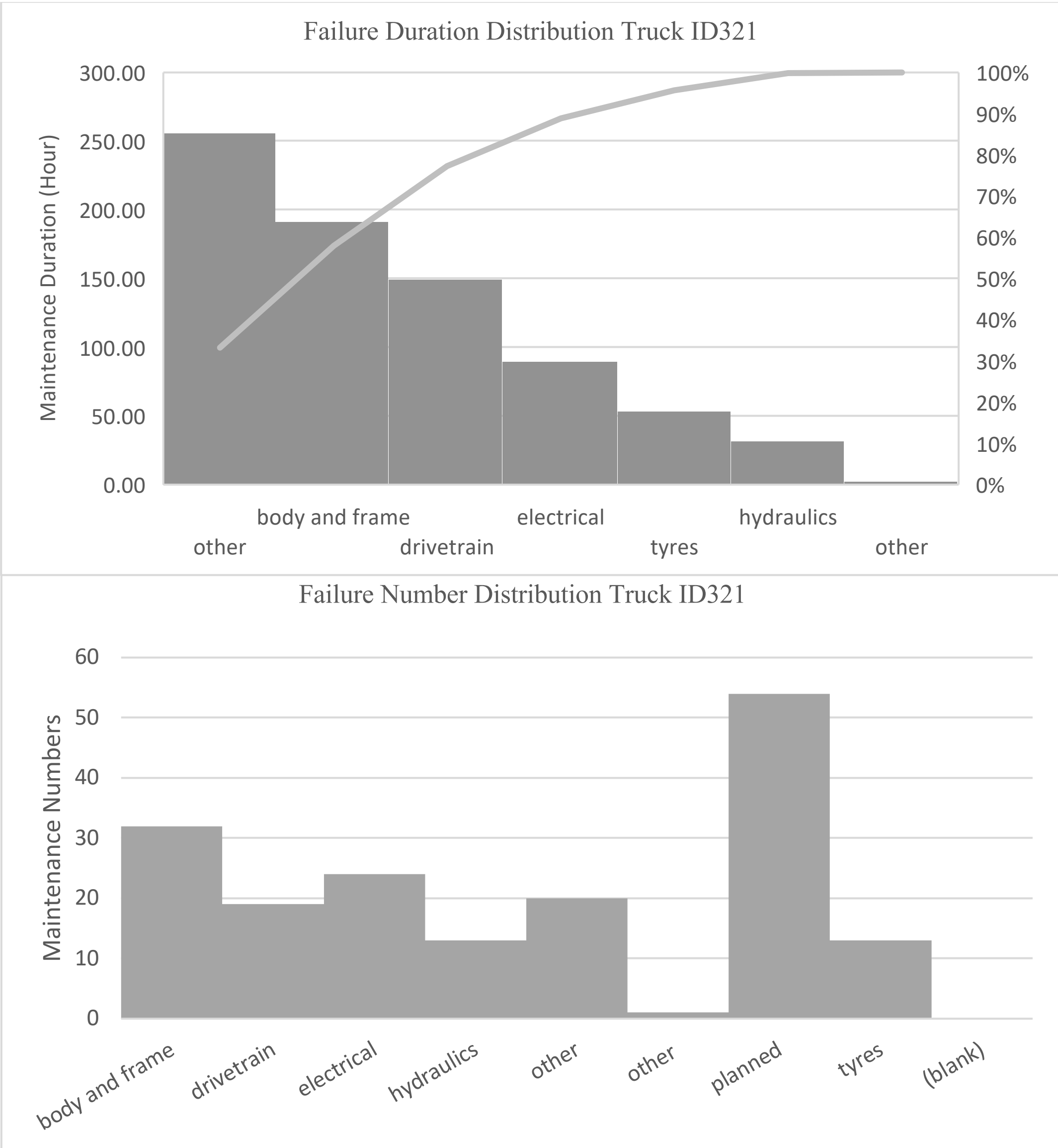


Figure 3.3 Failure Number and Duration Distributions of the Truck #321 Subsystems

Once the system was decomposed into subsystems, considering expert opinions, maintenance records, and equipment catalogs, then the maintenance records were allocated into related subsystems to determine their reliability and maintainability functions. On this basis, reliability functions will characterize surviving, i.e. operating, behaviors of subsystems, while maintainability functions will determine the time-to-repair behaviors of each subsystem in a maintenance condition. However, raw datasets require a preprocessing stage to understand their autocorrelation and time-dependency attitudes since the parametric values of reliability and maintainability behaviors can be determined differently in the case of time-dependency. Here, time-dependency means that related subsystems or components can be in a wear-out period that differs from their useful life period. Then, it becomes challenging to forecast upcoming failures, and distribution-fitting cannot be used in those cases since data behavior is highly variable in time. On this basis, regression equations holding time as an independent of the equation may be required to express the future subsystem or component failure events.

3.3 Data Preprocessing

This subsection discussed data preprocessing stages, including outlier detection, data dependency testing, and trend testing for individual truck subsystems' individual datasets using Minitab and ReliaSoft Weibull++ software.

3.3.1 Outlier Detection

Outlier is extremely high or low-value data in a data population that can disturb common data behavior. An outlier can be caused by measurement errors or rarely-observed but accurately measured high/low values. Including outliers in the analyses leads to damage in the parametric estimation of expected data characterization. Therefore, they should be detected and eliminated before the analysis. In the current study, maintenance downtime (time-to-repair, TTR) and lifetime (time between failures, TBF) datasets of subsystems for each truck were tested for outlier detection using Grubbs' test in Minitab. In a random sample taken from a population, an outlier is an observation that is abnormally distant from other values. In a sense, the choice of what constitutes abnormality is left up to the analyst (or a consensus process) in accordance with this definition (NIST/SEMATECH, 2012). Furthermore, according to Aslam (2020) the test checks the null hypothesis that a speculative value is an outlier compared to the other hypothesis that the value is not an outlier. Test's value is compared with the tabulated value at a fixed value of the level of significance. The null hypothesis is that the speculated value is an outlier is accepted if the Grubbs' value is smaller than the tabulated value. A sample illustration of the test for the TTR dataset of the Body and Frame subsystem of Truck ID321 is given in Figure 3.4.

It can be seen that, compared to majority of the data, the value of 1,291 falls away. Therefore, 1,291 can be defined as an outlier according to Grubbs test. Because, it doesn't behave as expected. If there were more data towards 1000s, it could have been seen as normal.

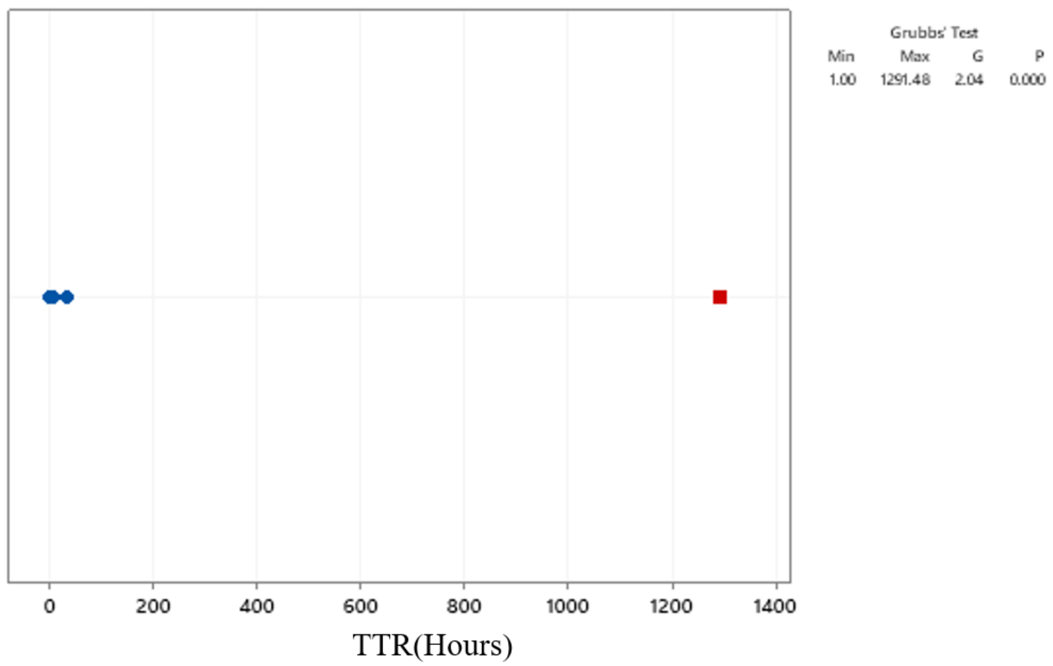


Figure 3.4 Outlier Plot for Truck#321 Body and Frame Sub-System's TTR

3.3.2 Data Dependency

After removing the outlier values, the resultant sets of TBF and TTR values were tested for data dependency. Data dependency tests evaluate the correlation between the sequential time-ordered values and determine if there is a biased effect between the values. This type of correlation is also called autocorrelation and can be discussed using the Pearson correlation test with lag1, lag2, and lag3 intervals. Lag1 tests determine the potential correlation between n order and (n+1) order data, Lag2 controls the correlation between n order and (n+2) order data, and Lag3 checks the correlation between n order and (n+3) order data. The Pearson test gives a coefficient called r-value, which refers to the correlation rate. For the absolute value of r higher than 0.7, there is a strong indication of autocorrelation for the tested lag-interval. Otherwise, the data is stated to be independent. In addition, a positive r value indicates a reverse correlation, while a positive r value points to a direct correlation between sequential data. Furthermore, Turney (2022) suggests the Pearson correlation coefficient (r) can be used to measure how close the observations are to a line of best fit. Extreme values of the correlation coefficient can be observed in Figure 3.5.

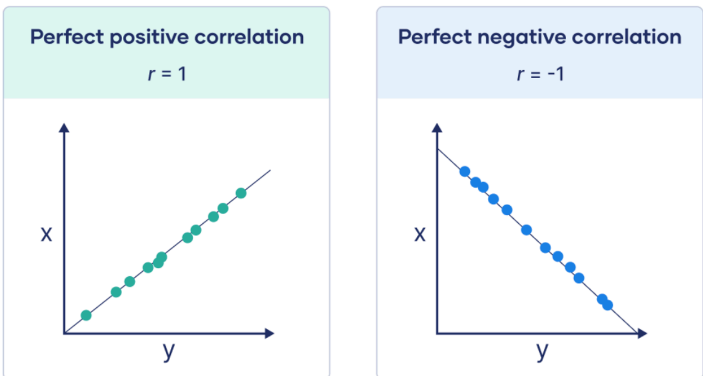


Figure 3.5 Visualization of Pearson Correlation Coefficient (Turney, 2022)

The Pearson test performed in Minitab for the TTR dataset of the Body and Frame subsystem of Truck ID321 is shown in Figure 3.6. The |r| value lower than 0.7 indicates that the dataset does not experience autocorrelation behavior. The test was applied for each TBF and TTR dataset of individual trucks. There is not any observed autocorrelation behavior for the Lag1 and Lag2 sequences of these datasets.

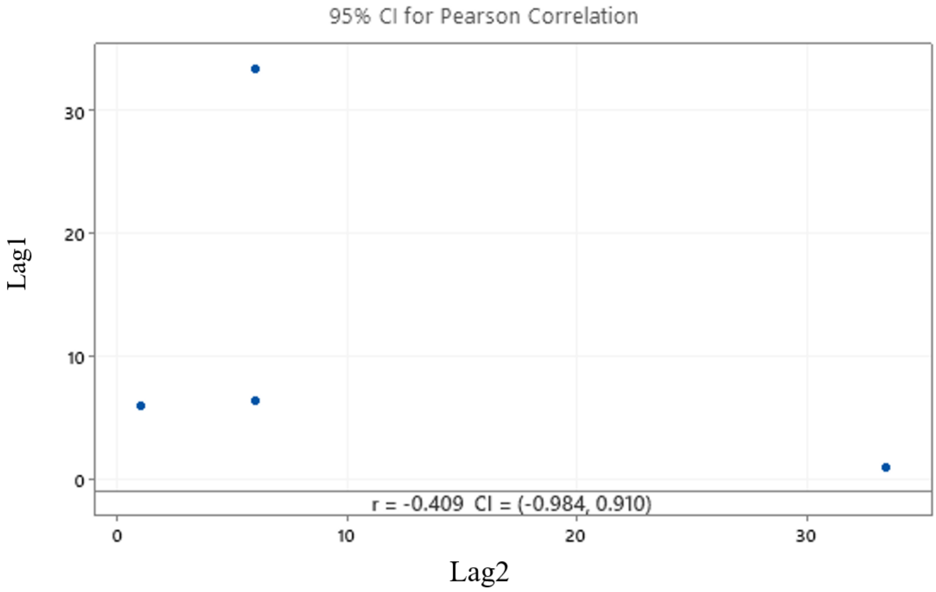


Figure 3.6 Pearson Correlation Test of Truck ID321 TTR Values of Body and Frame Sub-System Lag1&Lag2

3.3.3 Data Trend Tests

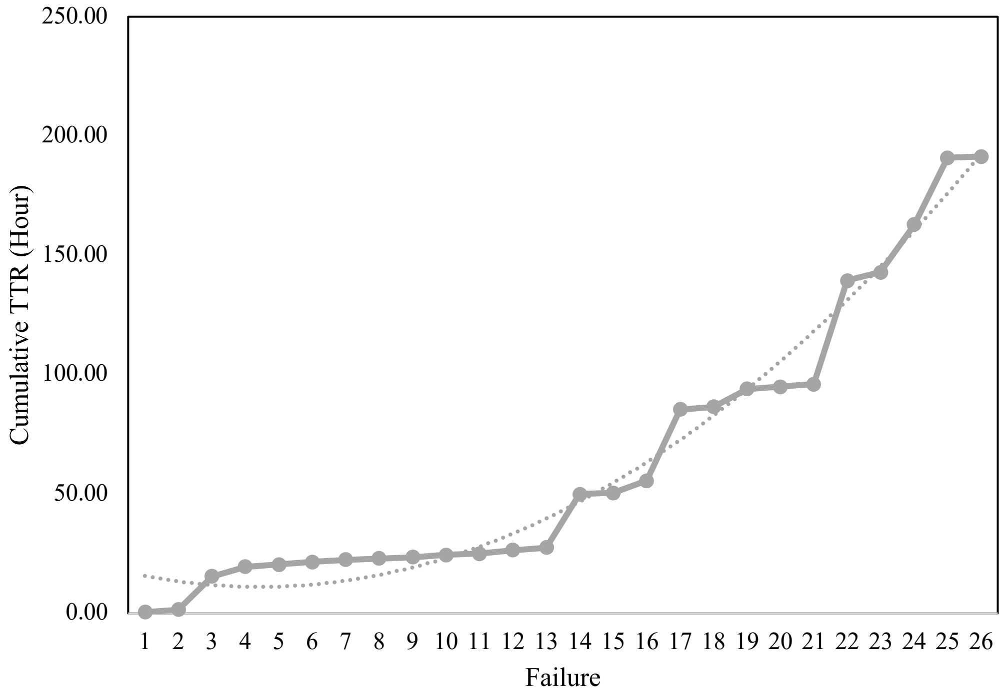
After eliminating outlier values and verifying that the TTR and TBF datasets are not with an autocorrelation behavior, these datasets were also tested for their potential time dependencies. Any equipment subsystem or component is expected to experience three different failure rate phases during its operation period. These are burn-in, useful life, and wear-out periods, as discussed earlier in Section 2. Burn-in period refers to the early phase of equipment utilization where the failure rate can be high initially but decrease over time due to accurate adaptation of equipment into operation. Then, the useful life of the equipment is observed, and equipment components are failed with almost expected lifetimes. Following a useful lifetime period, equipment components are exposed to increasing failure rates in short intervals due to the deterioration of system components. In that case, the predictability of failure occurrences decreases with increasing failure frequency. Suppose the wear-out period is not interrupted with a modified maintenance policy. In that case, the equipment is expected to be evaluated as salvage since equipment availability drops drastically so that the resultant production loss will require renewal or substation of equipment with a new one.

In this section, data trend tests will detect any subsystem with an increasing failure rate (wear-out) or a stable failure rate (useful life). If subsystem TBF/TTR values do not follow any trend in time, then it means that useful life is active for the subsystem and the related dataset is out of time dependency. This type of dataset can be fitted in distributions. Otherwise, if data trend in time is observed, it means that data cannot be characterized using best-fit distributions, and time-dependent functions should be determined. Qualitative and quantitative trend tests can investigate data trend behavior.

The qualitative trend test uses graphical illustrations and subjective interpretation where the cumulative time between failure values is drawn, as shown in Figure 3.7. A straight-line behavior of the plot dots refers to a stable behavior without a trend. At this point, Figure 3.7 points to some potential data trend behavior.

On the other hand, Quantitative Trend Tests use mathematical expressions to estimate the data trend over time. Four quantitative hypothesis testing methods were utilized for this study, as listed below.

- Crow-AMSAA Test
- Laplace Test
- CPNT Test
- Lewis-Robinson Test



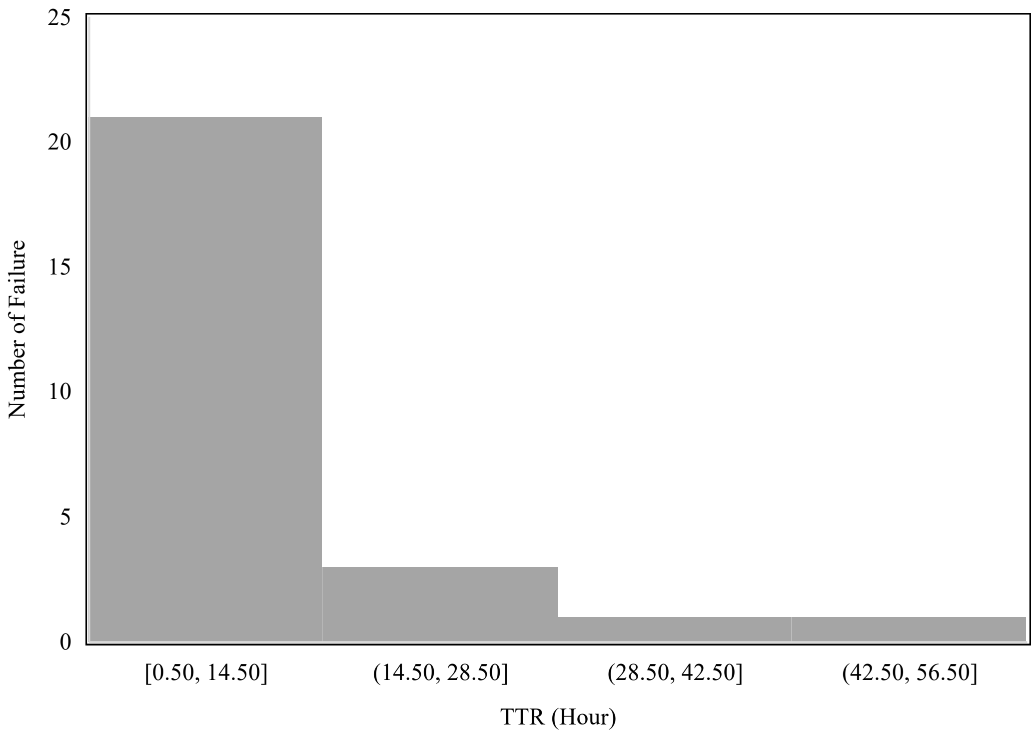


Figure 3.7 Cumulative TTR Plot and Number of Failure Graph of Truck ID321 Body and Frame Subsystem

The Crow-AMSAA model is a hypothesis testing method where the null hypothesis (Ho) indicates that time-ordered data follow the homogeneous Poisson process point to non-trend behavior. If the null hypothesis is rejected, the alternative hypothesis (H1) defends that data follows the non-homogenous Poisson process with a potential data trend. If the null hypothesis is accepted, then the dataset can be fitted into the best-fit distribution. The Crow-AMSAA model basically investigates reliability growth within a particular phase (Weibull, 2005).

Ho: HPP

H1: NHPP

$$\hat{\beta} = \frac{N}{\sum_{i=1}^{N-1} \ln\left(\frac{T_N}{T_i}\right)} \tag{3.1}$$

Reject Ho if:

$2N/\hat{\beta} < \chi^2_{2N,1-\alpha/2}$

$2N/\hat{\beta} > \chi^2_{2N,\alpha/2}$

The test parameter, $\hat{\beta}$, is determined using the number of failures (N) and cumulative time between failures up to i^th failure (T_i). Data trend is rejected if $2N/\hat{\beta} < \chi^2_{2N,1-\alpha/2}$ or $2N/\hat{\beta} > \chi^2_{2N,\alpha/2}$ where χ^2 and α are the chi-squared distribution score and confidence interval, respectively.

On the other hand, the Laplace test uses the hypothesis testing criteria given in Equation 3.2. If, for the predetermined U_L value, $U_L > z_{\alpha/2}$ or $U_L < -z_{\alpha/2}$ where $z_{\alpha/2}$ is the standardized normal distribution score, then the null hypothesis is rejected, and the data is expected to be with a trending behavior (Wang and Coit, 2005).

Ho: HPP

H1: NHPP

$$U_L = \frac{\sum_{i=1}^{N-1} T_i - (N-1)\frac{T_N}{2}}{T_N\sqrt{\frac{N-1}{12}}} \tag{3.2}$$

Reject Ho if:

$U_L > z_{\alpha/2}$

$U_L < -z_{\alpha/2}$

The Pairwise Comparisons or PCNT decided that the data is following a trend behavior if $U_L > z_{\alpha/2}$ or $U_L < -z_{\alpha/2}$where U is the number of conditions where $X_j > X_i$ for $j > i$ (Wang and Coit, 2005).

Ho: Renewal H1: Not Renewal	$U_P = \dfrac{U - N(N-1)/4}{\sqrt{\dfrac{(2N+5)(N-1)N}{72}}}$	Reject Ho if: $U_L > z_{\alpha/2}$ $U_L < -z_{\alpha/2}$

(3.3)

The Lewis-Robinson test is a modification of the Laplace test where the null hypothesis validates the Renewal process. The method uses the coefficient of variance, $CV[X]$, differently (Gustin, 2011).

Ho: Renewal H1: Not Renewal	$U_{LR} = \dfrac{U_L}{CV[X]}$	$CV[X] = \sqrt{Var[X]/\bar{x}}$	Reject Ho if: $U_L > z_{\alpha/2}$ $U_L < -z_{\alpha/2}$

(3.4)

Hypothesis test results of the TBF and TTR datasets for Truck ID321 can be observed in Table 3.1 and Table 3.2. The test results for the other trucks can be examined in Appendix A.

Table 3.1 Trend Test Results of the TTR Datasets of Truck ID321 Subsystems

Test Name	**Test Parameters**	**Truck Subsystems**				
		Electrical	**Drivetrain**	**Hydraulics**	**Tyre**	**Body**
Crow AMSAA	$2N/\hat{\beta}$ $\chi^2_{2N,1-\alpha/2}$ $\chi^2_{2N,\alpha/2}$	10.1 3.3 20.5 Accept Ho	74.4 32.4 71.4 Reject Ho	38.5 19.8 52.0 Accept Ho	28.3 6.9 28.9 Accept Ho	43.0 15.3 44.5 Accept Ho
Laplace	U_L $z_{\alpha/2}$	-0.87 1.95 Accept Ho	-2.60 1.95 Reject Ho	0.56 1.95 Accept Ho	-2.13 1.95 Reject Ho	-1.16 1.95 Accept Ho
PCNT	U_p $z_{\alpha/2}$	0.00 1.95 Accept Ho	0.65 1.95 Accept Ho	0.58 1.95 Accept Ho	1.48 1.95 Accept Ho	1.15 1.95 Accept Ho
Lewis Robinson	U_{LR} $z_{\alpha/2}$	-0.71 1.95 Accept Ho	-1.67 1.95 Accept Ho	0.32 1.95 Accept Ho	-1.89 1.95 Accept Ho	-0.94 1.95 Accept Ho
	DECISION	Non-trend	Trend	Non-trend	Non-trend	Non-trend

Table 3.2 Trend Test Results of the TBF Datasets of Truck ID321 Subsystems

Test Name	**Test Parameters**	**Truck Subsystems**				
		Electrical	**Drivetrain**	**Hydraulics**	**Tyre**	**Body**
Crow AMSAA	$2N/\hat{\beta}$ $\chi^2_{2N,1-\alpha/2}$ $\chi^2_{2N,\alpha/2}$	15.6 9.6 34.2 Accept Ho	71.2 38.8 80.9 Accept Ho	35.9 27.6 64.2 Accept Ho	22.1 12.4 39.4 Accept Ho	37.4 16.8 47.0 Accept Ho
Laplace	U_L $z_{\alpha/2}$	1.13 1.95 Accept Ho	-1.00 1.95 Accept Ho	0.14 1.95 Accept Ho	0.49 1.95 Accept Ho	-1.37 1.95 Accept Ho
PCNT	U_p $z_{\alpha/2}$	-0.80 1.95 Accept Ho	0.98 1.95 Accept Ho	-0.99 1.95 Accept Ho	-0.41 1.95 Accept Ho	1.53 1.95 Accept Ho
Lewis Robinson	U_{LR} $z_{\alpha/2}$	0.92 1.95 Accept Ho	-1.22 1.95 Accept Ho	0.13 1.95 Accept Ho	0.49 1.95 Accept Ho	-1.38 1.95 Accept Ho
	DECISION	Non-trend	Non-trend	Non-trend	Non-trend	Non-trend

The hypothesis testing results show that some truck subsystems' TBF or TTR datasets follow trend behavior. As mentioned earlier, any dataset with trend behavior cannot be evaluated with bet-fit distributions since both stable and wear-out data may be included in the same dataset without homogeneity. Therefore, these datasets should be analyzed using Renewal Function with an imperfect maintenance model.

Table 3.3 lists the truck subsystems having trend behavior in their datasets.

Table 3.3 The Truck Subsystems with Data Trend Behavior

Truck ID	**Sub-system**	**Failed Tests**
322	Electrical	TBF&TTR
323	Drivetrain	TBF
323	Hydraulics	TBF
324	Tyres	TBF&TTR
325	Body	TBF&TTR
326	Hydraulics	TBF

3.4 Estimation of Reliability (TBF) and Maintainability (TTR) Functions

Each truck subsystem's TTR and TBF datasets are evaluated using either best-fit distributions or imperfect maintenance concepts, depending on data trend behavior. Imperfect maintenance models allow determining parametric values of data characterization with a restoration value between 0 and 1. The value of 0 means that any maintenance action returns the failed component just back to the before-failure condition called as bad as old. This condition is also called minimal repair. Here, the failed component is restored, but the trend in failure rate is not changed. The restoration factor of 1 refers to perfect maintenance, also called as good as new. A dataset with trend behavior is expected to have a restoration factor $0 \leq RF < 1$. This factor will not equal 1 since RF of 1 indicates that there is not any trend since the component is restored to an as good as new condition that eliminates accumulation in failure rate. This restoration factor can be determined in two different assumptions on whether the maintenance is eliminating the cumulative hazard from the very first hours of the observation period or the hazard just from the previous maintenance. Details of the imperfect maintenance concept can be examined in Mettas and Zhao (2005).

Parametric values of the obtained TBF and TTR functions will be given and discussed in Section 4.3.

CHAPTER 4

FAULT TREE ANALYSIS OF A TRUCK FLEET FOR DIFFERENT MAINTENANCE SCENARIOS

4.1 Introduction

This chapter focuses on the fault tree analysis of a truck fleet operated in an open pit coal mine. The analysis intends to reveal system reliability variations of individual trucks and truck fleet according to different maintenance scenarios. Accordingly, Section 4.2 will discuss the fault tree construction for the mining truck. Section 4.3 will mention the maintenance scenarios that will be considered in the analyses. Section 4.4 will perform a comparative investigation between the scenarios according to their contributions to the truck fleet's uptime and downtime profiles.

4.2 Construction of a Fault Tree Diagram for Mining Truck Fleet

Fault tree analysis is a common method used for reliability analysis of different systems, including transportation devices, manufacturing machinery, and infrastructural items. Fault trees are constructed by using various gates that refer to structural and/or functional dependencies in a system. The most frequently-used gates are AND gate, OR gate, standby gate, and Voting gate. A fault tree analysis estimates system failure probability (reverse of reliability) considering the reliability behaviors of its subsystems and components and their top-to-bottom dependencies described by the related gates. Therefore, the reliability is determined starting from the lowermost event to the uppermost event.

If any two or more sub-events are combined with a series dependency under an event, then these events are combined with AND gate. It means that all the sub-events should fail for the failure of the main event. On the other hand, if any failure of sub-events is enough for the failure of the main event, OR gate is used to define the dependency. On the other hand, the voting gate states that at least k out of n sub-events should fail for the failure of the main event. For instance, a fault tree having an event with 3 out of 4 voting gate points to that there are four sub-events; if at least three of them fail, then the event will fail. Otherwise, the event will survive even though there are some failed sub-events if the number of failed sub-events is less than three. Last, stand-by configurations imply that some inactive events are being activated in case of failure of similar events. There are also some special gates such as load sharing, Priority AND gate, and XOR gate that can be used in complex interactions in a system. Here, the load sharing gate is used in cases where surviving probability of an event is changing dynamically with the failure of its sub-events. On the other hand, the XOR gate states that exactly one sub-event should fail for the failure of the main event. It is similar to the OR gate, but the OR gate allows the failure of more than one sub-event. Last, the Priority AND gate can be used for the events where sub-events should fail in a specific order to prevent the survival of the main event.

The fault tree diagram for the truck fleet was created using ReliaSoft BlockSim 7 software. The main intention in this analysis is to reveal the expected downtime and uptime profiles of trucks using dynamic simulation of fault tree diagrams. Failure records of a truck fleet operated in a coal mine, machinery catalogs, and expert opinions were regarded to develop the fault tree diagram. As discussed earlier in Section 3.2, a truck is detected to be decomposed into the following subsystems:

i. Body and Frame: This part is the largest section of the truck. The damper, main construction (frame) creating a space for engines and all other mechanical and electrical items, and shock observers are detected to be prone to failures according to the maintenance records. Even though many different items are covered in this subsystem, this subsystem could not be decomposed into its lowermost components due to the lack of enough explanations in the records. Therefore, related failure records were considered together for the subsystem without data classification of components. This condition is also valid for the other subsystems. Therefore, in the fault tree analysis, subsystems will refer to the lowermost events.

ii. Electrical: Many electrical components such as starters, cables, batteries, alternators, lights, and other electrical items are covered in this subsystem. Due to insufficient explanations in the records and enough failure data to be analyzed, all related electrical failures were taken together under the electrical subsystem.

iii. Drivetrain: Engine body, gearbox sub-components, fuel injection items, intake and exhaust air system items, lubrication units, and cooling units were included in this subsystem. As in the other subsystems, this subsystem could not be decomposed into its small components due to inefficient descriptions in the maintenance records.

iv. Hydraulics: Steering, braking, and other related items were covered in this subsystem. This subsystem was evaluated as a whole.

v. Tires: Tires and wheels are the components of this subsystem, and it is taken without any component breakdown.

An event block represents each sub-system, and they were configured in a series dependent on AND gate in each truck. Reliability (time between failures, TBF) and maintainability (time to repair, TTR) functions of each subsystem are transferred from ReliaSoft Weibull 7 software to ReliaSoft BlockSim 7. At this point, ReliaSoft Weibull 7 software is used to determine best-fit distribution functions for non-trend datasets and imperfect maintenance functions for trend datasets, as discussed in detail in Section 3.3.

In addition, six trucks were included in the analysis. Therefore, a total of 30 subsystems, seven subsystems for each truck, were considered in the reliability analysis of the truck fleet. Here, the fleet reliability was expressed by the voting gate. It means that production can be sustained with k out of n number of trucks in the fleet at least, where n is the total truck number (Figure 4.1).

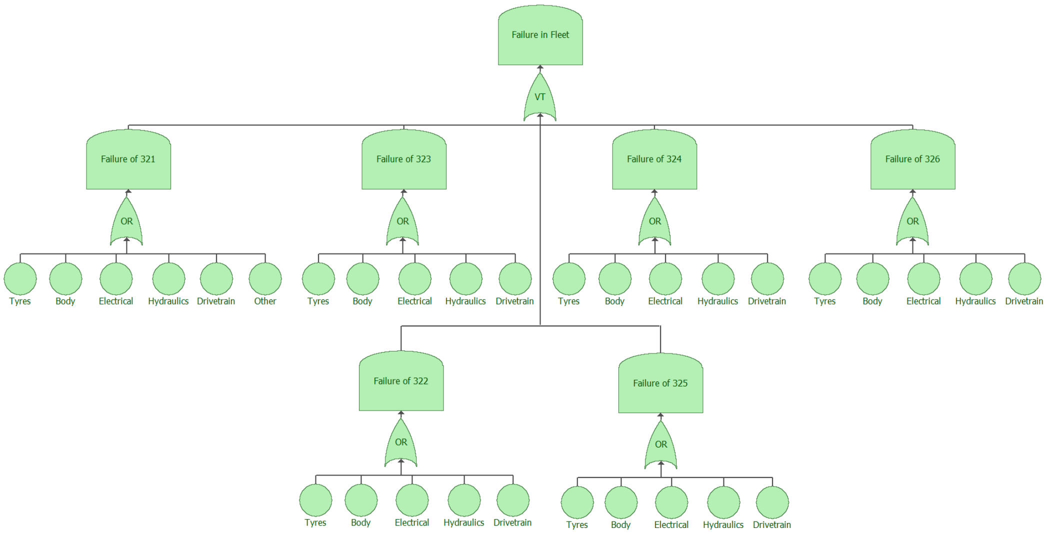


Figure 4.1 Fault Tree Diagram of the Truck Fleet

4.3 Evaluation of the Input Datasets

Fault tree analysis of the truck fleet required pre-determination of the following input parameters:

- Reliability functions of the subsystems ($f(x)_{ij}$): Surviving characterization for each subsystem (i) of truck (j) can be performed depending on if the time between failures (TBF_{ij}) dataset of the related subsystem follows any ascending or descending trend in time, as discussed in Section 3.3. Accordingly, if the trend behavior of a time series dataset is proved statistically, then the function parameters of this dataset can be determined using the general renewal function with an imperfect maintenance concept. This function allows estimating 2-parameter Weibull Distribution parameters with a restoration factor between 0.0 and 1.0, which refers to minimal and perfect maintenance. If any time-based trend is not detected in a dataset, then the function parameters can be determined by distribution fitting. Once maintenance records were decomposed into a subsystem of each truck, these individual datasets were analyzed using Reliasoft Weibull software. The resultant $\mathrm{f(x)_{ij}}$ parameters are tabulated in Table 4.1.

- Maintainability functions of the subsystems ($\mathrm{g(x)_{ij}}$): Time to repair ($\mathrm{TTR_{ij}}$) values of subsystem (i) of truck (j) were analyzed in Reliasoft Weibull 7 software following a similar procedure with $\mathrm{f(x)_{ij}}$ (Table 4.2). These functions will allow assigning random maintenance durations for the subsystems. Similar to $\mathrm{f(x)_{ij}}$, any time-dependent trend in the maintenance durations is regarded when determining the parametric values of $\mathrm{g(x)_{ij}}$. A statistically-proved increase in TTR values in time may point to increased maintenance time for similar failure modes due to exposure to more serious failure because of subsystem deterioration.

As observed from Table 4.1 and Table 4.2, the functions are defined in terms of 3-parameter Weibull distribution, 2-parameter Weibull distribution, General Renewal process, and 2-parameter lognormal distribution, normal distribution, or 2-parameter exponential distribution. Here, the General Renewal process is applied to the time-dependent trend behavior subsystems. Descriptive parameters of this process can be identified with Weibull distribution parameters. For both Weibull distribution and the General Renewal process, the Eta parameter, also called shape parameter β, refers to behavior of failure rate. The functions with $\beta < 1$ exhibit a failure rate decreasing with time. It is understood that the related subsystems have infant mortality failure characteristics that are also observed in the very early stages of using these subsystems. Subsystems generally with complex components may show this behavior due to over-maintenance free from deterioration. If $\beta \cong 1$, then the function exhibits constant and very predictable failure rate (useful life). The corresponding subsystems have expected failure frequency without any over or under-maintenance activities. In addition, when the β closes to 1, then the Weibull distribution is reduced to the exponential distribution. The subsystems with $\beta > 1$, they are prone to have a deterioration.

Table 4.1 Reliability (TBF) Functions of Truck Subsystems

	Truck ID 321	Truck ID 322	Truck ID 323	Truck ID 324	Truck ID 325	Truck ID 326
Electrical	Weibull-3P Beta 0.78 Eta 1429.75 Gamma -24.58	General Renewal Process Beta(W) 1.78 Eta(W) 5578.94 RF 0	Weibull-2P Beta 1.13 Eta 796.21	Weibull-3P Beta 0.87 Eta 1059.52 Gamma 7.15	Normal-2P Mean 1102.83 Std 963.00	Weibull-3P Beta 1.07 Eta 1320.23 Gamma -40.25
Drivetrain	Weibull-3P Beta 0.97 Eta 2407.78 Gamma -72.42	Weibull-2P Beta 0.66 Eta 950.62	General Renewal Process Beta(W) 0.43 Eta(W) 880.65 RF 0.997	Weibull-2P Beta 0.72 Eta 1296.34	Weibull-3P Beta 1.28 Eta 1863.98 Gamma -239.66	Exponential-2P Lambda 5.02E-04 Gamma -30.60
Hydraulics	Weibull-3P Beta 0.80 Eta 2701.70 Gamma 142.71	Weibull-3P Beta 1.15 Eta 1457.28 Gamma -110.33	General Renewal Process Beta(W) 1.62 Eta(W) 2000.43 RF 0.99	Weibull-3P Beta 0.79 Eta 1598.17 Gamma 0.94	Weibull-3P Beta 0.63 Eta 1655.28 Gamma -9.06	General Renewal Process Beta(W) 0.50 Eta(W) 190.76 RF 0
Tyre	Weibull-3P Beta 0.43 Eta 495.86 Gamma 92.67	Weibull-3P Beta 0.70 Eta 827.90 Gamma -6.84	Weibull-3P Beta 1.13 Eta 1551.65 Gamma -97.42	General Renewal Process Beta(W) 1.76 Eta(W) 2880.18 RF 0.34	Weibull-3P Beta 0.38 Eta 628.42 Gamma 11.41	Weibull-2P Beta 0.56 Eta 382.72
Body	Weibull-3P Beta 0.95 Eta 1148.52 Gamma -13.85	Weibull-3P Beta 0.84 Eta 927.99 Gamma 46.75	Weibull-2P Beta 1.04 Eta 1504.40	Lognormal-2P Mean 5.76 Std 1.06	General Renewal Process Beta(W) 0.58 Eta(W) 66.58 RF 0.66	Lognormal-2P Mean 6.41 Std 1.24

Table 4.2 Maintainability (TTR) Functions of Truck Subsystems

	Truck ID 321	Truck ID 322	Truck ID 323	Truck ID 324	Truck ID 325	Truck ID 326
Electrical	Lognormal-2P Mean 0.45 Std 1.09	General Renewal Process Beta(W) 0.31 Eta(W) 0.88 RF 0.97	Weibull-3P Beta 0.40 Eta 9.06 Gamma 0.32	General Renewal Process Beta(W) 0.45 Eta(W) 0.90 RF 0.86	Weibull-2P Beta 1.52 Eta 1.54	Weibull-3P Beta 0.34 Eta 18.37 Gamma 0.48
Drivetrain	Weibull-3P Beta 0.52 Eta 7.67 Gamma 0.43	General Renewal Process Beta(W) 0.42 Eta(W) 0.35 RF 0.73	Weibull-3P Beta 1.11 Eta 43.99 Gamma -4.15	Weibull-3P Beta 0.49 Eta 3.73 Gamma 0.49	Weibull-3P Beta 0.44 Eta 2.39 Gamma 0.49	General Renewal Process Beta(W) 0.35 Eta(W) 1.68 RF 0.96
Hydraulics	General Renewal Process Beta(W) 0.49 Eta(W) 0.61 RF 0	General Renewal Process Beta(W) 0.35 Eta(W) 0.27 RF 0.74	Weibull-3P Beta 0.44 Eta 9.37 Gamma 0.49	Loglogistic-2P Mu 0.34 Sigma 0.43	Exponential-2P Lambda 3.55E-02 Gamma -0.15	Weibull-3P Beta 0.21 Eta 2.15 Gamma 0.99
Tyre	Weibull-3P Beta 0.63 Eta 10.48 Gamma 0.57	Lognormal-2P Mean 1.80 Std 1.48	General Renewal Process Beta(W) 0.33 Eta(W) 23.12 RF 0.99	General Renewal Process Beta(W) 0.43 Eta(W) 0.65 RF 0.52	Lognormal-2P Mean 1.47 Std 1.31	Weibull-3P Beta 0.69 Eta 5.84 Gamma 0.33
Body	General Renewal Process Beta(W) 0.45 Eta(W) 1.20 RF 0.97	General Renewal Process Beta(W) 0.33 Eta(W) 0.31 RF 0.90	General Renewal Process Beta(W) 0.43 Eta(W) 0.55 RF 9.26E-02	General Renewal Process Beta(W) 0.37 Eta(W) 0.39 RF 0.97	General Renewal Process Beta(W) 0.41 Eta(W) 0.70 RF 0.98	General Renewal Process Beta(W) 0.31 Eta(W) 5.03E-02 RF 0.73

In addition, the Eta parameter of the Weibull distribution or General Renewal process, also called scale parameter η, refers to the change of the abscissa scale of functions. In other words, it determines the approximate accumulation point of data. Last, 3-parameter Weibull distributions have a third parameter differently, given as Gamma parameter that is also called location parameter γ. This parameter is used to imply a free zone. It means that it is not possible to observe any point before γ value. As an example, TBF values of the Hydraulics subsystem of Truck ID 321 are fitted into Weibull-3P with $\beta = 0.796$, $\eta = 2701.69$, and $\gamma = 142.71$. In this subsystem, since $\beta < 1$, then it is in infant mortality behavior with decreasing failure rate. The value $\eta = 2701.69$ implies that the probability distribution function is accumulated in this value, and $\gamma = 142.71$ states that the probability of a failure before 142.71h of operating after any maintenance is impossible. Therefore, the least expected time between failure values is 142.71h.

In the General Renewal process, there is an additional description in the tables shown by RF that states the restoration factor. Since the subsystems defined with this process are with a time-dependent trend behavior, then RF values should be less than 1, inherently. As discussed in Section 3.4, RF values with 0 and 1 points to minimal (as bad as old) and perfect (as good as new) behavior. For instance, TBF values of the Electrical subsystem of Truck ID 322, which were detected to have a trend in Section 3.3.3, have an RF value of 0. On the other hand, TTR values of the same subsystem have an RF value of 0.97, indicating that maintenance durations have just started deviating from expected durations. If this situation is not interrupted with a revision in the available maintenance policy, the RF value may decrease in time.

On the other hand, normal distribution points to a symmetrical distribution of data around the Mean value with a variation described by standard deviation. If TBF values are fitted into normal distribution well, then an observable deterioration of subsystem can be concluded. Lognormal distribution fits the logarithmic values of the data set similar to normal distribution.

Besides, the subsystems whose data can be fitted in exponential distribution have very predictable operating and maintenance durations with an expected value of $1/Lambda$. Typically, a single parameter $(Lambda, \lambda)$ is used to define the exponential distribution. However, it is seen that a second parameter $(Gamma, \gamma)$ is also available to identify the starting position of the related probability functions.

The reliability and maintainability curves of the subsystems of Truck ID 321 can be observed in Figure 4.2 and Figure 4.3, respectively. The reliability and maintainability curves for the other trucks can be observed in Appendix A.

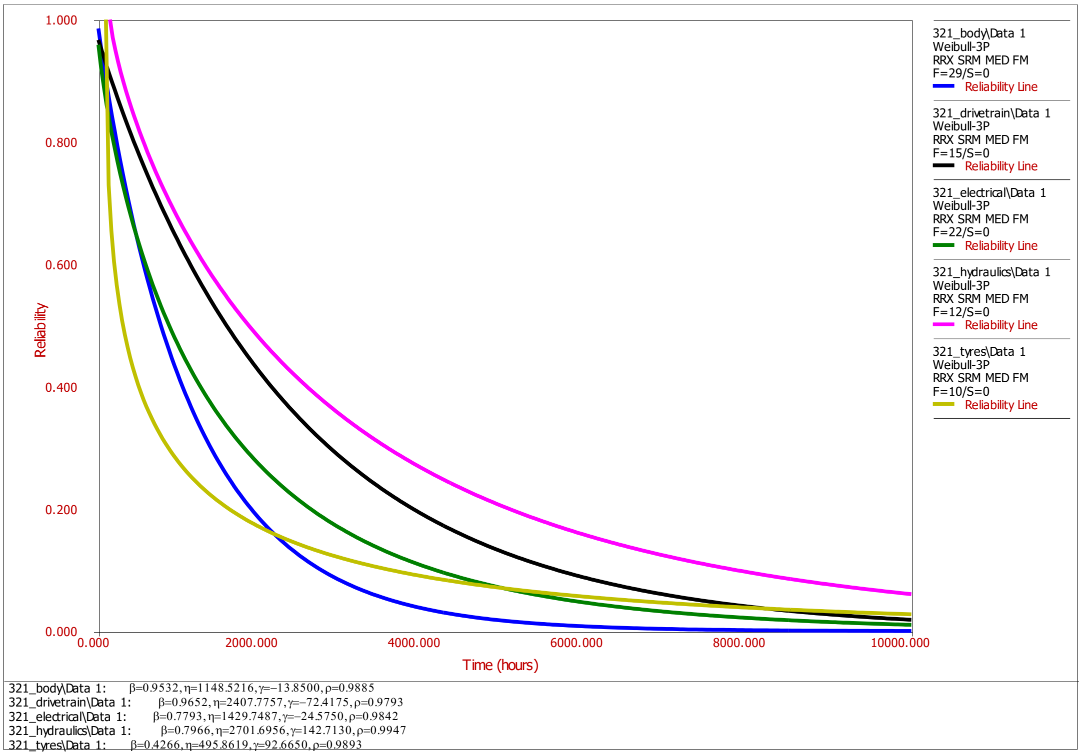


Figure 4.2 Reliability Curves of Truck ID321 subsystems

Expected TBF and TTR values of the truck subsystems are determined as shown in Table 4.3 and Table 4.4, respectively. Table 4.4 reveals an observable variation in maintenance duration, especially for Truck ID323 and Truck ID326.

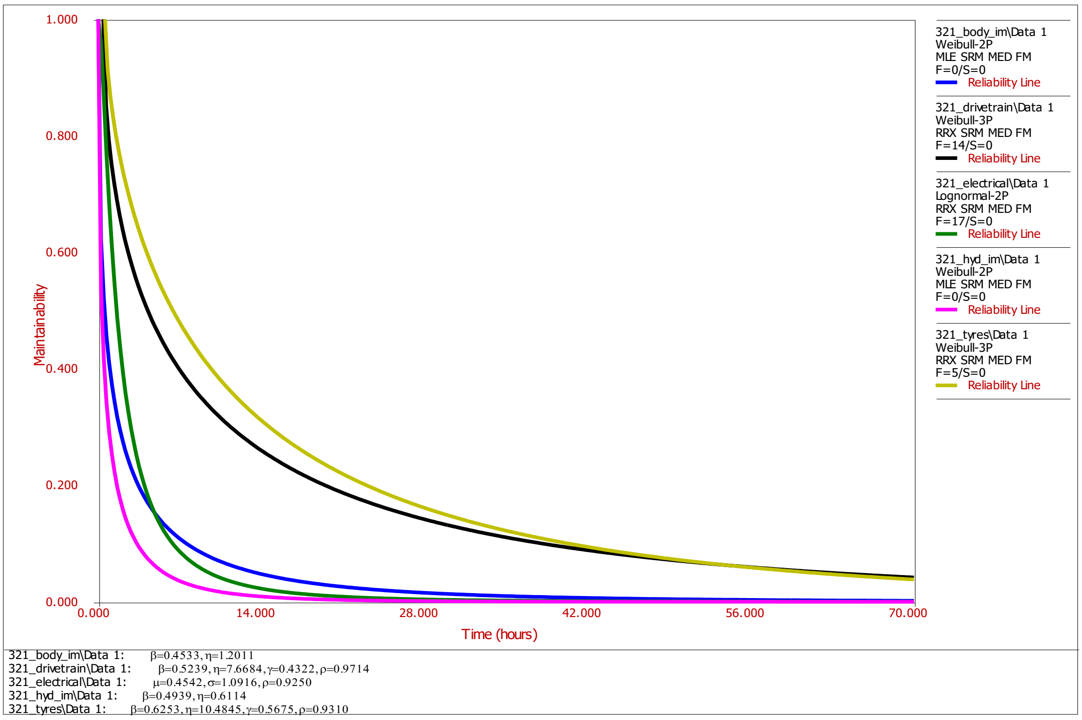


Figure 4.3 Maintainability Curves of Truck ID321 subsystem

Table 4.3 Expected TBF Values (hours) of the Truck Subsystems

	Truck ID321	Truck ID322	Truck ID323	Truck ID324	Truck ID325	Truck ID326
Electrical	1627.0	4964.0	761.6	1142.3	1102.8	1244.9
Drivetrain	2373.4	1268.3	240.8	1601.0	1487.8	1959.7
Hydraulics	3213.2	1276.6	2409.4	1818.8	2315.2	382.0
Tyre	1485.8	1040.9	1388.6	2564.7	2376.0	636.3
Body	1159.7	1064.1	1480.7	558.2	104.4	1314.4

Table 4.4 Expected TTR Values (hours) of the Truck Subsystems

	Truck ID321	Truck ID322	Truck ID323	Truck ID324	Truck ID325	Truck ID326
Electrical	2.9	7.3	29.6	2.3	1.4	99.1
Drivetrain	14.6	1.0	38.1	8.1	6.8	8.6
Hydraulics	1.3	1.3	24.8	1.9	28.0	205.5
Tyre	15.5	18.1	142.7	1.8	10.3	7.8
Body	2.9	1.8	1.5	1.6	2.2	0.4

- Direct maintenance cost (DC_{ij}): Direct financial consequences of maintenance activities for i^{th} subsystem of j^{th}truck should be inputted to understand the economic burden of maintenance activities.
- Indirect maintenance cost (IDC_{ijk}): Unit production loss in cases where the production is interrupted by any maintenance downtime. Both direct and indirect cost values used in the analyses can be viewed in Table 4.5.

Table 4.5 Maintenance Cost Items

Costs	321	322	323	324	325	326
Electrical	563.56	160.75	960.46	450.76	177.83	2559.90
Drivetrain	1126.26	306.09	719.12	145.41	362.65	307.68
Hydraulic	15.43	67.60	85.57	179.16	0.05	0.0391
Tires	333.64	39498	17825	371.65	1407.20	135.82
Body	296.29	98.08	174.49	292.67	265.84	125.96

The cost values shown here are the mixture of different failure modes with varying frequencies of occurrence for the trucks. Therefore, there can be considerable differences in the results. One truck might have experienced tire failure that led to a replacement, whereas others could have been an easy fix such as a patch-up.

4.4 Fault Tree Analysis Results for Alternative Maintenance Scenarios

After introducing datasets for each sub-system, fault tree analyses were performed for different maintenance interactions. The analysis has a dynamic simulation structure where the subsystems interact continuously on a pre-defined time interval. The algorithm checks each subsystem's status and the dependencies between each truck's subsystem to reveal system availability variations. Simulation is highly stochastic since maintainability (TTR), and reliability (TBF) values are randomly assigned from the distribution values pre-determined real datasets.

Target time defines how many simulation loops can be performed. The model starts at $active\ time,\ t_a = 0$ and interactions are measured until $t_a = t_t$ where t_t is the target observation period. Target time needs to be sufficiently large to obtain representative results of the system. On this basis, some subsystems may have failure occurrences in longer intervals while others may fail in higher frequency. Therefore, the period should collect enough number observations from each truck subsystem. When the simulation is started, failures occur using the defined probability density functions of TBFs ($f(x)_{ij}$) and TTRs ($g(x)_{ij}$), given in Table 4.1 and Table 4.2. Accordingly, the assigned TBF value of one subsystem will directly affect the failure occurrence times of other dependent subsystems in the same trucks since the dependent subsystems will not be able to operate once the other failed subsystem is recovered. Since all truck subsystems are assumed to combine with the OR gate, any sub-system failures will interrupt the truck operation.

The interaction between system availability and maintenance policy is analyzed in seven cases, considering corrective maintenance, regular inspections, preventive component replacement, and spare part conditions. For each case, uptime/downtime characteristics of truck subsystems, number of maintenance activities, and resultant financial and availability results will be investigated.

Maintenance Case01 (Base Model) – *Corrective Maint. & Regular Inspection*:

- Subsystems fail randomly according to $f(x)_{ij}$.
- Failed subsystems are recovered with corrective maintenance for a TTR duration assigned randomly from $g(x)_{ij}$. Perfect maintenance is assumed. It means the subsystems are recovered to as good as new conditions after maintenance.
- Since the OR gate is active between the subsystems of the same truck, then other non-failed subsystems are stopped operating for the assigned TTR value of the failed component

- Here, inspections are performed with fixed inspection intervals, and preventive maintenance is performed when any subsystem is detected to have a minor fault that can turn into a failure if not maintained. The delay time concept is included in the detection of approaching failures. According to this concept, some subsystems can give an alert with anomalies in vibration, sound, and similar factors after a threshold level of the operating time. For instance, if 90% is assumed for the delay time and if the assigned TBF value is 200h, then the subsystem will give an alert in the last 10% of 200h (20h). If this alert period overlaps with the regular inspection times, the related subsystem will be maintained preventively since any failure has not occurred yet. This kind of preventive maintenance is assumed to be completed within inspection hours.

- Spare part inventory and maintenance crew numbers are assumed to be unlimited.

- The simulation was performed for the different observation periods, $t_t = 8766h$, $t_t = 17532h$, and $t_t = 26298h$. Simulation results are balanced in 250 simulations, as given in Figure 4.4. A representative view of the simulation monitoring screen for 0-1000h can be examined in Figure 4.5.

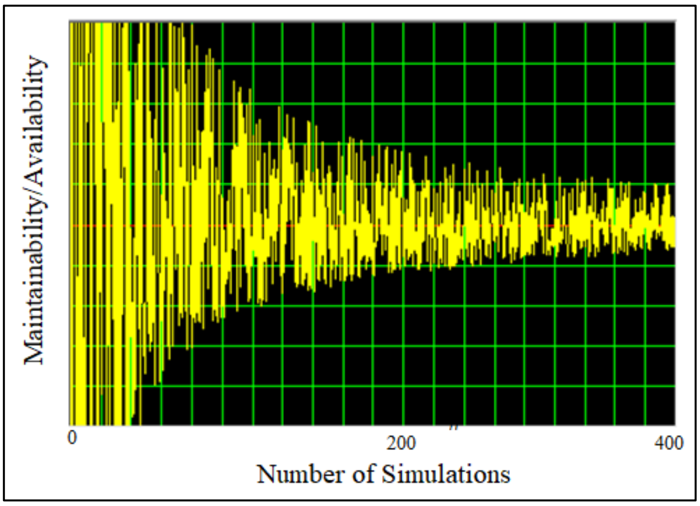


Figure 4.4 Determination of the Representative Simulation Number

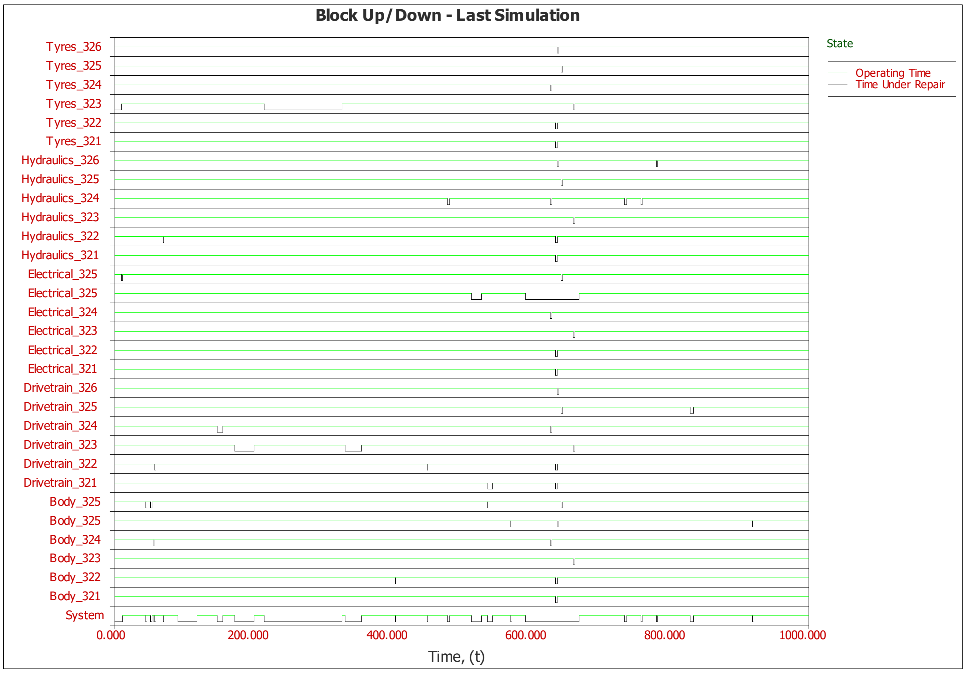


Figure 4.5 A Representative View of Simulation Monitoring Screen

The truck fleet's mean availability and cumulative cost values obtained from the Case01 simulation results can be investigated in Figure 4.6 and Figure 4.7.

Figure 4.6 Mean Availabilities of the Trucks for Case01

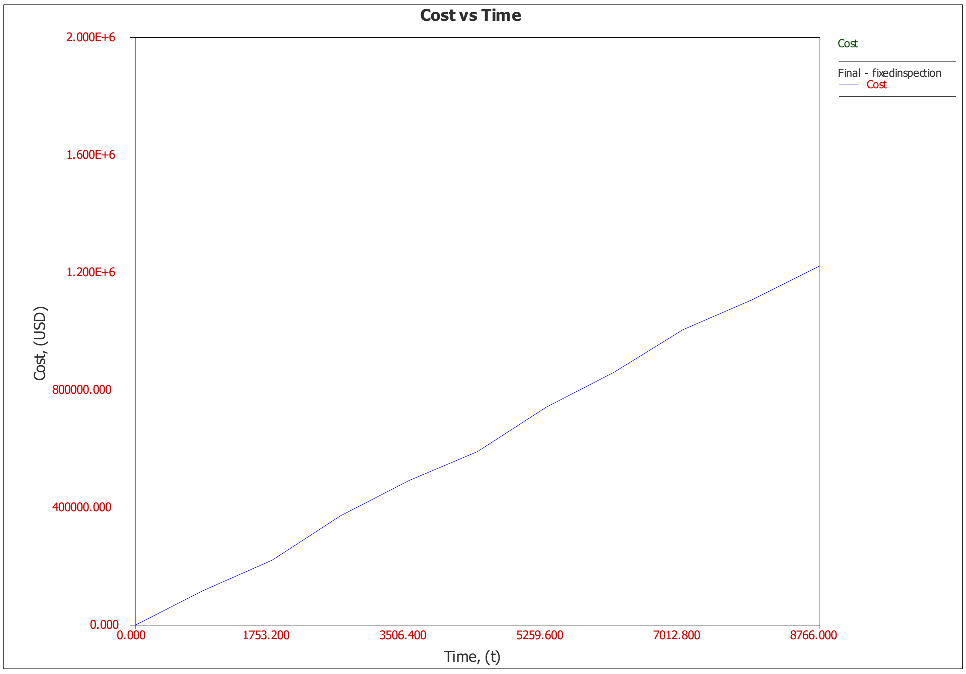


Figure 4.7 Cumulative Direct and Indirect Cost of Maintenance for Case01

In addition, the cumulative number of failures in time can be viewed in Figure 4.8. Linear behavior from the graph may refer to expected failure behavior in the general truck fleet. On the other hand, downtime and failure number characterization of individual subsystems can be examined in Figure 4.9 and Figure 4.10, respectively.

It is seen from the figures that the Hydraulic subsystem has an observable effect on both maintenance downtime and failure number of Truck ID326. On the other hand, the Body subsystem of Truck ID325 is seen to fail frequently but recovered in short durations. It is revealed that similar subsystems are acting differently for different trucks in terms of contribution to downtime and maintenance numbers. Therefore, the effects of maintenance on the reliability of subsystems in the same system and between the trucks need to be analyzed collectively, as performed in this study.

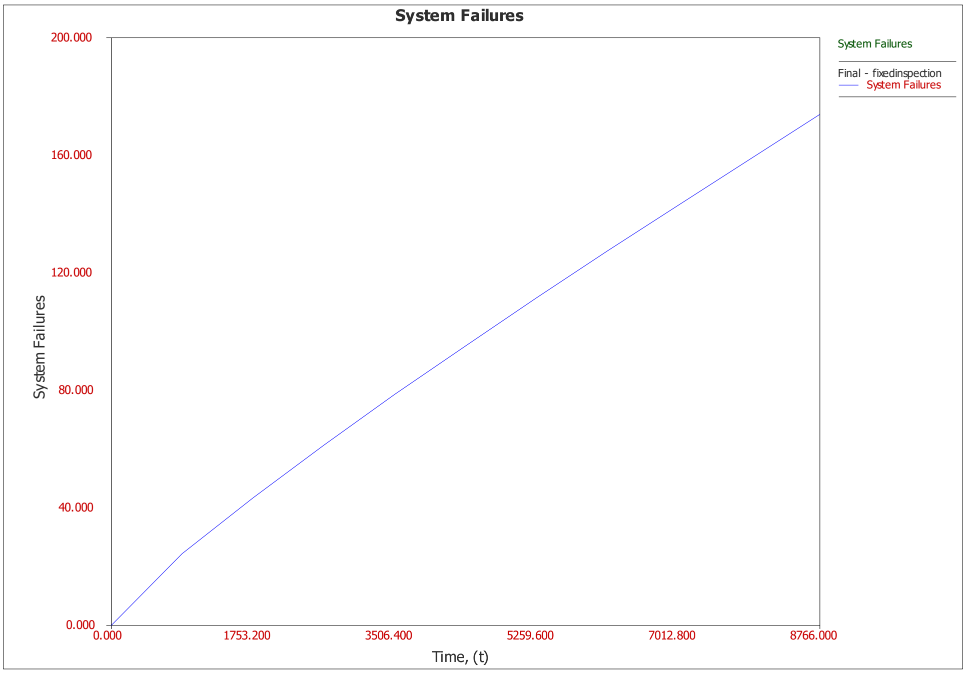


Figure 4.8 Cumulative System Failure Numbers in Time for Case01

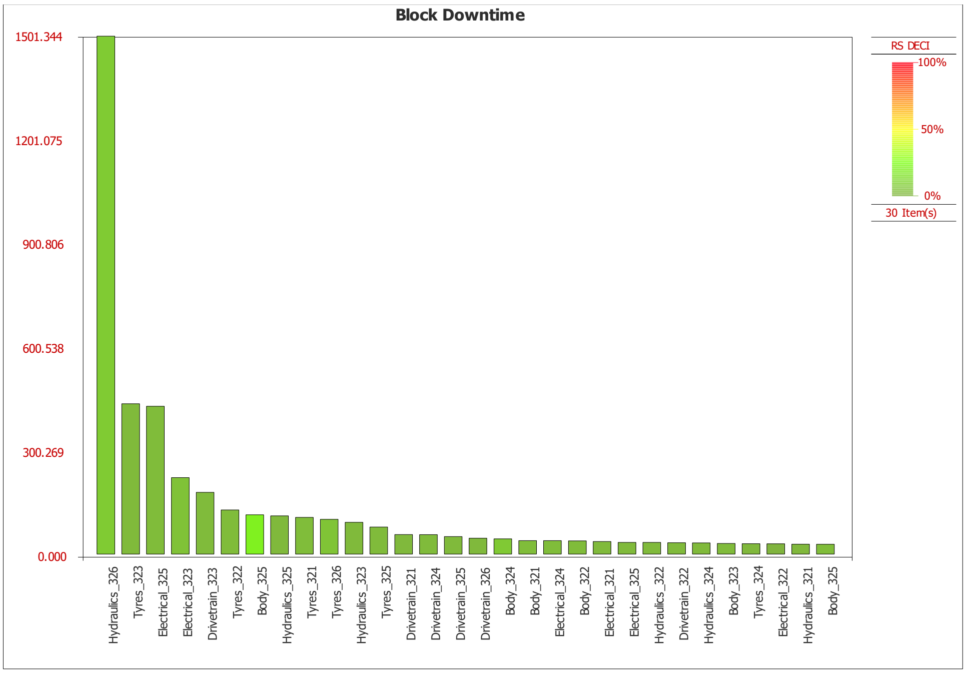


Figure 4.9 Maintenance Downtime Profiles of the Truck Subsystems for Case01

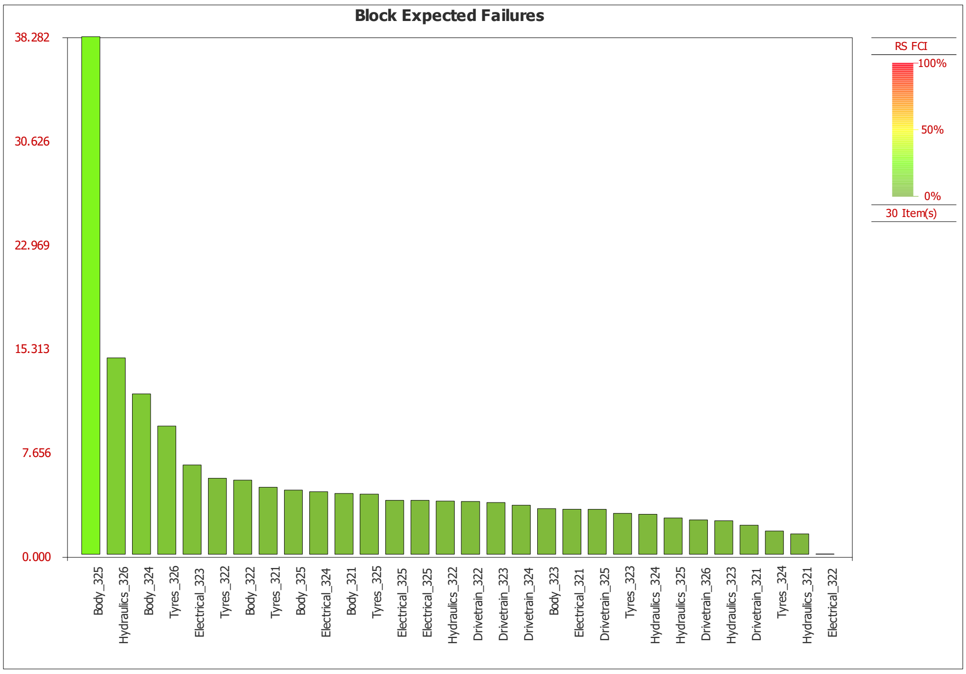


Figure 4.10 Failure Number Profiles of the Truck Subsystems for Case01

In addition, the failure criticality index (FCI), downtime, availability, and failure number profiles of the most critical subsystems are shown in Table 4.6. FCI is an index that is the ratio of system reliability to subsystem reliability in the time. If subsystem reliability is less, then the criticality will be higher.

Table 4.6 Summary of the Simulation for Case01

Block Failure Criticality		Availability Rating	
Name	**FCI**	**Name**	**Availability**
Blocks		**Blocks**	
Body_325	22.01%	Hydraulics_326	82.87%
Hydraulics_326	8.41%	Tyres_323	94.98%
Body_324	6.88%	Electrical_326	95.06%
Sub-systems		**Sub-systems**	
Body	6.60%	Hydraulics	96.52%
Tires	2.86%	Tires	98.27%
Hydraulics	2.76%	Electrical	98.44%
Electrical	2.16%	Drivetrain	99.13%
Drivetrain	1.91%	Body	99.38%

Failures Ranking		Block System Downing Events	
Name	**Exp.#ofFailures**	**Name**	**#ofEvents**
Blocks		**Blocks**	
Body_325	38.28	Body_325	43.63
Hydraulics_326	14.62	Hydraulics_326	16.78
Body_324	11.96	Body_324	15.19
Sub-systems		**Sub-systems**	
Body	68.89	Body	81.96
Tires	30.05	Tires	36.27
Hydraulics	28.89	Hydraulics	35.00
Electrical	23.38	Electrical	30.87
Drivetrain	20.21	Drivetrain	25.00

Block Downtime Ranking	
Name	**Downtime Hour**
Blocks	
Hydraulics_326	1501.34
Tyres_323	440.22
Electrical_326	432.77
Sub-systems	
Hydraulics	1827.85
Tires	912.27
Electrical	822.32
Drivetrain	456.51
Body	329.35

Maintenance Case02 - *Corrective Maint. & Regular Inspection & Group Inspection*:

- Differently from the Base Model (Case-1), the group inspection concept (opportunistic maintenance) is also included. According to Horenbeek *et al.* (2013), group replacement occurs when a group of components is replaced at a fixed time and/or when the system reaches a certain age. Here, group IDs are created for each truck, and corrective maintenance of any subsystem triggers visual inspection for the other subsystems of the same truck, which are not operable anyway. If any approaching failure is detected for non-failed subsystems according to delay time, then preventive maintenance is performed for the related subsystems. Therefore, a subsystem failure can create an opportunity for the preventive maintenance of another subsystem.
- Similar to Case-1, random failures of subsystems and random corrective maintenance durations in case of any subsystem failure are considered in Case-2. In addition, the regular inspection concept is also kept in the model, and there are not any maintenance crew and spare parts limitations. The simulation observation period was taken similarly as $t_t = 8766h$.

A representative view of the simulation monitoring screen for 0-1000h can be examined in Figure 4.11. Furthermore, it can clearly be seen from the graph that the subsystems were downed many more times. Further graphs will show the results of this situation more clearly. The truck fleet's mean availability and cumulative cost values obtained from the Case02 simulation results can be investigated in Figure 4.12 and Figure 4.13.

In addition, the cumulative number of failures in time can be viewed in Figure 4.14. Furthermore, downtime and failure number characterization of individual subsystems can be examined in Figure 4.15 and Figure 4.16, respectively. It is seen from the figures that the Hydraulic subsystem of Truck ID326 and Body subsystem of Truck ID 325 have kept their trend. Their issues contribute greatly to the low system availability for the fleet.

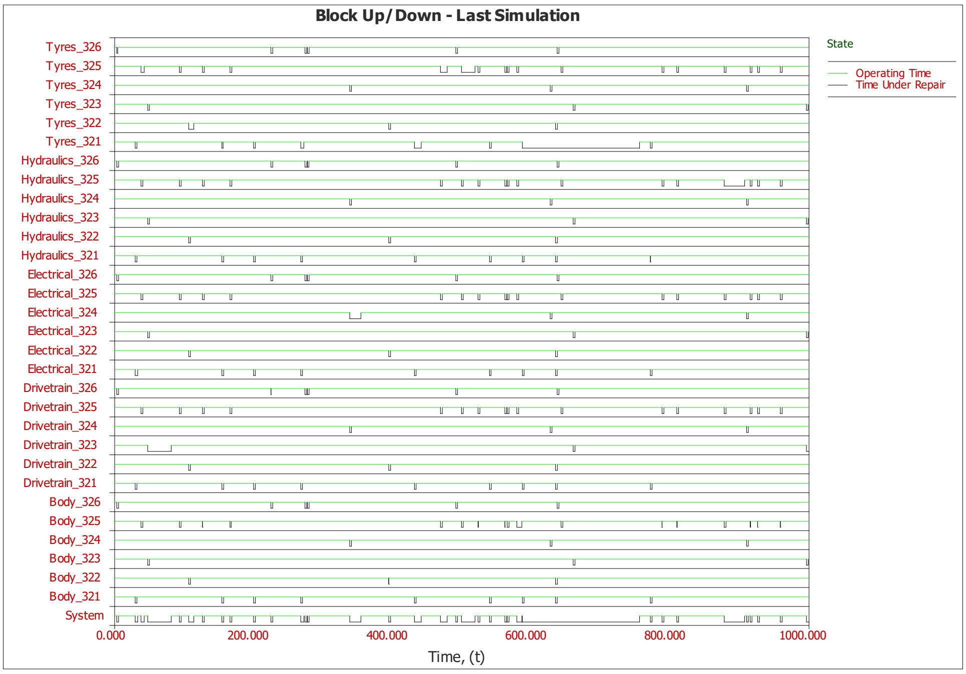


Figure 4.11 A Representative View of Simulation Monitoring Screen for Case02

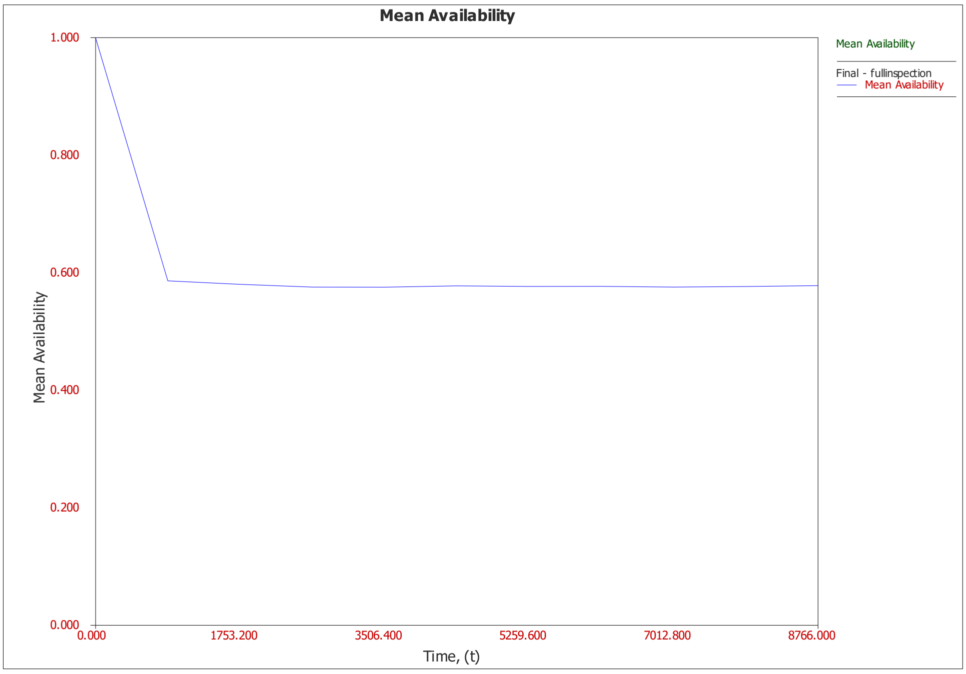


Figure 4.12 Mean Availabilities of the Trucks for Case02

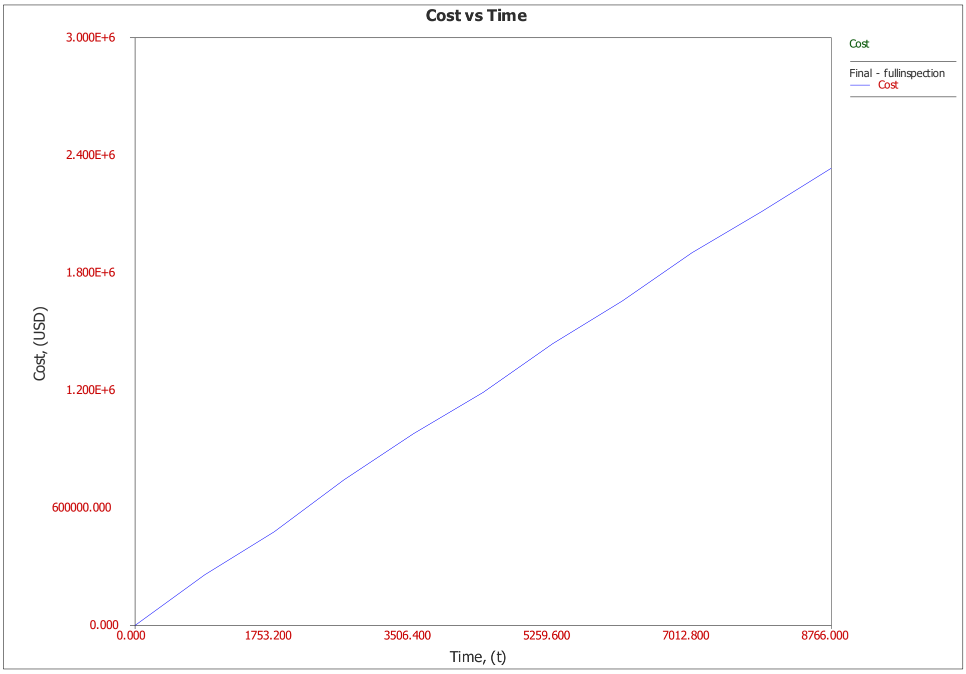


Figure 4.13 Cumulative Direct and Indirect Cost of Maintenance for Case02

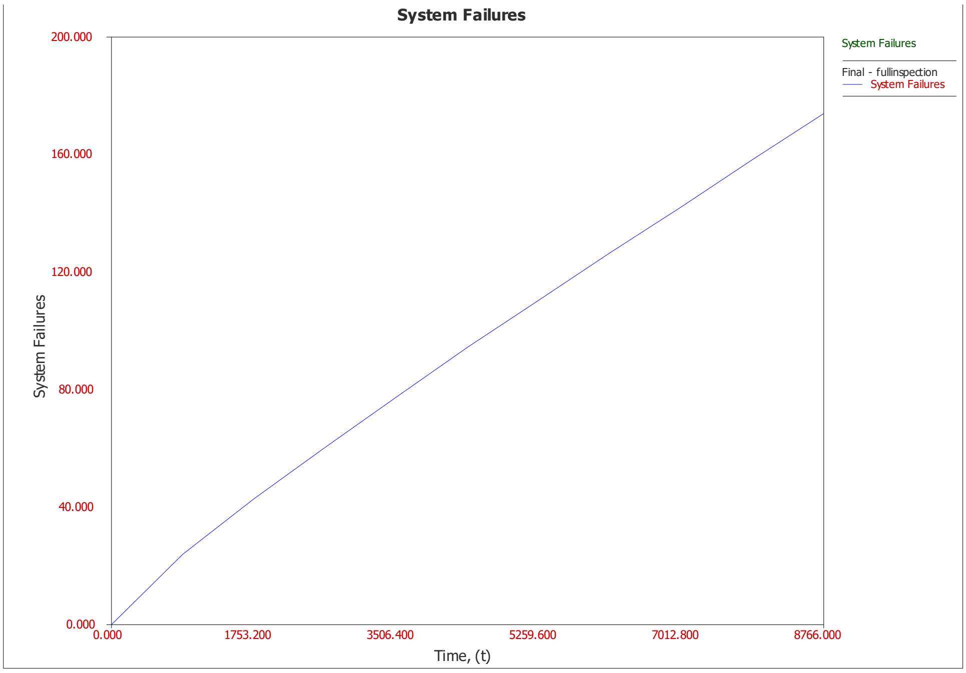


Figure 4.14 Cumulative System Failure Numbers in Time for Case-2

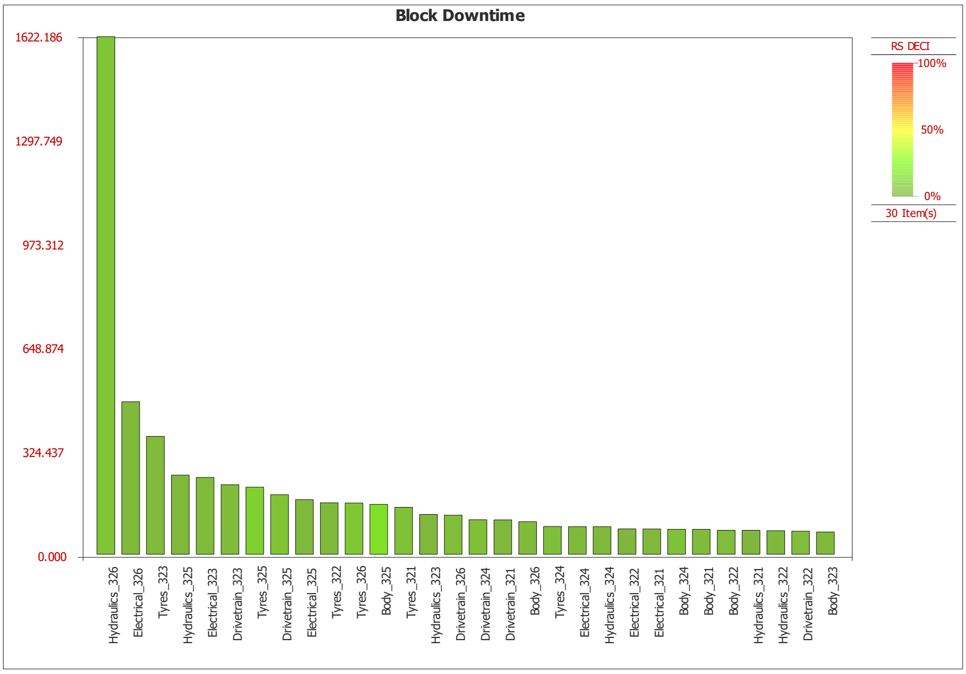


Figure 4.15 Maintenance Downtime Profiles of the Truck Subsystems for Case02

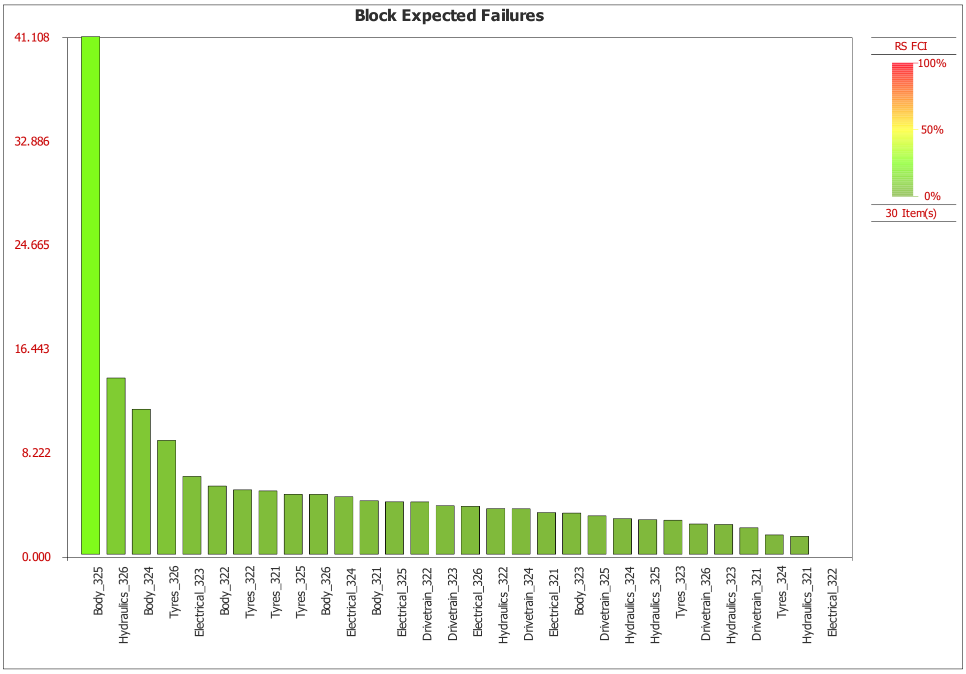


Figure 4.16 Failure Number Profiles of the Truck Subsystems for Case02

In addition, the failure criticality index (FCI), downtime, availability, and failure number profiles of the most critical subsystems are shown in Table 4.7.

Table 4.7 Summary of the Simulation for Case02

Block Failure Criticality		Availability Rating	
Name	**FCI**	**Name**	**Availability**
Blocks		**Blocks**	
Body_325	23.63%	Hydraulics_326	81.49%
Hydraulics_326	8.11%	Electrical_326	94.50%
Body_324	6.69%	Tyres_323	95.73%
Sub-systems		**Sub-systems**	
Body	6,80%	Hydraulics	98.86%
Tires	2,77%	Tires	97.77%
Hydraulics	2,65%	Electrical	95.7%
Electrical	2,17%	Drivetrain	97.78%
Drivetrain	1,91%	Body	98.39%

Failures Ranking		Block System Downing Events	
Name	**Exp.#ofFailures**	**Name**	**#ofEvents**
Blocks		**Blocks**	
Body_325	41.11	Body_325	47.25
Hydraulics_326	14.10	Tyres_325	30.92
Body_324	11.64	Tyres_326	20.485
Sub-systems		**Sub-systems**	
Body	11.83	Body	15.37
Tires	4.84	Tires	15.46
Hydraulics	4.64	Hydraulics	6.34
Electrical	3.81	Electrical	5.52
Drivetrain	3.35	Drivetrain	10.57

Block Downtime Ranking	
Name	**Downtime Hour**
Blocks	
Hydraulics_326	1622.19
Electrical_326	482.54
Tyres_323	374.69
Sub-systems	
Hydraulics	99.51
Tires	195.23
Electrical	376.85
Drivetrain	194.90
Body	141.70

<u>Maintenance Case03 - *Corrective Maint. & Group Inspection*</u>:

- Differently from Case02, the group inspection concept alone is included in Case03, and the regular inspection concept is removed from the model. Regular inspections are commonly applied in production industries, and related machinery is down constantly at regular time intervals. Even though it can provide many benefits for anomaly detection, it may decrease system availability if inspection intervals are short more than required and the system is down unnecessarily. Therefore, it is intended to see if regular inspections are really necessary for the current truck fleet.
- Similarly, the other settings were the same.

A representative view of the simulation monitoring screen for 0-1000h can be examined in Figure 4.17. Furthermore, the truck fleet's mean availability and cumulative cost values obtained from the Case-1 simulation results can be investigated in Figure 4.18 and Figure 4.19.

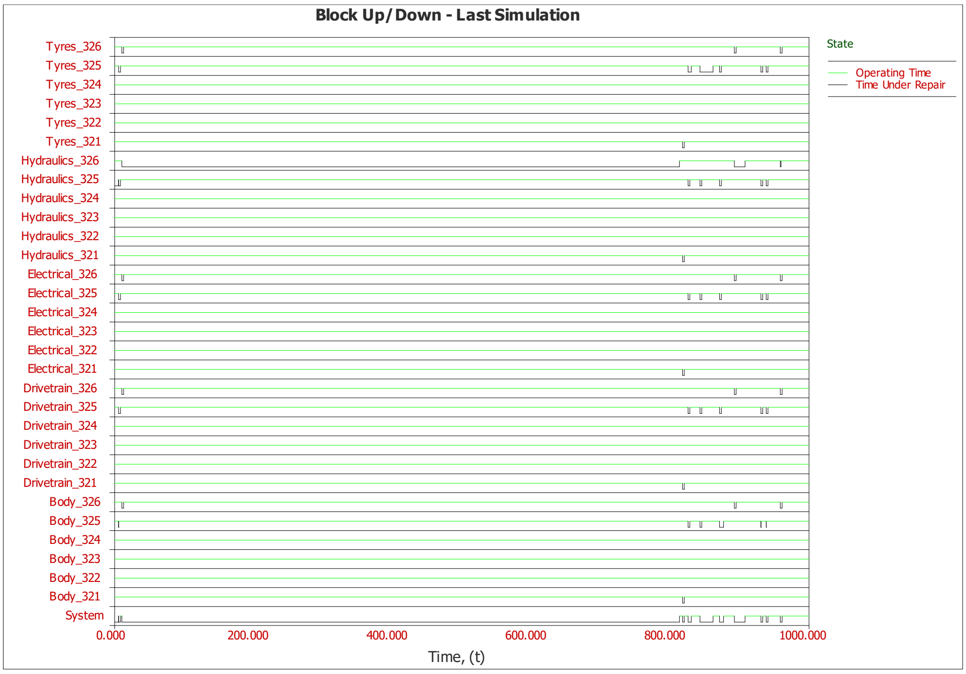


Figure 4.17 A Representative View of Simulation Monitoring Screen for Case03

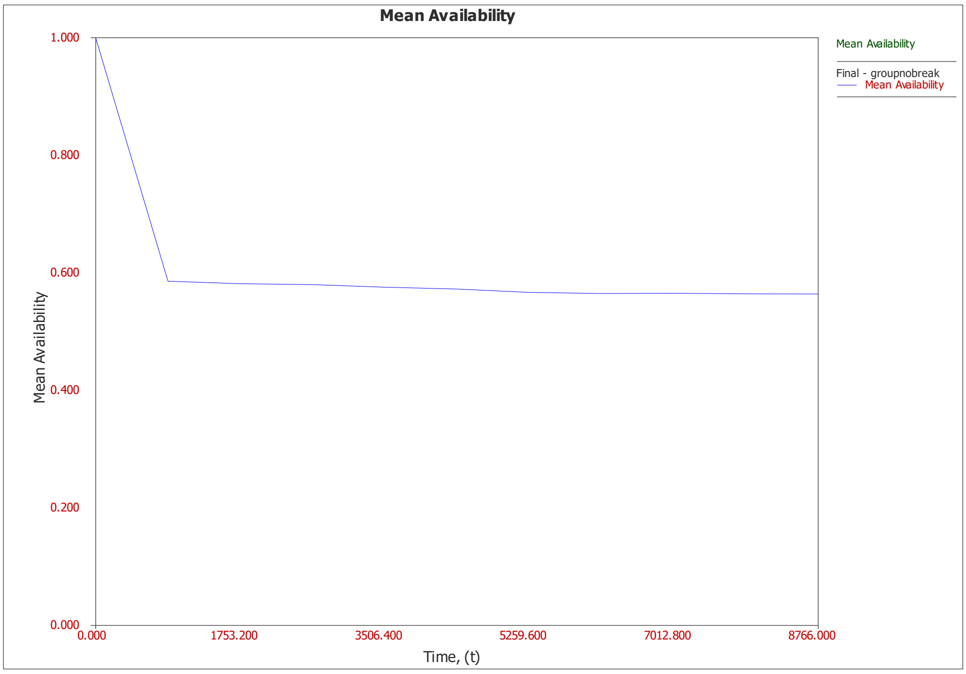


Figure 4.18 Mean Availabilities of the Trucks for Case03

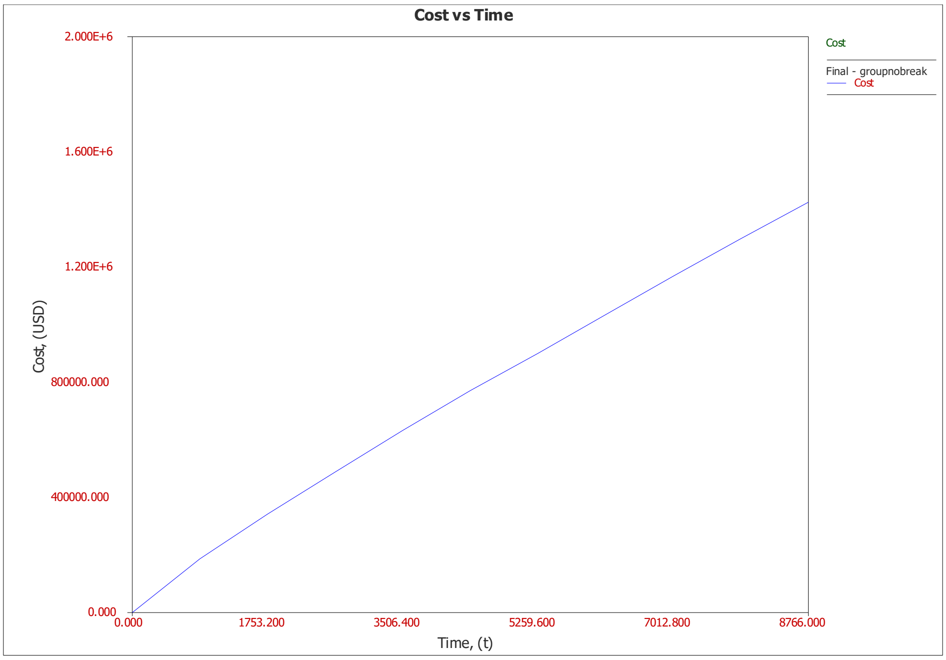


Figure 4.19 Cumulative Direct and Indirect Cost of Maintenance for Case03

In addition, the cumulative number of failures in time can be viewed in Figure 4.20. Furthermore, downtime and failure number characterization of individual subsystems can be examined in Figure 4.21 and Figure 4.22, respectively.

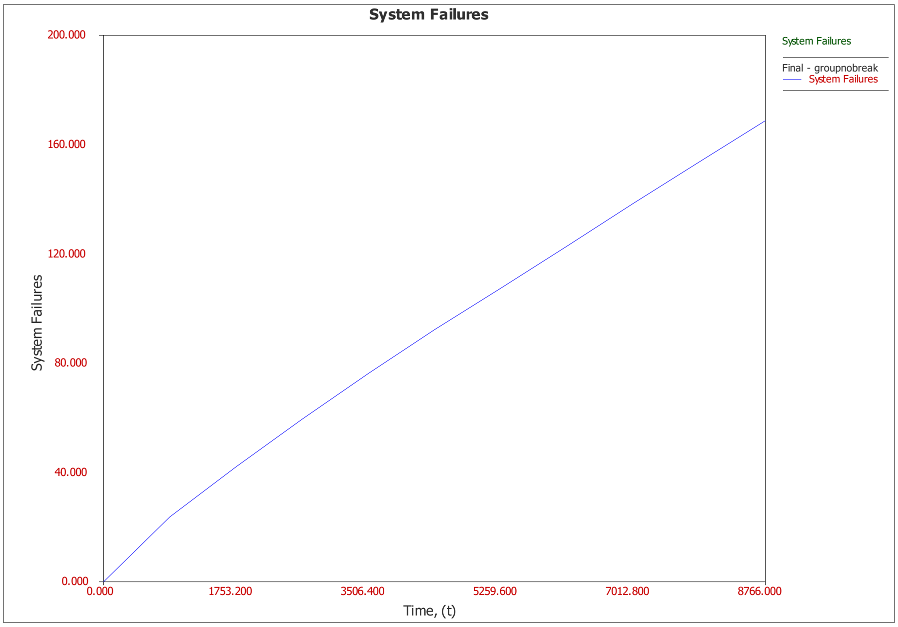


Figure 4.20 Cumulative System Failure Numbers in Time for Case03

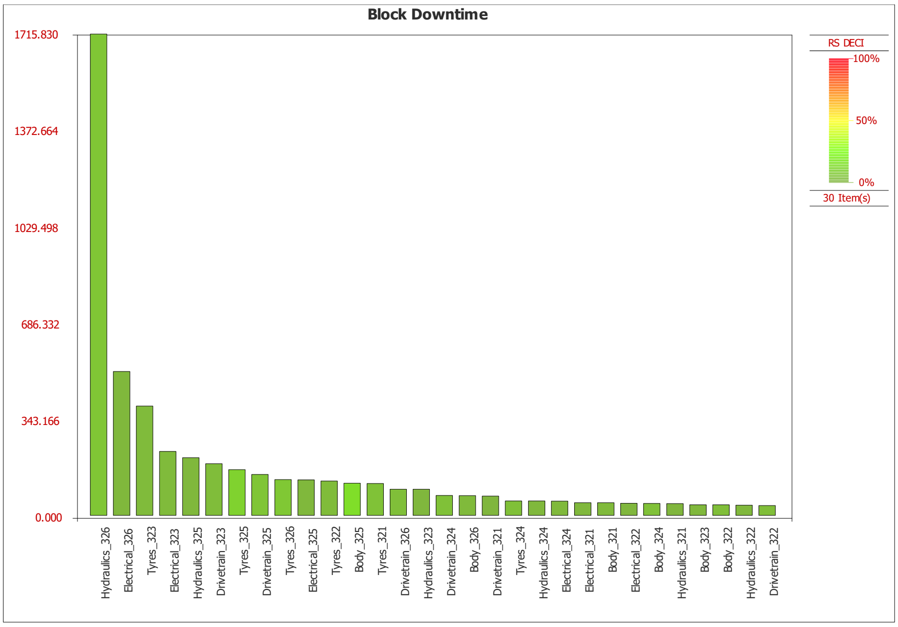


Figure 4.21 Maintenance Downtime Profiles of the Truck Subsystems for Case03

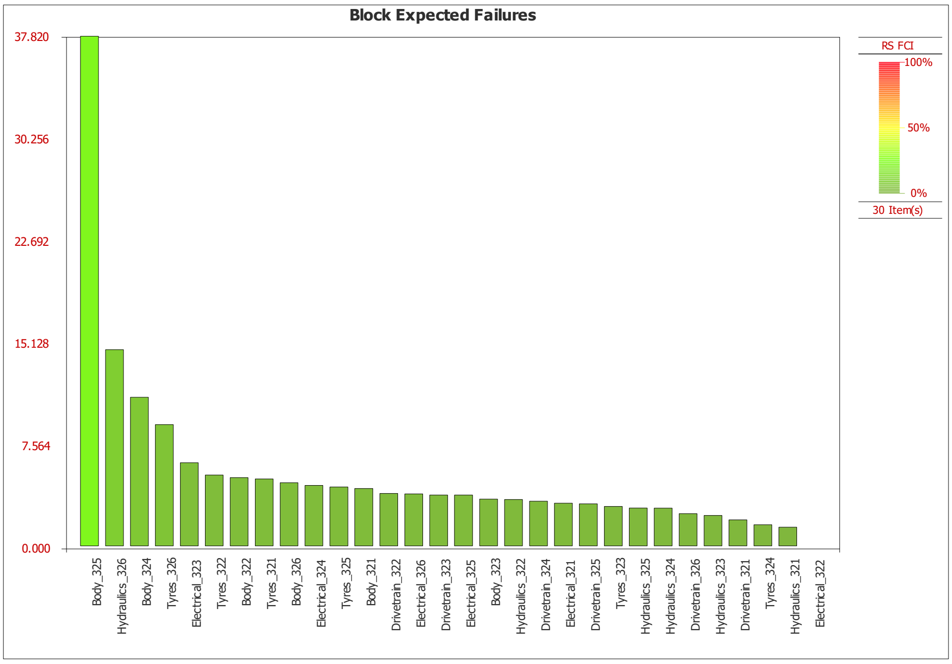


Figure 4.22 Failure Number Profiles of the Truck Subsystems for Case03

In addition, the failure criticality index (FCI), downtime, availability, and failure number profiles of the most critical subsystems are shown in Table 4.8.

Table 4.8 Summary of the Simulation for Case03

Block Failure Criticality		Availability Rating	
Name	**FCI**	**Name**	**Availability**
Blocks		**Blocks**	
Body_325	22.41%	Hydraulics_326	80.43%
Hydraulics_326	8.68%	Electrical_326	94.10%
Body_324	6.60%	Tyres_323	95.49%
Sub-systems		**Sub-systems**	
Body	6.61%	Hydraulics	99.26%
Tires	2.84%	Tires	98.09%
Hydraulics	2.76%	Electrical	95.86%
Electrical	2.18%	Drivetrain	98.01%
Drivetrain	1.89%	Body	98.79%

Failures Ranking		Block System Downing Events	
Name	**Exp.#ofFailures**	**Name**	**#ofEvents**
Blocks		**Blocks**	
Body_325	37.82	Body_325	38.67
Hydraulics_326	14.65	Tyres_325	27.91
Body_324	11.14	Tyres_326	18.87
Sub-systems		**Sub-systems**	
Body	11.16	Body	12.55
Tires	4.82	Tires	13.99
Hydraulics	4.68	Hydraulics	5.39
Electrical	3.71	Electrical	4.05
Drivetrain	3.21	Drivetrain	9.40

Block Downtime Ranking	
Name	**Downtime Hour**
Blocks	
Hydraulics_326	1715.83
Electrical_326	517.59
Tyres_323	395.47
Sub-systems	
Hydraulics	64.79
Tires	167.96
Electrical	363.92
Drivetrain	174.01
Body	106.37

Maintenance Case04 - *Corrective Maint. & Regular Inspection & Spare Part Policy*:

- Considerations of the Base Model are included in Case04 with the addition of the tire spare part inventory problem. In this way, it is aimed to see the effect of spare parts inventory on system availability. The spare part policy of the tire is discussed alone since the other subsystems could not be decomposed into their individual components due to the lack of enough information in the maintenance records.

A representative view of the simulation monitoring screen for 0-1000h can be examined in Figure 4.23.

Figure 4.23 A Representative View of Simulation Monitoring Screen for Case04

Mean availability and cumulative cost values of the truck fleet obtained from the Case-1 simulation results can be investigated in Figure 4.24 and Figure 4.25.

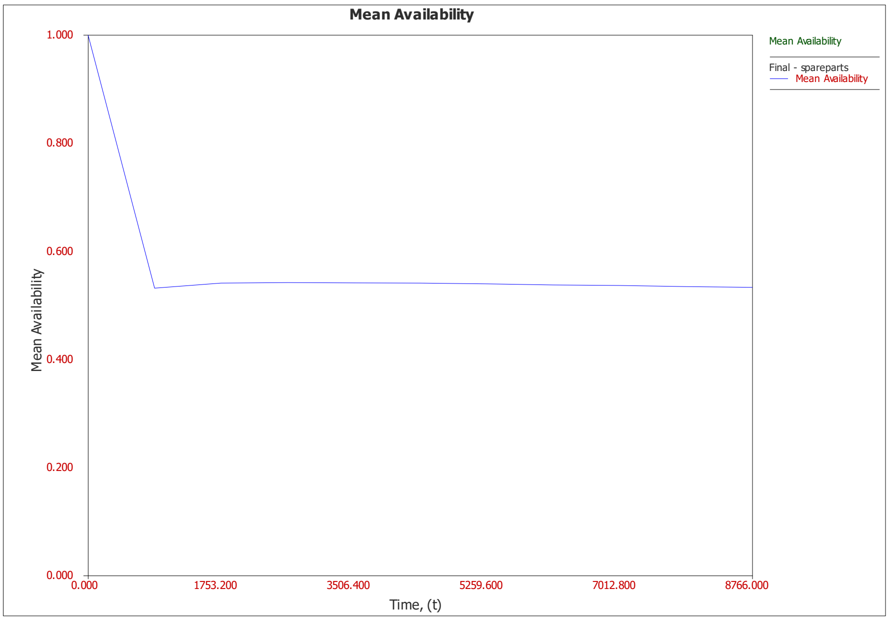


Figure 4.24 Mean Availabilities of the Trucks for Case04

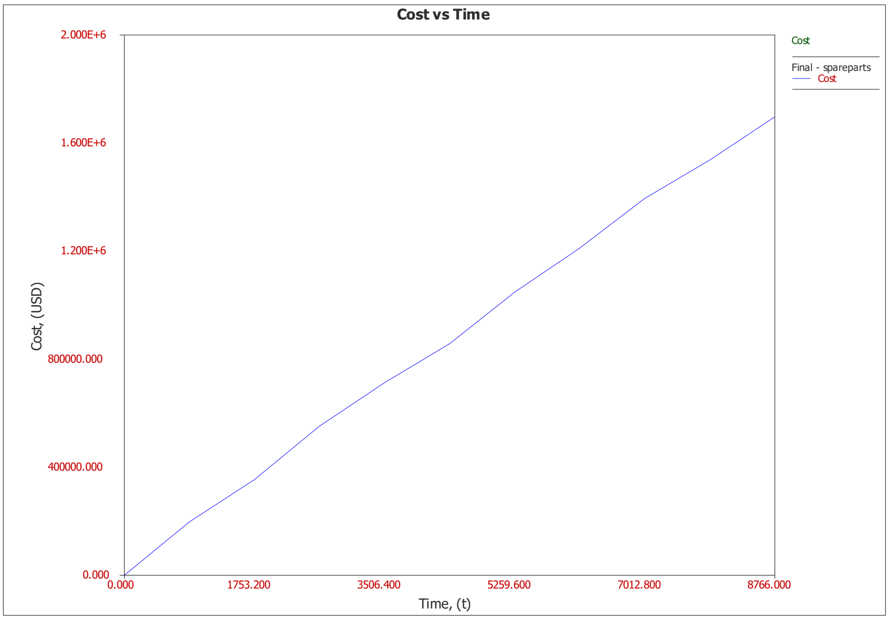


Figure 4.25 Cumulative Direct and Indirect Cost of Maintenance for Case04

This case had the worst availability and costs. Downing system to wait for parts and added cost can be easily seen in the results. In addition, the cumulative number of failures in time can be viewed in Figure 4.26. Furthermore, downtime and failure number characterization of individual subsystems can be examined in Figure 4.27 and Figure 4.28, respectively.

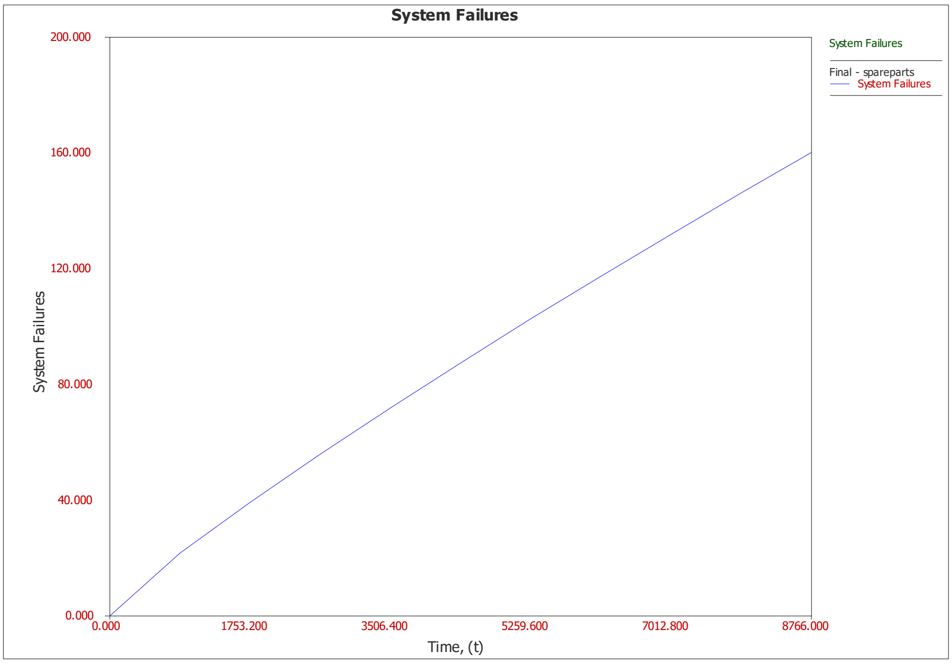


Figure 4.26 Cumulative System Failure Numbers in Time for Case04

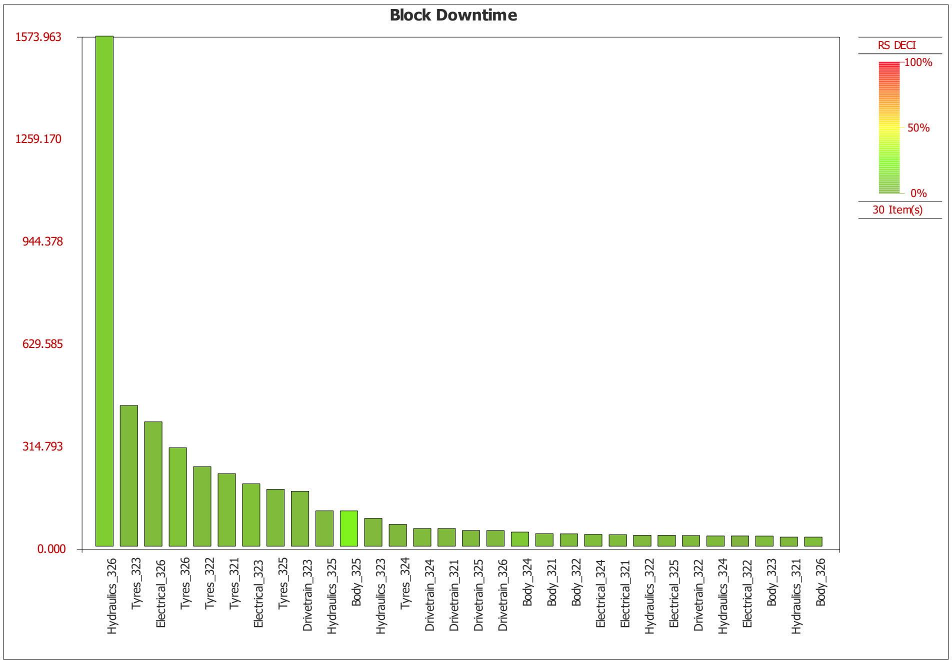


Figure 4.27 Maintenance Downtime Profiles of the Truck Subsystems for Case04

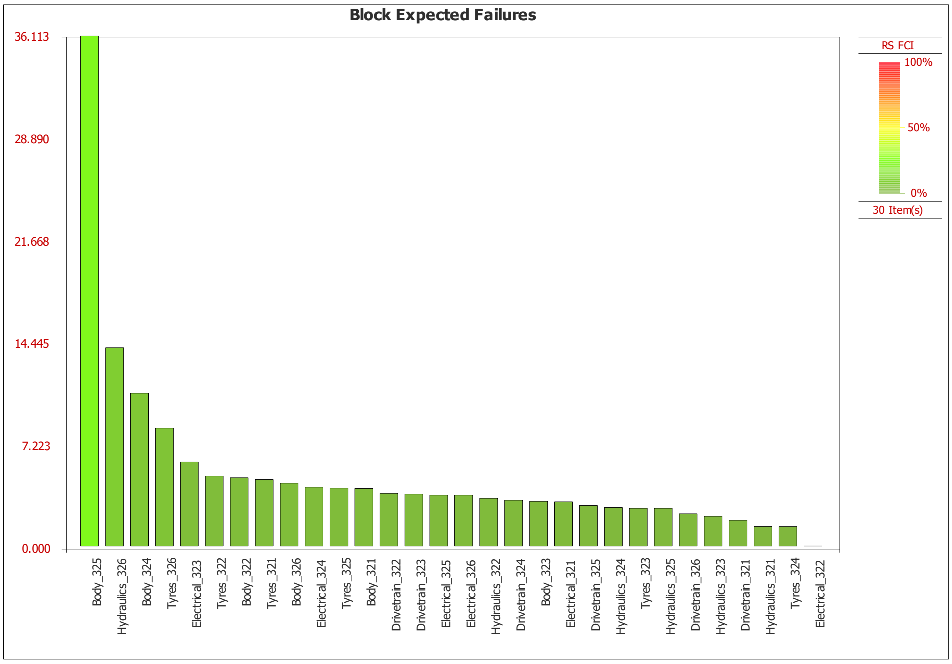


Figure 4.28 Failure Number Profiles of the Truck Subsystems for Case04

In addition, the failure criticality index (FCI), downtime, availability, and failure number profiles of the most critical subsystems are shown in Table 4.9. FCI is an index that is the ratio of system reliability to subsystem reliability in time. If subsystem reliability is less, then the criticality will be higher.

Table 4.9 Summary of the Simulation for Case04

Block Failure Criticality		Availability Rating	
Name	**FCI**	**Name**	**Availability**
Blocks		**Blocks**	
Body_325	22.54%	Hydraulics_326	82.04%
Hydraulics_326	8.83%	Tyres_323	95.00%
Body_324	6.82%	Electrical_326	95.57%
Sub-systems		**Sub-systems**	
Body	6.67%	Hydraulics	99.38%
Tires	2.78%	Tires	97.18%
Hydraulics	2.81%	Electrical	96.40%
Electrical	2.14%	Drivetrain	98.58%
Drivetrain	1.89%	Body	99.16%

Failures Ranking		Block System Downing Events	
Name	**Exp.#ofFailures**	**Name**	**#ofEvents**
Blocks		**Blocks**	
Body_325	36.11	Body_325	41.09
Hydraulics_326	14.13	Hydraulics_326	16.29
Body_324	10.92	Body_324	13.89
Sub-systems		**Sub-systems**	
Body	10.68	Body	12.67
Tires	4.49	Tires	5.42
Hydraulics	4.52	Hydraulics	5.46
Electrical	3.54	Electrical	4.66
Drivetrain	3.08	Drivetrain	3.79

Block Downtime Ranking	
Name	**Downtime Hour**
Blocks	
Hydraulics_326	1573.96
Tyres_323	438.21
Electrical_326	388.47
Sub-systems	
Hydraulics	54.15
Tires	246.90
Electrical	315.47
Drivetrain	124.64
Body	74.02

Maintenance Case05 - *Corrective Maint. & Regular Inspection with RF=0.25*

- Considerations of the Base Model are included in Case05. However, the maintenance is assumed to be not perfect. Therefore, corrective maintenance and preventive maintenance in regular inspections will recover the subsystem at a level between as bad as old (minimal repair) and as good as new (perfect repair). For Case05, the restoration factor of the maintenance activities is assumed to be 0.25. In this way, it is intended to see how ineffectiveness in maintenance applications may affect the system's reliability.

A representative view of the simulation monitoring screen for 0-1000h can be examined in Figure 4.29. Mean availability and cumulative cost values of the truck fleet obtained from the Case05 simulation results can be investigated in Figure 4.30 and Figure 4.31. This case was the best performing. It increased the cost slightly for huge gains in availability and uptime.In addition, the cumulative number of failures in time can be viewed in Figure 4.32. Furthermore, downtime and failure number characterization of individual subsystems can be examined in Figure 4.33 and Figure 4.34, respectively.

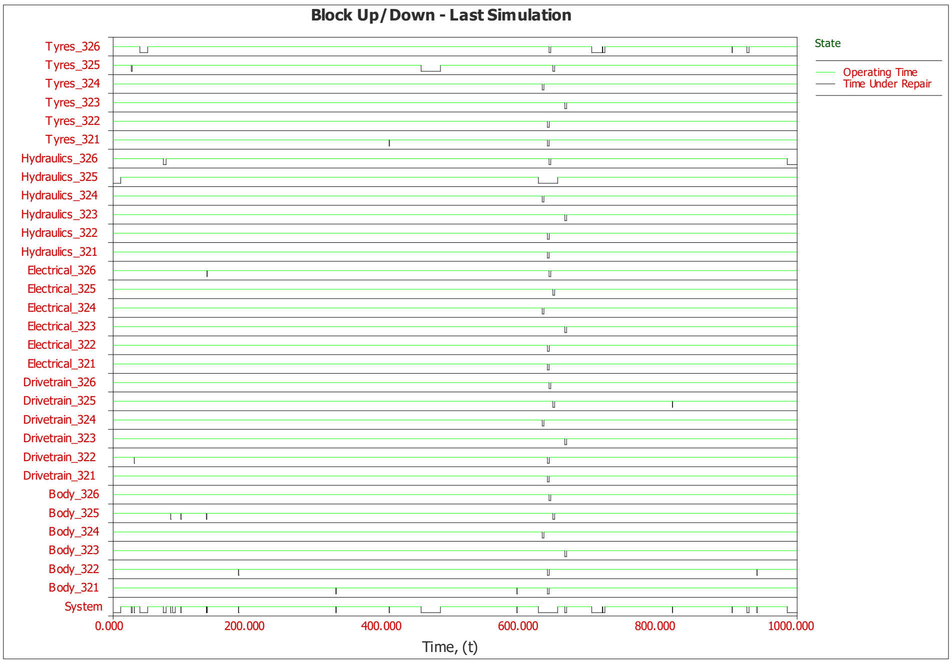


Figure 4.29 A Representative View of Simulation Monitoring Screen for Case05

Figure 4.30 Mean Availabilities of the Trucks for Case05

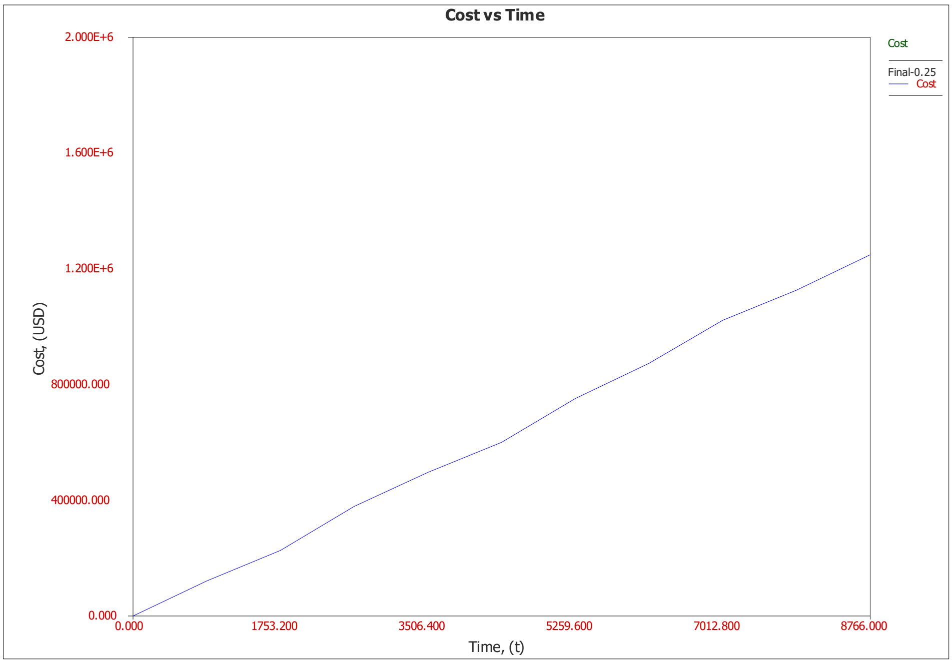


Figure 4.31 Cumulative Direct and Indirect Cost of Maintenance for Case05

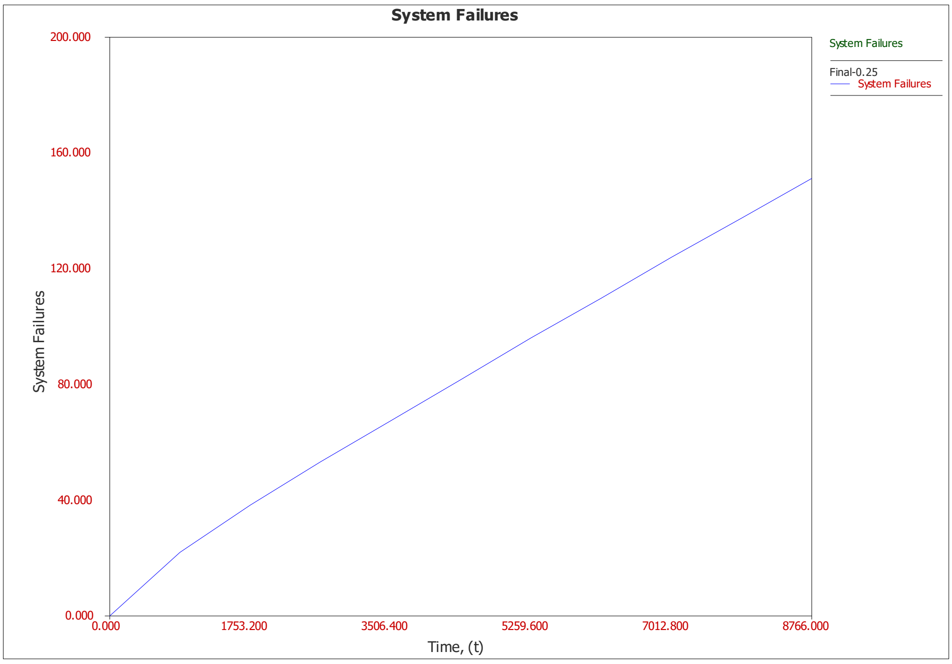


Figure 4.32 Cumulative System Failure Numbers in Time for Case05

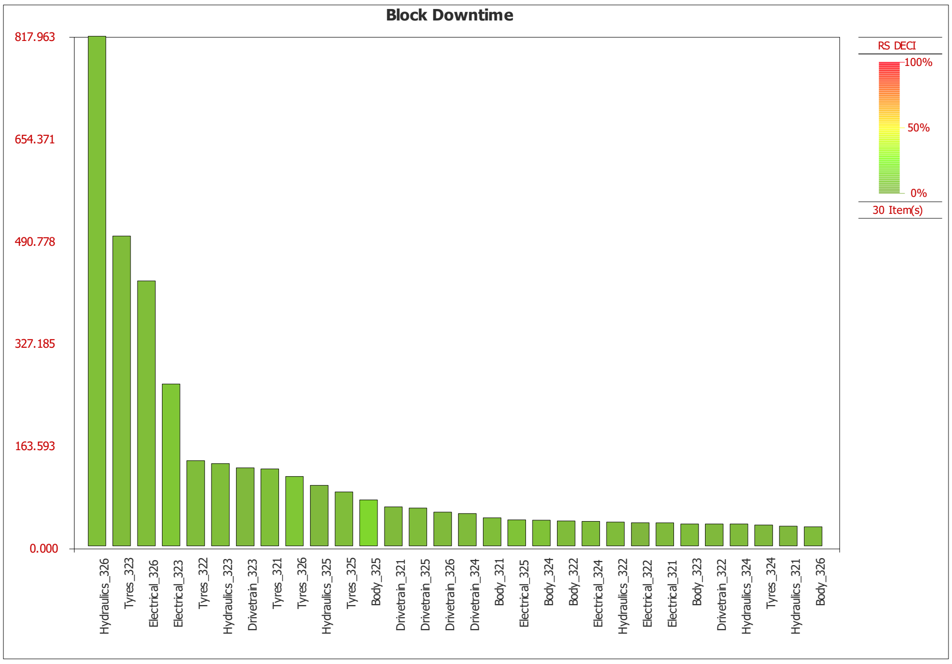


Figure 4.33 Maintenance Downtime Profiles of the Truck Subsystems for Case05

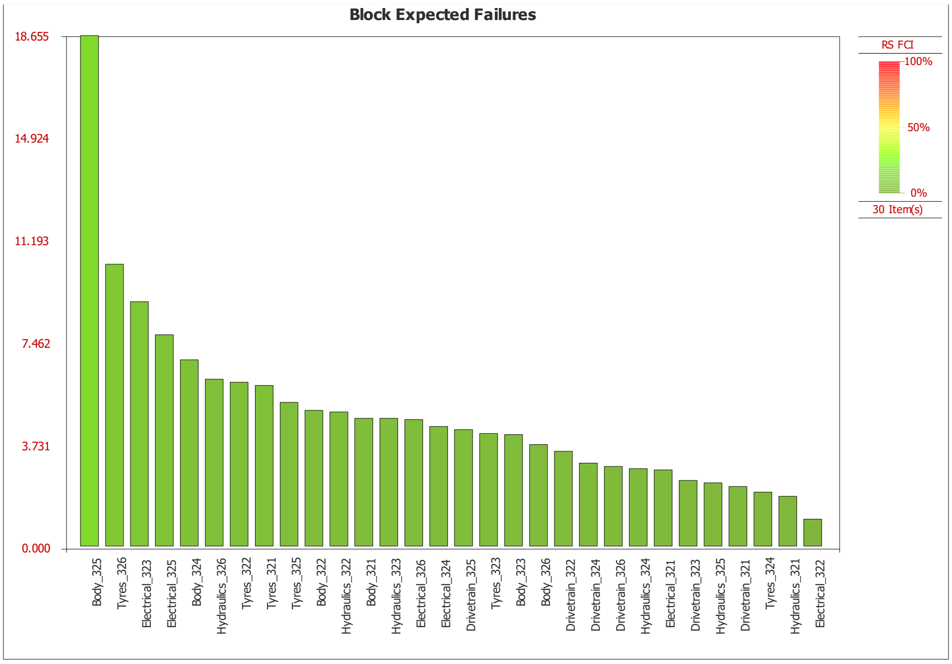


Figure 4.34 Failure Number Profiles of the Truck Subsystems for Case05

In addition, the failure criticality index (FCI), downtime, availability, and failure number profiles of the most critical subsystems are shown in Table 4.10.

Table 4.10 Summary of Simulation Over a Year for Case05

Block Failure Criticality		**Availability Rating**	
Name	**FCI**	**Name**	**Availability**
Blocks		**Blocks**	
Body_325	12.34%	Hydraulics_326	90.67%
Tyres_326	6.83%	Tyres_323	94.31%
Electrical_323	5.93%	Electrical_326	95.13%
Sub-systems		**Sub-systems**	
Body	4.76%	Hydraulics	99.46%
Tires	3.68%	Tires	98.09%
Hydraulics	2.53%	Electrical	97.78%
Electrical	3.27%	Drivetrain	98.37%
Drivetrain	2.05%	Body	99.22%

Failures Ranking		**Block System Downing Events**	
Name	**Exp.#ofFailures**	**Name**	**#ofEvents**
Blocks		**Blocks**	
Body_325	18.66	Body_325	22.77
Tyres_326	10.34	Tyres_326	12.64
Electrical_323	8.97	Electrical_323	12.38
Sub-systems		**Sub-systems**	
Body	7.19	Body	9.08
Tires	5.64	Tires	6.88
Hydraulics	3.83	Hydraulics	5.03
Electrical	4.96	Electrical	6.83
Drivetrain	3.10	Drivetrain	4.11

Block Downtime Ranking	
Name	**Downtime Hour**
Blocks	
Hydraulics_326	817.96
Tyres_323	498.62
Electrical_326	426.78
Sub-systems	
Hydraulics	47.50
Tires	167.49
Electrical	194.63
Drivetrain	142.83
Body	68.12

Maintenance Case06 - *Corrective Maint. & Regular Inspection with RF=0.75*

- The model is exactly the same as Case05. The only difference is that the restoration rate after maintenance activities is assumed to be 0.75.

A representative view of the simulation monitoring screen for 0-1000h can be examined in Figure 4.35.

Figure 4.35 A Representative View of Simulation Monitoring Screen for Case06

The truck fleet's mean availability and cumulative cost values obtained from the Case06 simulation results can be investigated in Figure 4.36 and Figure 4.37. In addition, the cumulative number of failures in time can be viewed in Figure 4.38. Furthermore, downtime and failure number characterization of individual subsystems can be examined in Figure 4.39 and Figure 4.40, respectively.

Figure 4.36 Mean Availabilities of the Trucks for Case06

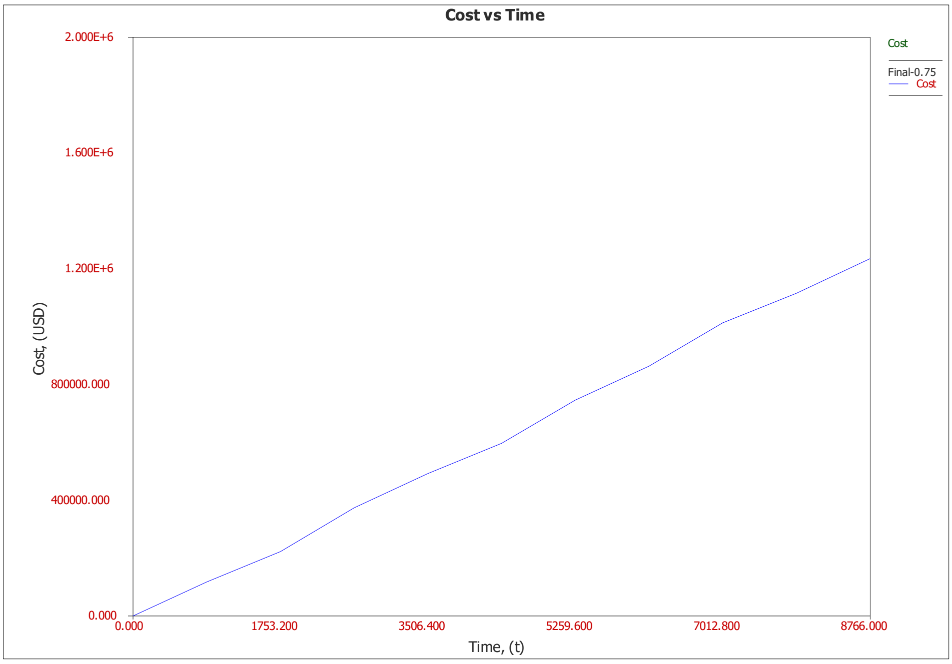


Figure 4.37 Cumulative Direct and Indirect Cost of Maintenance for Case06

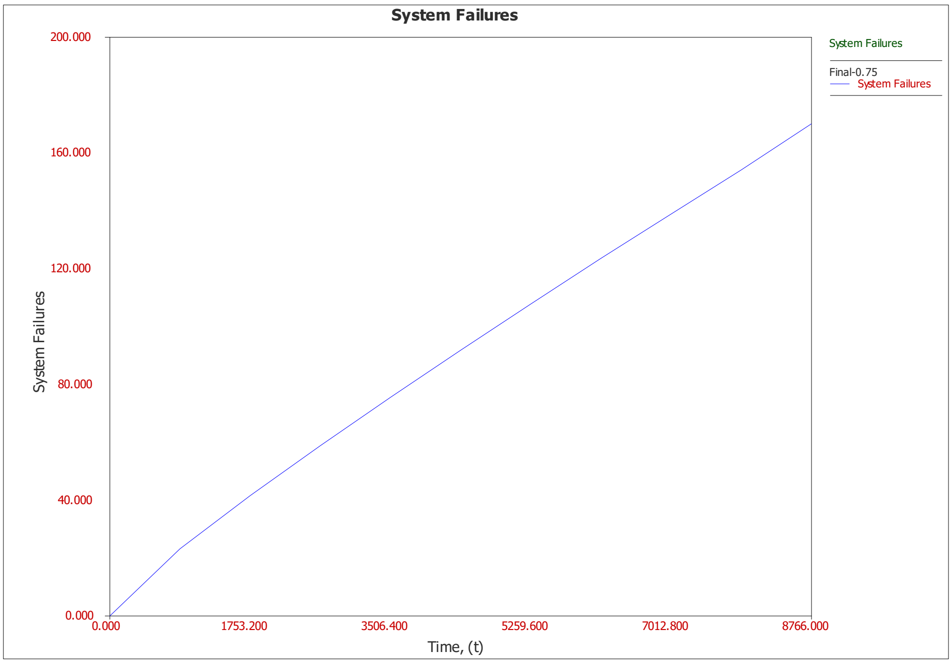


Figure 4.38 Cumulative System Failure Numbers in Time for Case06

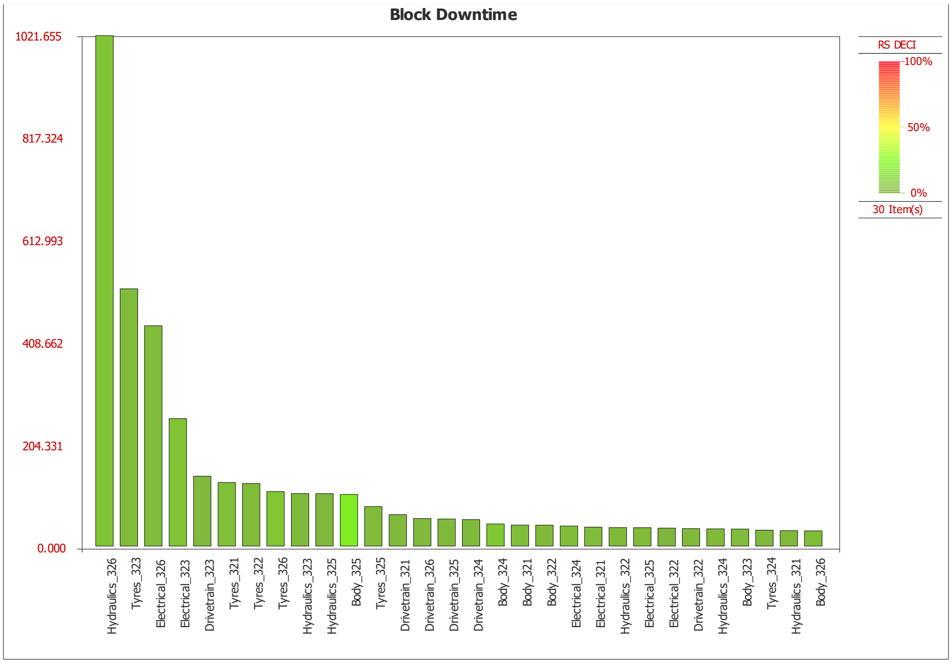


Figure 4.39 Maintenance Downtime Profiles of the Truck Subsystems for Case06

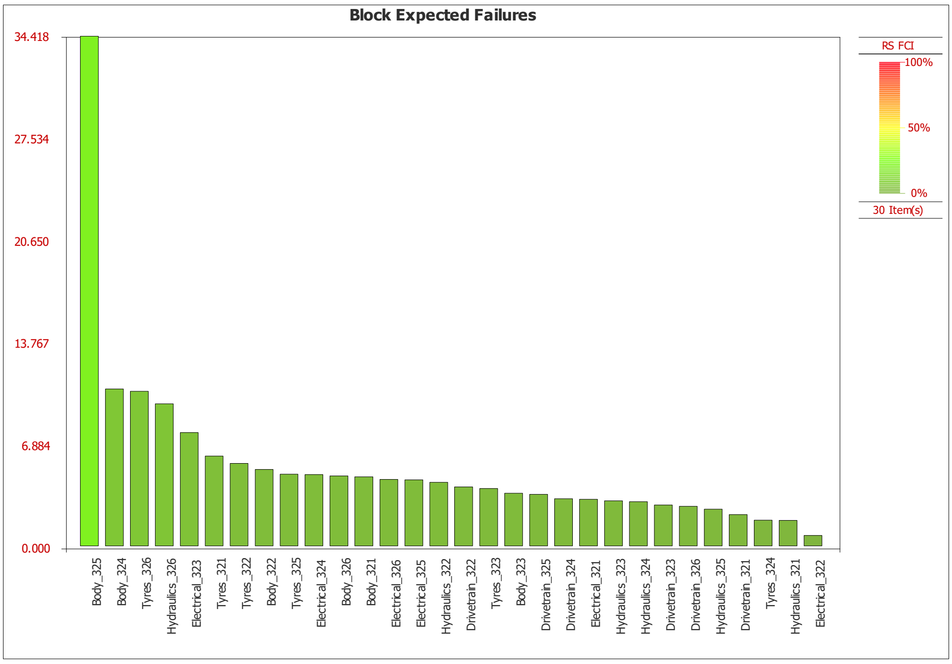


Figure 4.40 Failure Number Profiles of the Truck Subsystems for Case06

In addition, the failure criticality index (FCI), downtime, availability, and failure number profiles of the most critical subsystems are shown in Table 4.11.

Table 4.11 Summary of Simulation Over a Year for Case06

Block Failure Criticality		Availability Rating	
Name	FCI	Name	Availability
Blocks		Blocks	
Body_325	20.23%	Hydraulics_326	88.35%
Body_324	6.29%	Tyres_323	94.10%
Tyres_326	6.20%	Electrical_326	94.94%
Sub-systems		Sub-systems	
Body	6.24%	Hydraulics	99.39%
Tires	3.22%	Tires	98.09%
Hydraulics	2.43%	Electrical	97.43%
Electrical	2.54%	Drivetrain	98.35%
Drivetrain	1.86%	Body	99.20%

Failures Ranking		Block System Downing Events	
Name	Exp.#ofFailures	Name	#ofEvents
Blocks		Blocks	
Body_325	34.42	Body_325	39.68
Body_324	10.70	Body_324	13.95
Tyres_326	10.54	Tyres_326	12.57
Sub-systems		Sub-systems	
10,62	10.62	Body	12.81
5,54%	5.54	Tires	6.68
4,14%	4.14	Hydraulics	5.21
4,34%	4.34	Electrical	5.91
3,16%	3.16	Drivetrain	4.04

Block Downtime Ranking	
Name	Downtime Hour
Blocks	
Hydraulics_326	1021.66
Tyres_323	516.76
Electrical_326	443.27
Sub-systems	
Hydraulics	53.24
Tires	169.89
Electrical	225.47
Drivetrain	144.63
Body	70.40

Maintenance Case07 – *Detection of Preventive Replacement for Tires*

- Case07 is totally different from the other cases. Here, preventive replacement probabilities of individual components are investigated. Since there is not enough data and description to decompose subsystems into individual components, preventive replacement condition was checked only for tires. BlockSim. Caroline (2012) states that two main requirements should be satisfied for the potential applicability of preventive component replacements as discussed below:
    - The candidate components should be in a wear-out period. In other words, the component's failure rate should exhibit an increase in time. As discussed in Section 4.3, $\beta > 1$ of Weibull distribution or General Renewal Process, and normal distribution refers to the wear-out period. The tire components having these types of TBF functions can be candidates.
    - The cost for planned replacements should be considerably less than the cost for unplanned replacements. In addition, the component should be eligible for replacement practically instead of repair. It should be noted that if the preventative maintenance tasks are not performed quite enough, the corrective maintenance costs increase. Otherwise, the total maintenance cost will increase unnecessarily if the preventive maintenance is carried out more than required. Therefore, a balance point should be determined to optimize preventive maintenance tasks.

An illustration of how an optimal component replacement time can be determined is seen in Figure 4.41.

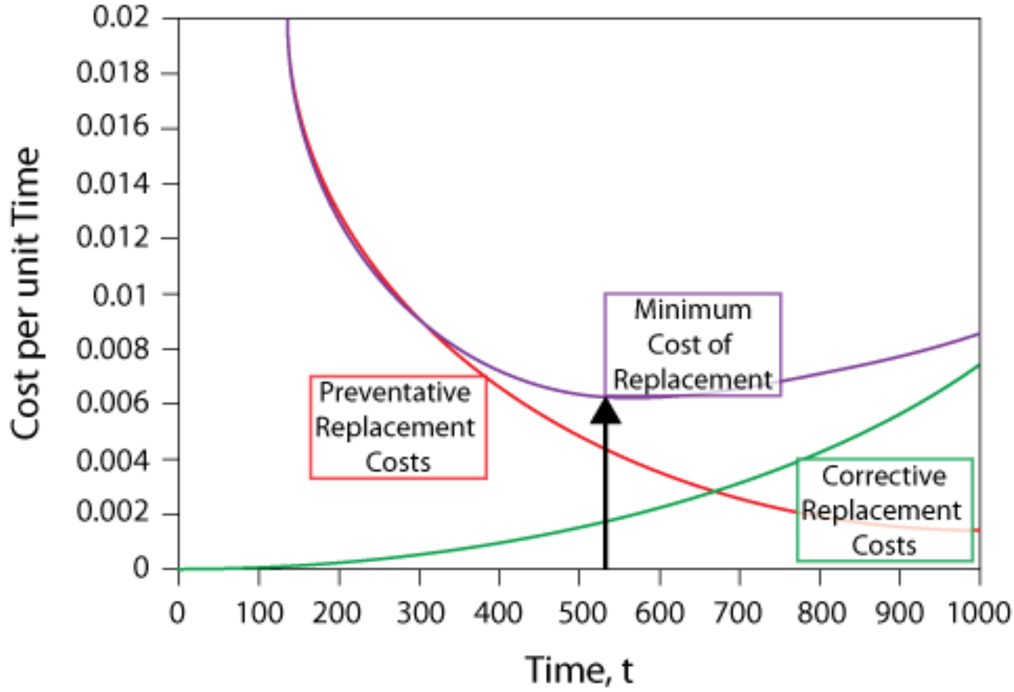


Figure 4.41 Optimum Component Replacement Decision (Caroline, 2012)

Furthermore, the optimum component replacement can be formalized as:

$$CPUT(t) = \frac{\text{Total Expected Replacement Cost per Cycle}}{\text{Expected Cycle Length}} = \frac{C_P \cdot R(t) + C_U \cdot [1 - R(t)]}{\int_0^t R(s)\, ds} \tag{4.1}$$

It was detected from the analyses that the curve converges to infinity. In other words, it isn’t feasible to replace tire parts preventively. Therefore, this scenario was defined as non-applicable.

Comparative Evaluation of the Maintenance Cases:

A comparative table showing the results from all the scenarios can be seen in Table 4.12.

Table 4.12 Comparative Table

General	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**	**Scenario 5**	**Scenario 6**
Mean Availability (All Events):	0.6	0.58	0.56	0.53	0.67	0.64
Std Deviation (Mean Availability):	0.18	0.17	0.18	0.15	0.15	0.15
Expected Number of Failures:	173.94	173.96	168.75	160.20	151.22	170.12
Std Deviation (Number of Failures):	47.88	46.02	49.92	41.88	33.55	40.41
MTTFF:	6.06	6.76	6.49	6.43	5.99	5.31
System Uptime/Downtime						
Uptime:	5203.24	5067.37	4943.77	4676.36	5837.63	5578.36
CM Downtime:	3458.43	3376.08	3612.37	3995.16	2811.42	3076.89
Inspection Downtime:	104.34	322.55	209.86	94.48	116.94	110.75
Total Downtime:	3562.77	3698.63	3822.23	4089.64	2928.37	3187.64
System Downing Events						
Number of Failures:	173.94	173.96	168.75	160.20	151.22	170.12
Number of CMs:	173.94	173.96	168.75	160.20	151.22	170.12
Number of Inspections:	40.55	151.81	108.45	36.77	45.35	42.97
Total Events:	214.49	325.78	277.20	196.97	196.56	213.09
Costs						
Total Costs (USD):	1,222,972.66	2,334,060.53	1,425,069.46	129,084,676.30	1,248,040.26	1,234,904.78

Overall simulation results for the Case01 Model can be seen in Table 4.13. The system availability is obtained at 60%, with an expected failure number of 174 a year. During 8766h (a year), the system is seen to be down for 3,458h and 104h for corrective maintenance and inspections, respectively. A total of 214 maintenance activities are expected to be performed, with an approximate direct and indirect maintenance cost of $1,222,972. The detailed scenario results for the other cases are given in Appendix B.

Table 4.13 The Simulation Results for Case01 Model

General	
Mean Availability (All Events):	0.60
Std Deviation (Mean Availability):	0.18
Expected Number of Failures:	173.94
Std Deviation (Number of Failures):	47.88
MTTFF:	6.06
System Uptime/Downtime	
Uptime:	5203.24
CM Downtime:	3458.43
Inspection Downtime:	104.34
Total Downtime:	3562.77
System Downing Events	
Number of Failures:	173.94
Number of CMs:	173.94
Number of Inspections:	40.55
Total Events:	214.49
Costs	
Total Costs (USD):	1,222,972.66

4.5 Discussion and Limitations

4.5.1 Interpretation of the Results

The mining industry continually seeks to reduce operating costs while, at the same time, increasing equipment reliability and availability (Ruschel *et al.*, 2017).

Reducing maintenance and spare part budget for machinery would increase the profits directly. However, unplanned downtimes due to a lack of proper maintenance and spare part policy can cause observable production losses and machine damage, leading to a catastrophic financial burden and loss of market for the company. Preventive maintenance is an effective tool to improve machine safety and health and is defined as 'actions carried out on time- or machine-run-based schedule that detect, prevent, or mitigate degradation of a component or system to maintain or extend its useful life by controlling degradation to an acceptable level.' It is observed from the production industries that preventive maintenance can provide a financial saving of more than 18% of the operating cost (Sullivan *et al.*, 2010). However, the type and necessity of preventive actions in a maintenance policy should be validated. Otherwise, it can create a redundant financial burden and production loss due to unnecessary system downs.

This thesis study investigates alternative maintenance scenarios for mining trucks that include different work packages so that each scenario's financial return and availability contributions can be revealed comparatively. The results indicate that an over-maintenance condition was detected for the current fleet. Scenario 5, which improves the system availability most, states that the effectiveness level of the current maintenance policy can be dropped to some extent. In other words, the analyses detect that over-maintenance causes frequent downtimes that decrease the availability and do not provide too much contribution to expected financial return.

It was also seen from the current study that data collection significantly impacts the usability of the available datasets. If the data was collected unsystematically, it could lead to the loss of data that would have been useful otherwise. To avoid this, data collection algorithms and systems need to be implemented. Firstly, the information has to be collected systematically using standard data collection and storage templates with the approval of mine management. Secondly, datasets should be monitored and verified in pre-defined periods. It will ensure the minimization of human and system-based errors. Finally, related software to keep data organized and safe must be used to prevent issues. The system described above should prepare the data to be analyzed directly without preprocessing, saving significant time and resources while minimizing data loss.

In addition, the simulation scenarios show that many possible hidden causes are included in the numerical results that should be highlighted with in-place investigations. For instance, the weights of maintenance durations according to components and why the same components are consuming more time in the repairs for different equipment should be investigated with the realities available in the mining area. As another example, how to decrease maintenance effectiveness to avoid over-maintenance should be discussed with the experts in the field, considering available and applicable maintenance work packages. Therefore, for a more comprehensive and clear evaluation of each scenario, a data collection system should be developed and activated at the start of the observation period, and the related people assigned for data collection should be appropriately trained in compliance with the analyses to be performed in the future. Otherwise, the current simulation results only give where to focus without much detail but do not give the branching of the underlying causes.

4.5.2 Limitations

It should be noted that any analysis or simulation's safety relies on input datasets' reliability. Therefore, as discussed before, the current study evaluates and inputs the field data where some missing, improper, or unclear explanations are included. Therefore, some pre-processing states were performed before introducing the inputs. Therefore, some minor deviations from actual activities in the field can be observed in the results. Additionally, limited assistance from the experts and maintenance crew was provided by the company in the interpretation phases of data processing and simulation. Therefore, some qualitative outcomes of the simulations may not comply with the mine's actual maintenance task, crew, and spare part conditions. In brief, the simulation results require further investigation with the related experts.

In addition, there is a lack of information on the prehistory of the trucks. On this basis, any information on where these trucks are operated in which conditions is not available. The simulation results showed that some trucks are experiencing more frequent failures with longer maintenance duration. It can be a strong indicator that the operators and operational conditions of the trucks can differ. Thus, each truck's prehistory, operational conditions, and driver-based errors need to be included in the simulations for a more comprehensive analysis. At this point, scenarios with similar types of machinery working in different conditions, such as ore and waste trucks with different routes with varying gradients, road conditions, machine interactions, and weather, may fail in comparing the maintenance scenarios. Therefore, equipment's current and previous operational conditions can be crucial when determining more realistic simulation outcomes.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Haul truck reliability is one of the most challenging issues in the mining industry due to its difficulty in predicting working environment and weather conditions, periodic operational and production requirements, and machine performance. Production rates and cash flow especially in a surface mine depend on the productivity of this mining equipment. At this point, a maintenance policy available in a mining area should ensure that trucks are operated above desired availability level by keeping operating costs below the allowable limits. However, since haul trucks are massive and complex systems exposed to multiple operational uncertainties and failure modes in tough operating conditiıns, it is difficult to reveal their stochastic uptime and downtime profiles and resultant budget, spare part, and maintenance requirements.

This thesis study presents a comparative simulation of multiple maintenance scenarios for a truck fleet by introducing their subsystems' random uptime and downtime characteristics. Accordingly, the study methodology entails (i) identification of the system dynamics and classification of truck sub-systems, (ii) characterization of uptime/downtime behaviors, (iii) development of system configuration with fault trees and integration of TTR and TBF functions, (iii) introducing different maintenance scenarios for the same truck configuration, (iv) implementation of the case study using dynamic fault tree simulation, and (v) analyzing the alternative policies in terms of failure statistics, system availability and maintenance cost. On this basis, six different maintenance scenarios were defined: i) Corrective maintenance and regular inspection, ii) corrective maintenance, regular inspection, and group inspection, iii) corrective maintenance and group inspection,

iv) corrective maintenance, regular inspection, and spare part policy, v) corrective maintenance and regular inspection with restoration factor of 0.25, and vi) corrective maintenance and regular inspection with restoration factor of 0.75. Additionally, applicability of preventive component replacement was analyzed for truck tires.

The developed dynamic simulation model using fault tree analysis was applied to a truck fleet operated in a surface coal mine in Türkiye. This fleet contains six HD785-type trucks. SAP maintenance records were used to characterize time-to-repair (TTR) and time between failure (TBF) datasets. Six different maintenance scenarios were simulated 400 times each. The simulation results show that the fifth scenario having corrective maintenance and regular inspection with a restoration factor of 0.25, gives the highest availability value, which is 67 percent. The results revealed that the fleet is over-maintained, and preventive measures in the policy can be reduced slightly to increase availability. On the other hand, the first scenario, including corrective maintenance and regular inspection alone, minimized the total maintenance cost most among the alternative maintenance scenarios. However, it is seen that the availability dropped from 67 to 60 percent and the total maintenance cost could not be improved much compared to the fifth scenario. Therefore, the fifth scenario is the most appropriate maintenance policy for the fleet.

5.2 Recommendations

The recommendations that can be considered in future studies are given as follows:

i. Maintenance data records should be in terms of failure modes instead of subsystems or components. Therefore, templates or systems that can be used for systematical data recording and failure mode labeling should be developed for more detailed and realistic analyses.

ii. Maintenance crew information about the number of qualified people and their skills should be examined jointly in future research.

iii. Maintenance cost variations for similar failure modes of different equipment can be examined by considering operational and environmental aspects.

iv. Different redundancy conditions in the equipment fleet and prioritizing equipment number and type for production can be regarded.

v. The trade-off between over-maintenance and under-maintenance can be detailed by revealing the on-site and off-site affecting parameters.

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APPENDICES

A. Hypothesis Test Results for Other Trucks

Table A.1 Trend Test Results of the TTR Datasets of Truck ID322 Subsystems

Test Name	Test Parameters	Truck Subsystems				
		Tyres	**Body**	**Electrical**	**Hydraulics**	**Drivetrain**
Crow AMSAA	$2N/\hat{\beta}$	19.7	128.2	70.2	109.3	99.8
	$\chi^2_{2N,1-\alpha/2}$	15.3	40.5	19.8	30.8	32.4
	$\chi^2_{2N,\alpha/2}$	44.5	83.3	52.0	69.0	71.4
		Accept Ho	Reject Ho	Reject Ho	Reject Ho	Reject Ho
Laplace	U_L	1.57	-4.07	-2.90	-2.46	-3.62
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Reject Ho	Reject Ho	Reject Ho
PCNT	U_p	-0.71	2.37	1.89	1.79	2.43
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Reject Ho
Lewis Robinson	U_{LR}	1.19	-3.05	-1.96	-1.92	-2.74
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Reject Ho	Accept Ho	Reject Ho
	DECISION	Non-trend	Trend	Trend	Trend	Trend

Table A.2 Trend Test Results of the TBF Datasets of Truck ID322 Subsystems

Test Name	Test Parameters	Truck Subsystems				
		Tyres	**Body**	**Electrical**	**Hydraulics**	**Drivetrain**
Crow AMSAA	$2N/\hat{\beta}$	19.5	67.0	20.2	52.3	54.9
	$\chi^2_{2N,1-\alpha/2}$	16.8	37.2	22.9	27.6	29.2
	$\chi^2_{2N,\alpha/2}$	47.0	78.6	56.9	64.2	66.6
		Accept Ho	Accept Ho	Reject Ho	Accept Ho	Accept Ho
Laplace	U_L	1.21	-0.11	2.19	-0.40	0.69
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Accept Ho	Reject Ho	Accept Ho	Accept Ho
PCNT	U_p	-1.14	0.04	-2.13	0.87	-0.24
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Accept Ho	Reject Ho	Accept Ho	Accept Ho
Lewis Robinson	U_{LR}	1.06	-0.12	1.62	-0.45	0.47
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Accept Ho	Accept Ho	Accept Ho	Accept Ho
	DECISION	Non-trend	Non-trend	Trend	Non-trend	Non-trend

Table A.3 Trend Test Results of the TTR Datasets of Truck ID323 Subsystems

Test Name	Test Parameters	Truck Subsystems				
		Tyres	**Body**	**Electrical**	**Hydraulics**	**Drivetrain**
Crow AMSAA	$2N/\hat{\beta}$	13.5	85.8	65.8	57.1	45.7
	$\chi^2_{2N,1-\alpha/2}$	15.3	27.6	29.2	26.0	24.4
	$\chi^2_{2N,\alpha/2}$	44.5	64.2	66.6	61.8	59.3
		Reject Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
Laplace	U_L	3.04	-3.04	-1.50	-0.69	-0.88
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Reject Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
PCNT	U_p	-1.37	2.40	-0.08	-0.54	0.65
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
Lewis Robinson	U_{LR}	1.09	-3.38	-1.05	-0.47	-1.09
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
	DECISION	Trend	Trend	Non-trend	Non-trend	Non-trend

Table A.4 Trend Test Results of the TBF Datasets of Truck ID323 Subsystems

Test Name	Test Parameters	Truck Subsystems				
		Tyres	**Body**	**Electrical**	**Hydraulics**	**Drivetrain**
Crow AMSAA	$2N/\hat{\beta}$	16.9	33.8	39.3	25.9	54.9
	$\chi^2_{2N,1-\alpha/2}$	13.8	26.0	22.9	24.4	19.8
	$\chi^2_{2N,\alpha/2}$	41.9	61.8	56.9	59.3	52.0
		Accept Ho	Accept Ho	Accept Ho	Accept Ho	Reject Ho
Laplace	U_L	1.60	0.49	-0.91	1.29	-3.19
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Accept Ho	Accept Ho	Accept Ho	Reject Ho
PCNT	U_p	-1.46	0.31	0.52	-1.49	0.58
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Accept Ho	Accept Ho	Accept Ho	Accept Ho
Lewis Robinson	U_{LR}	1.81	0.54	-1.15	2.04	-1.64
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Accept Ho	Accept Ho	Reject Ho	Accept Ho
	DECISION	Non-trend	Non-trend	Non-trend	Non-trend	Trend

Table A.5 Trend Test Results of the TTR Datasets of Truck ID324 Subsystems

Test Name	Test Parameters	Truck Subsystems				
		Tyres	**Body**	**Electrical**	**Hydraulics**	**Drivetrain**
Crow AMSAA	$2N/\hat{\beta}$	35.1	110.7	53.3	20.2	18.9
	$\chi^2_{2N,1-\alpha/2}$	9.6	55.5	19.8	9.6	16.8
	$\chi^2_{2N,\alpha/2}$	34.2	104.3	52.0	34.2	47.0
		Reject Ho	Reject Ho	Reject Ho	Accept Ho	Accept Ho
Laplace	U_L	-2.04	-4.54	-2.33	-1.07	0.12
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Reject Ho	Reject Ho	Reject Ho	Accept Ho	Accept Ho
PCNT	U_p	2.06	1.03	1.40	-1.34	-0.54
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Reject Ho	Accept Ho	Accept Ho	Accept Ho	Accept Ho
Lewis Robinson	U_{LR}	-0.93	-2.43	-1.68	-0.71	0.07
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
	DECISION	Trend	Trend	Trend	Non-trend	Non-trend

Table A.6 Trend Test Results of the TBF Datasets of Truck ID324 Subsystems

Test Name	Test Parameters	Truck Subsystems				
		Tyres	**Body**	**Electrical**	**Hydraulics**	**Drivetrain**
Crow AMSAA	$2N/\hat{\beta}$	12.8	79.9	41.5	24.0	32.9
	$\chi^2_{2N,1-\alpha/2}$	12.4	74.2	32.4	15.3	22.9
	$\chi^2_{2N,\alpha/2}$	39.4	129.6	71.4	44.5	56.9
		Accept Ho	Accept Ho	Accept Ho	Accept Ho	Accept Ho
Laplace	U_L	2.01	1.42	0.98	0.27	0.50
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Reject Ho	Accept Ho	Accept Ho	Accept Ho	Accept Ho
PCNT	U_p	-1.78	-1.36	-1.34	-0.85	-0.04
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Accept Ho	Accept Ho	Accept Ho	Accept Ho
Lewis Robinson	U_{LR}	1.67	1.11	0.94	0.24	0.48
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Accept Ho	Accept Ho	Accept Ho	Accept Ho
	DECISION	Non-trend	Non-trend	Non-trend	Non-trend	Non-trend

Table A.7 Trend Test Results of the TTR Datasets of Truck ID325 Subsystems

Test Name	Test Parameters	Truck Subsystems				
		Tyres	**Body**	**Electrical**	**Hydraulics**	**Drivetrain**
Crow AMSAA	$2N/\hat{\beta}$	8.8	129.6	18.3	12.7	32.3
	$\chi^2_{2N,1-\alpha/2}$	3.2	69.1	16.8	5.6	13.8
	$\chi^2_{2N,\alpha/2}$	20.5	122.7	47.0	26.1	41.9
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
Laplace	U_L	-0.96	-3.41	0.65	-0.42	-0.88
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
PCNT	U_p	0.49	2.50	-0.25	-0.45	1.46
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
Lewis Robinson	U_{LR}	-0.82	-2.20	0.94	-0.47	-0.49
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
	DECISION	Non-trend	Trend	Non-trend	Non-trend	Non-trend

Table A.8 Trend Test Results of the TBF Datasets of Truck ID325 Subsystems

Test Name	Test Parameters	Truck Subsystems				
		Tyres	**Body**	**Electrical**	**Hydraulics**	**Drivetrain**
Crow AMSAA	$2N/\hat{\beta}$	12.9	158.7	48.5	13.1	33.1
	$\chi^2_{2N,1-\alpha/2}$	9.6	75.9	29.2	6.9	19.8
	$\chi^2_{2N,\alpha/2}$	34.2	131.8	66.6	28.8	52.0
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
Laplace	U_L	0.31	-2.91	0.38	0.36	-0.31
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
PCNT	U_p	-0.98	2.30	-0.65	0.45	-0.54
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
Lewis Robinson	U_{LR}	0.27	-2.71	0.44	0.31	-0.34
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Accept Ho
	DECISION	Non-trend	Trend	Non-trend	Non-trend	Non-trend

Table A.9 Trend Test Results of the TTR Datasets of Truck ID326 Subsystems

Test Name	Test Parameters	Truck Subsystems				
		Tyres	**Body**	**Electrical**	**Hydraulics**	**Drivetrain**
Crow AMSAA	$2N/\hat{\beta}$	5.9	132.4	65.4	16.5	53.3
	$\chi^2_{2N,1-\alpha/2}$	5.6	35.6	21.3	11.0	16.8
	$\chi^2_{2N,\alpha/2}$	26.1	76.2	54.4	36.8	47.0
		Accept Ho	Reject Ho	Reject Ho	Accept Ho	Reject Ho
Laplace	U_L	0.52	-5.45	-1.44	-0.55	-2.87
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Reject Ho
PCNT	U_p	0.45	3.86	0.87	-0.08	2.03
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Reject Ho
Lewis Robinson	U_{LR}	0.56	-3.65	-1.38	-0.38	-2.06
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Reject Ho	Accept Ho	Accept Ho	Reject Ho
	DECISION	Non-trend	Trend	Non-trend	Non-trend	Trend

Table A.10 Trend Test Results of the TBF Datasets of Truck ID326 Subsystems

Test Name	Test Parameters	Truck Subsystems				
		Tyres	**Body**	**Electrical**	**Hydraulics**	**Drivetrain**
Crow AMSAA	$2N/\hat{\beta}$	5.8	74.1	24.1	32.0	27.1
	$\chi^2_{2N,1-\alpha/2}$	6.9	37.2	19.8	8.2	12.4
	$\chi^2_{2N,\alpha/2}$	28.8	78.6	52.0	31.5	39.4
		Reject Ho	Accept Ho	Accept Ho	Reject Ho	Accept Ho
Laplace	U_L	1.66	-1.58	0.45	-2.31	-1.51
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Accept Ho	Accept Ho	Reject Ho	Accept Ho
PCNT	U_p	0.45	1.81	-0.72	1.73	1.48
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Accept Ho	Accept Ho	Accept Ho	Accept Ho
Lewis Robinson	U_{LR}	1.23	-1.44	0.56	-2.28	-1.61
	$z_{\alpha/2}$	1.95	1.95	1.95	1.95	1.95
		Accept Ho	Accept Ho	Accept Ho	Reject Ho	Accept Ho
	DECISION	Non-trend	Non-trend	Non-trend	Trend	Non-trend

B. General Results of Maintenance Scenarios

Table B.1 The Simulation Results for Case02 Model

General	
Mean Availability (All Events):	0.58
Std Deviation (Mean Availability):	0.17
Expected Number of Failures:	173.96
Std Deviation (Number of Failures):	46.02
MTTFF:	6.76
System Uptime/Downtime	
Uptime:	5067.37
CM Downtime:	3376.08
Inspection Downtime:	322.55
Total Downtime:	3698.63
System Downing Events	
Number of Failures:	173.96
Number of CMs:	173.96
Number of Inspections:	151.81
Total Events:	325.78
Costs	
Total Costs (USD):	2,334,060.53

Table B.2 The Simulation Results for Case03 Model

General	
Mean Availability (All Events):	0.56
Std Deviation (Mean Availability):	0.18
Expected Number of Failures:	168.75
Std Deviation (Number of Failures):	49.92
MTTFF:	6.49
System Uptime/Downtime	
Uptime:	4943.77
CM Downtime:	3612.37
Inspection Downtime:	209.86
Total Downtime:	3822.23
System Downing Events	
Number of Failures:	168.75
Number of CMs:	168.75
Number of Inspections:	108.45
Total Events:	277.20
Costs	
Total Costs (USD):	1,425,069.46

Table B.3 The Simulation Results for Case04 Model

General	
Mean Availability (All Events):	0.53
Std Deviation (Mean Availability):	0.15
Expected Number of Failures:	160.20
Std Deviation (Number of Failures):	41.88
MTTFF:	6.43
System Uptime/Downtime	
Uptime:	4676.36
CM Downtime:	3995.16
Inspection Downtime:	94.48
Total Downtime:	4089.64
System Downing Events	
Number of Failures:	160.20
Number of CMs:	160.20
Number of Inspections:	36.77
Total Events:	196.97
Costs	
Total Costs (USD):	129,084,676.30

Table B.4 The Simulation Results for Case05 Model

General	
Mean Availability (All Events):	0.67
Std Deviation (Mean Availability):	0.15
Expected Number of Failures:	151.22
Std Deviation (Number of Failures):	33.55
MTTFF:	5.99
System Uptime/Downtime	
Uptime:	5837.63
CM Downtime:	2811.42
Inspection Downtime:	116.94
Total Downtime:	2928.37
System Downing Events	
Number of Failures:	151.22
Number of CMs:	151.22
Number of Inspections:	45.35
Total Events:	196.56
Costs	
Total Costs (USD):	1,248,040.26

Table B.5 The Simulation Results for Case06 Model

General	
Mean Availability (All Events):	0.64
Std Deviation (Mean Availability):	0.15
Expected Number of Failures:	170.12
Std Deviation (Number of Failures):	40.41
MTTFF:	5.31
System Uptime/Downtime	
Uptime:	5578.36
CM Downtime:	3076.89
Inspection Downtime:	110.75
Total Downtime:	3187.64
System Downing Events	
Number of Failures:	170.12
Number of CMs:	170.12
Number of Inspections:	42.97
Total Events:	213.09
Costs	
Total Costs (USD):	1,234,904.78

C. Graphs for Comparative Evaluation of the Maintenance Scenarios

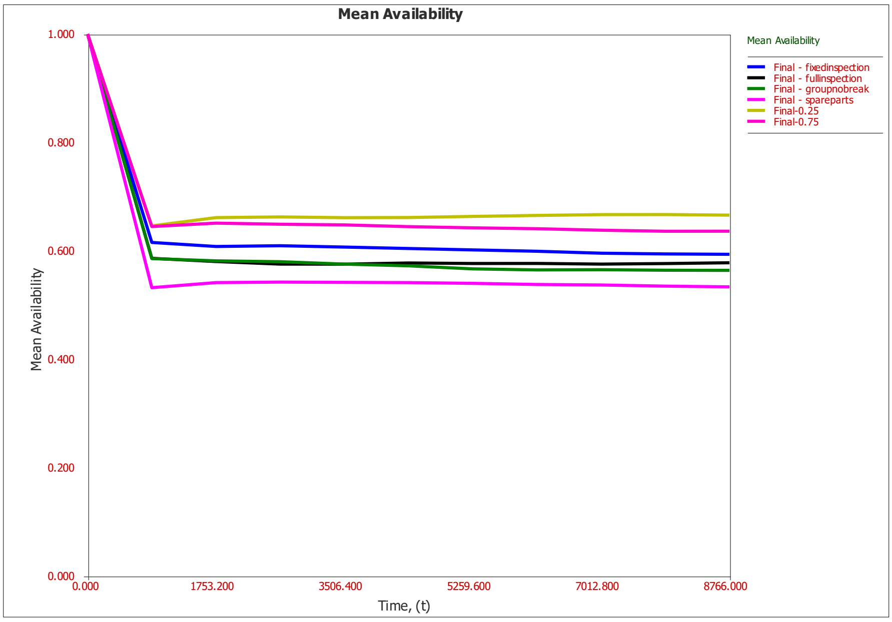

Figure C.1 System Availability in Time for Each Maintenance Scenario

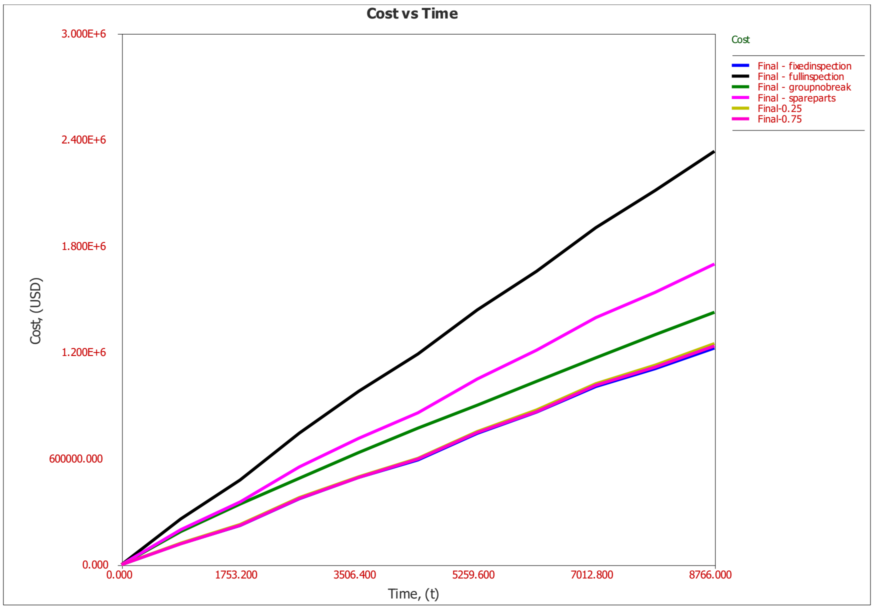

Figure C.2 Maintenance Cost in Time for Each Maintenance Scenario

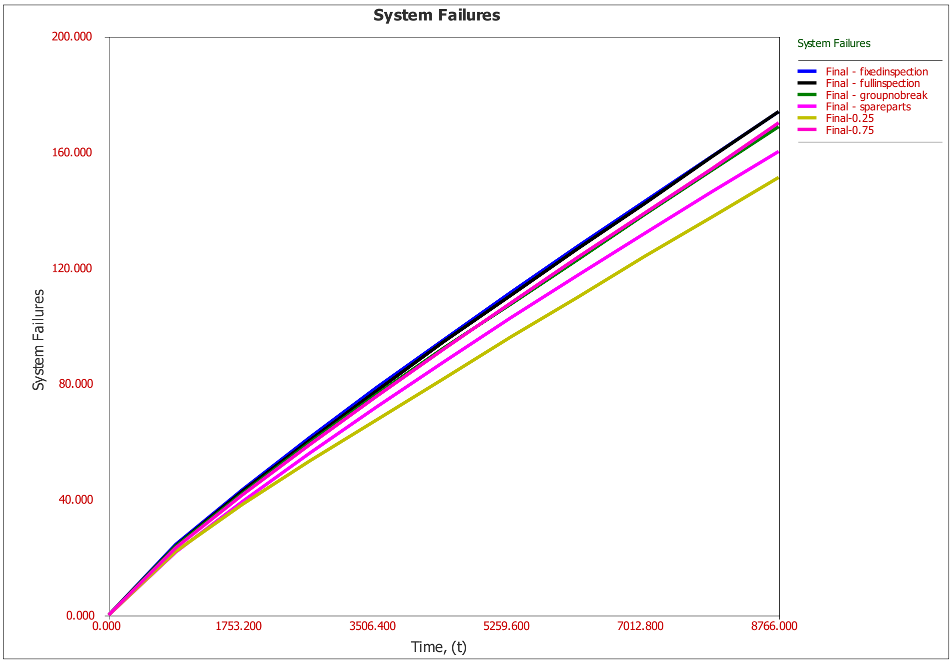

Figure C.3 Failure Numbers in Time for Each Maintenance Scenario