Reliability and Availability Assessment of a cargo locomotive bogie

A contribution to a RAMS Analysis in the FGC case study

Manuel Derichsweiler Bessa Pereira Leite

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Supervisor: Prof. António Ramos Andrade

Examination Committee

Chairperson: Prof. João Orlando Marques Gameiro Folgado

Supervisor: Prof. António Ramos Andrade

Member of the Committee: Prof. Virgínia Isabel Monteiro Nabais Infante

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Abstract

As a decarbonized viable option, railway transport is increasingly optimizing its operation and becoming an efficient service. There is the need to develop intelligent tools and methodologies that can support predictive maintenance. The bogie, as a leading system of the railway rolling stock, is responsible for a great fraction of its maintenance costs. In this thesis, the reliability and availability of a cargo locomotive bogie is assessed using the reference behaviour of a freight locomotive bogie of a Spanish train operating company as a case study. As part of a RAMS analysis, this work starts by performing a Failure Mode and Effect Analysis (FMEA) to identify and prioritize the most critical components of the bogie system. To quantify reference failure rates, a reliability assessment method is proposed which combines the Cooke's Classical model and the histogram technique. A reference use case of the bogie is obtained, a reliability block diagram (RBD) of its reliability-wise relationships is established and simulation models of both reliability and availability are modelled following a discrete event simulation approach. Emphasis is put on the variability of the stochastic parameters, which are modelled in alternative scenarios. The results confirm that such models are decisive to predict the reliability and availability of cargo locomotive bogie systems and serve as valuable diagnosis and prognosis models in the decision-making of railway maintenance.

Keywords

Railway maintenance; Asset management; Reliability; Availability; RAMS; Discrete event simulation (DES); Monte Carlo simulation (MCS).

Resumo

Como opção descarbonizada fiável, o transporte ferroviário tem captado cada vez maiores investimentos, para otimizar a sua operação e ser um serviço de maior eficiência. Consequentemente, a necessidade de desenvolver ferramentas e metodologias inteligentes, que melhor suportem uma manutenção preditiva, tem sido fulcral para atingir esses objetivos. O bogie, como sistema principal do material rolante ferroviário, é responsável pela maior fração dos custos de manutenção. Nesta tese, a fiabilidade e a disponibilidade de um bogie de uma locomotiva de carga são avaliadas, usando uma locomotiva de carga pertencente a uma empresa ferroviária espanhola como caso de estudo. Como parte de uma análise RAMS, este trabalho começa por identificar, através de uma Análise de modo e efeito de falha (FMEA), os componentes críticos do sistema do bogie. Para quantificar taxas de falha, é proposto um método de avaliação de fiabilidade, que combina o modelo clássico de Cooke e uma técnica de histograma. Um caso de estudo do bogie é obtido, um diagrama de blocos da fiabilidade (RBD) é estabelecido e modelos de simulação de fiabilidade e disponibilidade são modelados, seguindo uma abordagem de simulação de eventos discretos. De modo a analisar a variabilidade dos parâmetros, vários cenários são modelados. Os resultados confirmam que os modelos são soluções determinantes para prever a fiabilidade e disponibilidade dos sistemas de bogies de locomotivas de carga e servem como modelos de diagnóstico e prognóstico decisivos na tomada de decisão de manutenção ferroviária.

Palavras-Chave

Manutenção ferroviária; Gestão de ativos; Fiabilidade; Disponibilidade; RAMS; Simulação de eventos discretos; Simulação de Monte Carlo.

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Latin Symbols

A	Availability.
a	Minimum value of the PERT distribution.
B	Beta function.
b	Most likely value of the PERT distribution.
C_m	Modal Criticality.
C_i	Item Criticality.
C	Calibration score.
c	Maximum value of the PERT distribution.
D	Detectability.
E	Estimated value.
e	Expert.
erf	Error function.
F	Failure function – Cumulative density function.
f	Probability density function – failure density.
h	Hazard rate function – failure rate function.
I	Kullback-Leibler Divergence.
i,j,k	Indexes.
K	Overshoot.
L	Intrinsic range lower bound.
M	Number of Failure modes.
N	Number of simulations.
O	Occurrence.
p	Inter-quantile probability vector.
R	Reliability.
S	Severity.
S_i	Component's signal.
s	Empirical probability vector.
T	Time – Time as a random variable.
t	Time.
U	Intrinsic range upper bound.
U_i	Uniform pseudo random number.
w_e, w_e'	Normalized and unnormalized weight of each expert.
X	Random variable.
x	Realization in each inter-quantile.

Greek Symbols

α	Significance level.
β_m	Failure effect probability.
β	Shape parameter.
η	Scale parameter.
λ	Failure rate.
λ_p, λ_m	Failure rate of each Failure Mode.
μ	Mean.
$\vec{\mu}$	Mean vector.
ρ	Correlation factor.
σ	Standard deviation.
$\sigma_{i,j}$	Covariance of proportions i and j.
Φ	Standard normal cumulative distribution function.
Σ	Covariance matrix.

Superscript

$upper$, $lower$	upper / lower values of censored observations.

Subscript

e	expert.
i, j, k	Computational or mathematical indexes.
k/n	System with a $k - out - of - n$ configuration.
P	System in parallel.
S	System in series.

Abbreviations

AGAN	As Good as New.
BS	British Standards.
CDF	Cumulative density function.
D	Detectability.
DES	Discrete event simulation.
DM	Decision Maker.
DOF	Degree of freedom.
EN	European Norm.
ERA	European Railway Agency.
FGC	Ferrocarrils de la Generalitat de Catalunya.
FM	Failure Mode.
FMEA	Failure Mode and Effects Analysis.
FMECA	Failure Mode, Effects and Criticality Analysis.
FTA	Fault Tree Analysis.
GFS	Global Final Signal.
IEC	International Electrotechnical Commission.
KM	Kaplan-Meier estimator.
LCG	Linear Congruential Generator.
MDBF	Mean distance between failure.
MCS	Monte Carlo simulation.
MTBF	Mean time between failure.
MTTF	Mean time to failure.
O	Occurrence.
PDF	Probability density function.
PERT	Project Evaluation Research Technique.
RAMS	Reliability Availability Maintainability and Safety.
RBD	Reliability Block Diagram.
RPN	Risk Priority Number.
S	Severity.

SEJ	Structured Expert Judgment.
TCT	Total cumulative time of a component operating.
TOF	Time of failure.
TTR	Time to repair.
UIC	Union Internationale des Chemins de Fer.

1. Introduction

1.1. Motivation

As the world population grows and the demand for more uninterrupted services rises (e.g. electricity, public transportation, or communications), the dependency on highly mechanized and automated services, regarding the reliability and integrity of their physical assets, is continuously increasing. In fact, asset failure is gaining a relentless priority in system analysis, since a possible failure can mean not only an interruption of service but, in severe cases, the loss of human lives [1]. Additionally, to meet decarbonization milestones in the near future and to mitigate the dependence of fossil fuels in the transportation industry, the railway transport has had significant investment in order to achieve a more competitive and efficient service. Subsequently, to fulfil these needs, the railway industry has put focus in the development of adequate maintenance plans, which not only improve the railway system reliability and operationality but also reduce its lifecycle costs. As stated by the annual workplan and budget of *Shift2Rail* "…to meet these demands (higher costumer demands) and increase the operational performance of critical railway infrastructure assets, innovation must be delivered to enable a step-change in reliability, availability, maintainability and safety (RAMS) whilst also optimising asset capital and LCC." ([2], p.72). This is achieved with the assessment and development of component prediction methods based on predictive tools. Hence, there is a need to develop such tools in order to study not only the component and system degradation but also its impact on the real-time operation of the railway system. Moreover, condition-based and predictive maintenance strategies play a fundamental role in a centralized European rail traffic system, where common advanced monitoring solutions of railway assets serve as performance metrics for the development of digital maintenance rules. It is, therefore, significant that in order to meet such goals, the proper condition-based and prediction tools are developed, existing a clear interest regarding their research.

As the main driver of operating costs within the lifecycle of railway rolling stock, the railway bogie is designed to support the rail vehicle body and to distribute its weight through the locomotive. As a result of its functional purpose, its system tends to be more susceptible to wear, leading to higher lifecycle costs and active maintenance. This work addresses the reliability and availability of a freight locomotive bogie of a Spanish train operating company. The goal of this thesis is to develop a framework to assess the reliability and availability of a bogie system and therefore serve as a diagnosis and prognosis model in the decision-making of railway maintenance.

1.2. Literature Review

Several works, which follow a RAMS methodology, are devoted to study the reliability and availability of complex systems. These are briefly explained in this section, where significance is put first on reliability assessment methods, followed by the studies that apply discrete event simulation approaches to analyse the reliability and availability of systems.

1.2.1. Reliability Assessment Methods

Many studies to predict and calculate the reliability of single or complex systems have been conducted, while many generic methods are proposed in the literature, depending on the data and/or the application. One of them is reliability prediction, which has historically been used to denote the process of applying mathematical/statistical models and data for the purpose of estimating expected reliability of a system before real field data is available for the system [3]. Reliability prediction models were first developed during World War II, to provide a more reliable and stable electronic equipment to the military [3–5], which were subsequently developed to the *Manned Space Flight Program*, being regarded as the standard for reliability prediction to other commercial sources, other than the military world [6]. Although most of the efforts have been concentrated on electronic equipment, where reliability prediction models are well established, they have also been developed for mechanical systems [5,7–10]. As *Wu* and *Yan* [5] state, reliability prediction is a critical process of conceptual design when a system is not yet built, due to the limitation of operation data. These reliability models are indeed very useful during system definition and design phases, but according to Lu et. al [11], these models are of limited usefulness in day-to-day operation phases. *Lu et al.* [11] agree that in a day-to-day operation phase, it is extremely relevant to track and predict operational performance in real-time, where applications and environments are constantly changing.

When studying components that are designed to have a very long life cycle, despite facing all kinds of extreme operating conditions, the data obtained from maintenance and inspection activities is often scarce and is almost always censored since it is very likely that no critical failure has actually occurred. In addition, Si et al. [12] conclude in their review of statistical data-driven approaches for remaining useful life (RUL) estimations, that there is a challenge in addressing RUL estimation models in cases where very few or no data are available, since the majority of the existing statistical data-driven approaches are based only on available past observed data. As a result, the starting point to conceive a reliability assessment method is that commonly available operation data to model the reliability of long service-life components is insufficient, and there is a need to develop a methodology to predict the moment by which an asset reaches a certain degradation. One approach to overcome this scarcity of good data and assess uncertainties is, as Cooke mentions in his original study [13], to determine lifetime distributions based on the use of expert opinion/judgment. In accordance with Ter Berg et al. [14], one could argue to which degree historical data analysis can be assumed for an adequate benchmark for assessing variables in the long term, since such historical data only comprises short-term information for the asset of interest.

For optimal maintenance strategies and reliability assessments, expert judgment techniques were first used by Van Noortwijk et. al [15], where a method with the use of expert opinions for obtaining lifetime distributions for maintenance optimisation was proposed. This method includes a histogram technique for eliciting discretized lifetime distributions from experts, where the combination of the expert's opinion into a consensus distribution is obtained via a Bayes scheme, which is later updated with failure and maintenance data. Moreover, Oien [16] describes how the histogram technique, proposed by Van Noortwijk et. al [15], and expert judgment are adequate techniques for quantifying failure rates of components, in order to optimize maintenance and inspection intervals. In addition, Wang and Zhang [17] propose a method that uses expert judgments as additional information to predict the residual life distribution of the item from condition monitoring. Once again, the validity of these methods is dependent on historical data, which for long service-life components can be scarce. Moreover, according to Wang and Zhang [17], although the expert judgment technique is an added value to the decision process, it is also subject to problems such as the subjectivity on the experience and skills of the expert, which can produce inconsistent or misleading recommendations. Therefore, a performance-based expert judgment is usually a better tool to address uncertainties, since each expert weight is based on his/her performance. This idea leads to structured expert judgment, also known as the Cooke Method, which is a mathematical approach for decision making under uncertainties, that comprises the expert's know-how on the weight of her/his judgment. For the past years, this expert judgment technique has been applied in several industries, where most of the studies are conducted on natural hazards, in the ecosystems, in public health industries, as well as in the civil aviation or in the structural reliability industry [17–19]. This method allows the creation of performance-based probability distributions functions, which represent the uncertainty of interest. Nevertheless, if one wants to quantify a discretized point estimate, such as a failure quantity, the histogram technique is more appropriate. Therefore, a combination of a structured expert judgment and the histogram technique is proposed, based on Ter Berg et. al [14] and Van Noortwijk [15] work, which assesses the reliability of long service-life components.

1.2.2. Discrete Event Simulation

Several works devoted to the numerical simulation of the reliability and availability of complex systems can be found in the literature. Particularly, works using Monte Carlo Simulation (MCS) models together with a Discrete Event Simulation (DES) approach to assess the stochastic behaviour embedded in the reliability and maintainability analysis. However, no application comprises the railway bogie.

Since multiple variables in the reliability assessment field, such as Time to Failure (TTF), Time between Failures (TBF), Time to Repair (TTR), down time, and other stochastic variables, are represented by random variables, simulation approaches are very appropriate to model them by numerically approximating their stochastic behaviour with various simulation techniques. As a pioneer in the application of simulation models in reliability engineering, A. Chrisman proposes a DES model to study large-scale system reliability in his initial simulation studies [20], where a framework for assessing the reliability of complex electro-mechanical systems is additionally proposed by the author. A significant development of DES applications has been put in structural reliability analysis, where a review of applications is gathered by J. Faulin et. al [21] book. In fact, all applications follow the same methodology for performing a structural reliability and availability analysis through DES, which makes use of statistical distributions and techniques, such as survival analysis, to model component-level reliability. Emphasis is put on the differences between a standalone MCS versus a combinatorial of a DES with a MCS approach, where in addition to obtaining the structural lifetime generated by simulation, the DES also enables to acquire detailed understanding on the lifetime progression of the analysed structure. Moreover, Gascard et al. [22] suggest that in order to challenge the disadvantages of MCS, such as high computational efforts and times, a dynamic fault tree simulation performed with a DES approach is the best solution. With a DES approach, gate simulations that produce no change in the output of a gate are excluded enhancing the speed up of the simulation. More related to maintenance policies implementations, where the reliability and availability projections are crucial, A. Alrabghi and A.Tiwari [23] were the first to model complex maintenance systems using a DES algorithm, where condition-based, preventive, and corrective maintenance can be applied. Using A. Alrabghi and A.Tiwari work, O. Golbasi and M.O. Turan [24] develop a discrete-event simulation algorithm to evaluate and optimize maintenance policy decisions for production systems, with the addition of including opportunistic maintenance actions for different inspection intervals. Their DES algorithm proposes a bi-optimization criterion that can be either of maximizing availability or minimizing total maintenance cost, allowing multiple different scenarios to be modelled.

In the railway industry, some works comprise the use of DES to assess the reliability and availability of railway assets. Mielnik et. al [25] propose a dynamic DES to study the reliability of railway crossing signalling devices based on the track rail circuit. Rhayma et al. [26] analyse the behaviour of the railway track geometry by means of a numerical analysis which goes in accordance with a discrete event and MCS approach. Nevertheless, for railway rolling stock, reliability and availability evaluations following a DES algorithm has not been published, addressing the need for its study. Therefore, a combination of the DES algorithm with a MCS is implemented, where the aim is to assess maintenance policies and project the reliability and availability of railway rolling stock.

1.3. Thesis Goals, Contribution and Structure

The main goal of this dissertation is to study the availability and reliability of a cargo locomotive bogie in operation, proposing a framework to assess these properties, in order to contribute to the maintenance decision-making of railway rolling stock as a diagnosis and prognosis model. To pursue this objective, the following tasks are required, which typically are part of a RAMS methodology:

- Definition of the functional breakdown and the interdependencies of the entire bogie by means of a Failure Mode, Effects and Criticality Analysis (FMEA/FMECA);
- Modelling of a simulation model based on the functional breakdown and the reliability-wise relationships (RBD) of the bogie using a discrete event simulation approach;
- Testing different scenarios to examine a more rigorous real-case operation in order to understand the effect of different approaches in the reliability and availability projections of the total bogie system.

In the process of the studying the availability and reliability of the bogie system there are several novel aspects of this work that are worth emphasising:

- A proposed Reliability Assessment Method using expert judgment techniques to quantify uncertainties such as failure rates and survival curves of long service life components, which is applied to the wheelset subsystem;

- An alternative approach to model the availability and reliability of a complex system using a discrete event simulation approach where not only the stochastic behaviour of Time of Failure (ToF) and Time to Repair (TTR) is considered and represented with different distribution functions, but also failure correlation in different system levels.

All the studies and analyses are conducted with the use of the commercial software *Matlab*, together with its simulation program *Simulink* and the data analysis software *RStudio.*

This dissertation is structured as follows: the present chapter presents the motivation, a brief literature review and this works structure and objectives; Chapter 2 introduces the basic concepts of a RAMS Analysis, where its acronyms are described, and its development in the railway industry. In the same chapter, the concepts of a FMEA and FMECA analysis are presented and the theory behind the proposed reliability assessment method using expert judgment techniques is introduced; Chapter 3 presents the discrete event simulation theory and model formulation used to simulate the reliability and availability of the bogie. Emphasis is put on the construction of a DES model and the theoretical background of the most distribution functions that model the uncertain parameters of the bogie's operation; Chapter 4 focuses on the description of the project and case study, the freight locomotive and the bogie of the case study. A FMEA analysis is applied to the case study of interest and due to lack of information of the reference bogie, the proposed reliability assessment method is used to quantify failure rates of the wheelset subsystem, resulting in a consolidated FMECA analysis; in Chapter 5, the discrete event simulation model of the bogie system is presented and the simulation results of different operation scenarios are demonstrated and discussed; Chapter 6 presents the conclusions and future lines of development suggested by this work.

2. RAMS Analysis

This chapter contemplates the reliability, availability, maintainability, and safety (RAMS) analysis procedure on which this dissertation is developed. A brief introduction to RAMS analysis is presented, where all the associated concepts are explained. Then, the development of the RAMS methodology in the railway industry is described and the fundamental standards and railway applications are explored. The FMEA and FMECA analysis are briefly explained, as well as its application in the railway industry, which goes according to defined standards. To quantify uncertainties, embedded in the decision-making processes in rare events, expert judgment techniques are presented, followed by a proposed reliability assessment method, which aims to quantify such uncertainties in long service life components.

2.1. The RAMS Analysis

The RAMS (reliability, availability, maintainability, and safety) analysis process is an engineering guideline, that comprises analytical methods and integrative concepts for a system to meet its functional requirements. The RAMS analysis was firstly originated from the concepts of safety and reliability, which were introduced by the aerospace industry in the 1930, becoming a crucial engineering discipline in the late 1950's due to the application of stochastic events in the system failure analysis [27]. The analysis outlines the long-term operation of a system, which is characterized as an indicator of the systems global function, the systems basic function, the systems hierarchical dependency and, most importantly, the interdependencies of the systems functionalities. This is achieved through the definition, assessment and control of all hazards that influence the systems behaviour. Therefore, the RAMS analysis guarantees that a system can be relied upon the functionalities as specified as well as being available and safe at the same time. This emphasizes the main goal of the analysis, which is to increase productivity, reduce costs, and mitigate failure risks and undesirable events.

As part of the RAMS analysis and in order to better understand the concept embed in this engineering protocol, a definition and brief explanation of its acronyms, namely: reliability, availability, maintainability and safety, is needed.

2.1.1. Reliability

Reliability (R) is typically evaluated as the probability that an item performs its function for a required period, under specified environmental and operational conditions [28]. As a result, reliability estimations are used to evaluate design, compare design alternatives, trade-off system design factors, support test planning, monitor reliability improvements, and organize maintenance and logistics. Analytically, to better assess reliability and the analysis behind the area, the following concepts are relevant:

- Reliability function or survivor function $R(t)$;
- Failure function (or cumulative distribution function) $F(t)$;
- Hazard rate function $h(t)$ (failure rate function);
- Mean time to failure ($MTTF$);

From a mathematical point of view, reliability $R(t)$ is defined as the probability that an item successful operates in the time interval $[0, t]$, and is still operating at time t. Failure $F(t)$ is, contrarily, defined as the probability that an item fails within time interval $[0, t]$. Both failure and reliability functions can be defined as follows, respectively [4,27]:

$$F(t) = P(T \leq t) = \int_0^t f(t)dt \ , t > 0 \quad (2.1)$$

$$R(t) = P(T > t) = 1 - P(T \leq t) = 1 - F(t) = 1 - \int_0^t f(t)dt = \int_t^\infty f(t)dt \quad (2.2)$$

where T is a continuously distributed random variable, which represents the time to failure of an item, and $f(t)$ its probability density function (PDF). The failure function $F(t)$ is also referred to as the cumulative distribution function (CDF) of the continuous random variable T, while the reliability function is also referred to as the survivor function. Analytically, the PDF $f(t)$ is defined as follows :

$$f(t) = \frac{dF(t)}{dt} = \lim_{\Delta t \to 0} \frac{F(t + \Delta t) - F(t)}{\Delta t} = \lim_{\Delta t \to 0} \frac{P(t < T \leq t + \Delta t)}{\Delta t} \quad (2.3)$$

Alternatively, the PDF can be defined with the use of the reliability function $R(t)$, where $f(t) = -\frac{dR(t)}{dt}$. Figure 2.1 illustrates a typical reliability function $R(t)$, failure function $F(t)$ and probability density function $f(t)$ of a continuous random variable .

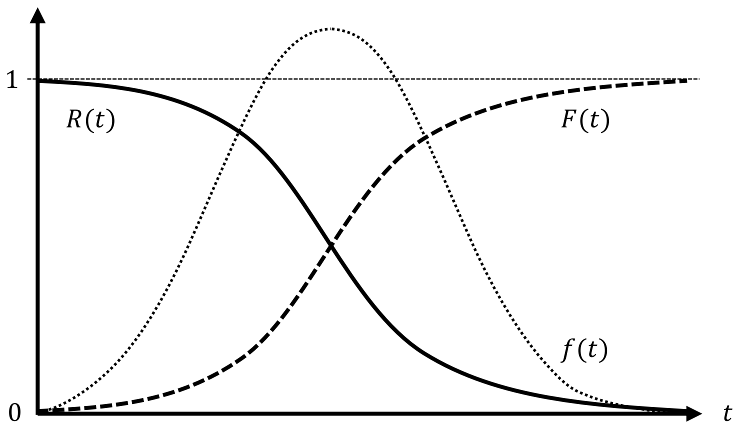


Figure 2.1 – Typical behaviour of a reliability function $R(t)$, failure function $F(t)$ and probabiliy density function $f(t)$ of a continuous random variable T

The hazard rate function $h(t)$, also known as the failure rate function, is defined in statistics as the "force of mortality" (FOM), which indicates the ability of an item to fail after time t has elapsed [4]. Therefore, mathematically, $h(t)$ is defined as the probability that an item is going to fail within time interval $[t, t + \Delta t]$, when one considers that the item is operating at time t. The hazard rate function $h(t)$ is determined as follows:

$$P(t < T \leq t + \Delta t \mid T > t) = \frac{P(t < T \leq t + \Delta t)}{P(T > t)} = \frac{F(t + \Delta t) - F(t)}{R(t)} \quad (2.4)$$

By dividing this probability by Δt and considering that $\Delta t \to 0$, one obtains the hazard rate function of the item.

$$h(t) = \lim_{\Delta t \to 0} \frac{F(t+\Delta t) - F(t)}{\Delta t} \frac{1}{R(t)} = \frac{f(t)}{R(t)} \tag{2.5}$$

Where $f(t)$ and $R(t)$ are the PDF and the reliability function of a continuous random variable T, respectively. Since the PDF $f(t)$ is the derivative of the CDF (failure function) $F(t)$, by combining equation (2.5) with equation (2.3), it is possible to relate directly the reliability function $R(t)$ with the hazard rate $h(t)$ of the item as follows:

$$h(t) = -\frac{d}{dt} \log R(t) \tag{2.6}$$

$$R(t) = e^{-\int_0^t h(t)dt} \tag{2.7}$$

Where the reliability function $R(t)$ is obtained by considering that the boundary conditions of its function is $R(0) = 1$ since an item is considered to be "as good as new" (AGAN) at its starting point. Consequently, one can verify that the reliability function $R(t)$ provides a continuous measure of the probability of non-failure, i.e. being operational, while the hazard rate function $h(t)$ gives an instantaneous measure of the proneness of failure. A summary of the relationships between the reliability function $R(t)$, the failure function $F(t)$, the PDF $f(t)$ and the hazard rate function $h(t)$ is demonstrated in Table 2.1.

Table 2.1 – Relationships between $R(t)$, $F(t)$, $f(t)$ and $h(t)$ (adapted from [4])

$Expressed\ by$:	$R(t)$	$F(t)$	$f(t)$	$h(t)$
$R(t) =$	1	$1 - F(t)$	$\int_t^\infty f(t)dt$	$e^{-(\int_0^t h(t)dt)}$
$F(t) =$	$1 - R(t)$	1	$\int_0^t f(t)dt$	$1 - e^{-(\int_0^t h(t)dt)}$
$f(t) =$	$-\frac{d}{dt}R(t)$	$\frac{d}{dt}F(t)$	1	$h(t) \cdot e^{-(\int_0^t h(t)dt)}$
$h(t) =$	$-\frac{d}{dt}\ln R(t)$	$\frac{dF(t)/dt}{1 - F(t)}$	$\frac{f(t)}{\int_t^\infty f(t)dt}$	1

Over the time a system or a component is operating, its lifetime is typically presented with three distinct periods of failure, which are graphically represented in a bathtub curve. The first stage of failure is known as the infant mortality, also referred to as burn-in period, where the failure rate is high, decreasing with the operating time. This may be clarified by undiscovered defects, which show up when an item starts its function and is related with the design and manufacturing problems that are not detected in control quality inspections. The item is less prone to fail as the time of service increases. The second phase is referred to as the useful life period, also known as the steady-state period, where the failure rate is characterized to be constant, operating at its lowest failure rate. Here, the failure causes are marked by customer use, usually assumed to be stress-related failures, where random fluctuations of stress exceed the items strength, causing it to fail (stochastic failures). The third and final period is called the wear-out period, where the failure rate of an item starts to increase. This increasing failure rate stands for the aging phenomena of an item, which is indicated by the wear-out, corrosion or fatigue that increases the proneness of a unit to fail. When analysing a system's reliability, the analysed behaviour is most typically performed with data gathered during the useful life period, or sporadically, during the wear-out phase [29]. The bathtub curve is graphically represented in Figure 2.2, clearly identifying the three periods of failure typically encountered in an asset.

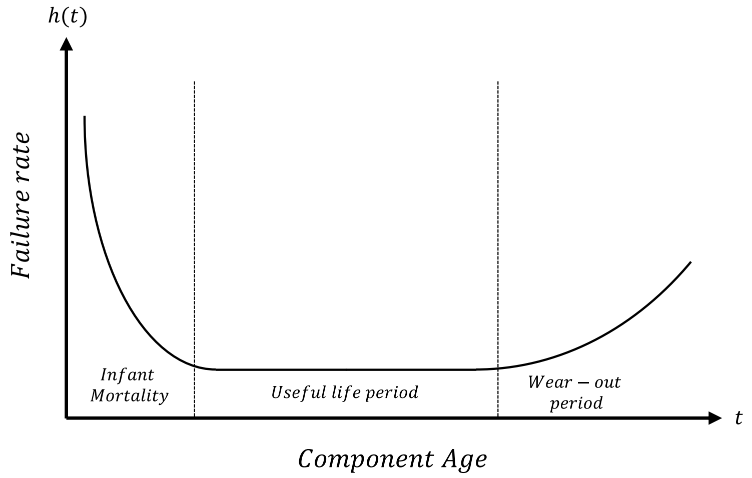


Figure 2.2 – The Bathtub Curve (adapted from [30])

The mean time to failure ($MTTF$) is defined as an indicator that measures the average amount of time a non-repairable item performs its function before it fails. If one considers a continuously random variable T, it is possible to analytically define the $MTTF$ with the estimated value of a distribution function, which is given as:

$$MTTF = E(T) = \int_0^\infty t \cdot f(t)dt \tag{2.8}$$

Any practical related estimation of the $MTTF$ or any stochastic failure prognosis based on the $MTTF$, requires that the system or component is working within its useful life period (see Figure 2.2), where failure rates are assumed to be quasi-static (constant). Assuming this, equation (2.8) can be simplified to:

$$MTTF = \frac{1}{\lambda} \tag{2.9}$$

where λ is the constant failure rate of the system or component. It is worth mentioning, that when studying the lifetime of an item, $MTTF$ is related to a non-repairable unit, whereas the mean time between failure ($MTBF$) is related to repairable items. Both are analytically described by the previous equations.

To perform a reliability analysis, the failure of a system or item is assumed to be represented by a distribution function with known distribution parameters. In reliability analysis, the most common distributions to model the degradation and failure of an asset are the Exponential distribution, the Normal distribution, the Weibull distribution, the Lognormal distribution, and the Gamma distribution. These distributions are mathematically explained in section 3.

2.1.2. Availability

Availability (A) is commonly defined as the probability that a system or a component is executing its required function at a given period of time when operating in normal conditions and maintained in accordance with its standards. It can be interpreted as the percentage of time a system or component is operational over some interval, having in mind its unsuccessful operation. Consequently, the availability is defined as follows [31]:

$$A = \frac{uptime}{downtime + uptime} \tag{2.10}$$

where $uptime$ is the period of time the system or component has been operational, i.e. available, and $downtime$ is the value of time the system or component is not operational, i.e. not available.

When taking into consideration that an unsuccessful operation is a consequence of failure, where the system requires maintenance to repair its functionality, the availability is given by:

$$A = \frac{MTTF}{MTTF + MTTR} \tag{2.11}$$

Where $MTTF$ is the mean time to failure of a system or component and $MTTR$ the mean time to repair of a maintenance task. As one can verify, the availability is dependent on both reliability and maintainability analysis, which is presented in the following subsection. In order to predict availability, both failure and repair, deterministic or stochastic behaviours must be considered.

2.1.3. Maintainability

Maintainability (M) is the probability that a maintenance activity performed to an item under given environmental and operational conditions can be achieved within an established period of time. Therefore, it is referred to as an item’s ability to undergo maintenance to restore its functionality. There are several measures to quantify maintainability, nonetheless, the most widely used term is the mean time to repair ($MTTR$).

Within maintenance, there are two types of actions that are commonly performed in an asset: a preventive maintenance action and a corrective maintenance action. A preventive maintenance action is a scheduled action intended to reduce the probability of failure and the degradation of the asset. A corrective maintenance action is performed in response to unplanned or unscheduled downtimes of items, typically as a result of an unexpected failure, intended to restore an asset’s function to a predetermined state. Within preventive maintenance actions, there are three distinctive types of establishing a maintenance task: predictive, periodic and condition-based maintenance tasks. The predictive maintenance task is based on the prediction of failure, where through diagnostic tools and measurements, such as sensors, the failure of an asset can be predicted, resulting in a maintenance task to repair or replace the item before it actually fails. The periodic maintenance task is based on a scheduled calendar, usually defined with previous experiences of the use of the item or defined with the established design of the item [27,30]. Typically, well defined tasks such as inspections, repairs, adjustments, or alignments are performed. The condition-based maintenance task is based on triggers, where the maintenance task is performed when individual or groups of parameters cross a certain threshold and/or sensors which analyse the condition of the item continuously (very related to a predictive maintenance task) .

2.1.4. Safety

Safety (S) is defined as a parameter which indicates the level of risk associated with a system or component. It is related to all the previous concepts (reliability, availability and maintainability) since a combination of these ensures high levels of safety. Therefore, it is a result of a RAM guideline, which guarantees the freedom of unacceptable harm with regard to operation, maintenance, people, environment and equipment. The objective of a RAMS management process is either to determine and mitigate the most significant failures which present a high impact to safety or to eradicate the consequences of failures throughout a systems life cycle. Consequently, as part of the safety characteristics, the risk assessment process embedded in a RAMS analysis should be performed to determine the degree of safety necessary to define each specific situation [32]. Generally, the degree of safety is characterized by safety criteria which are defined by manufacturers and legal authorities in standards and go in accordance with local rules.

Note: Both reliability and maintainability terms and actions are analysed in a system or item to guarantee and optimise its availability and safety. Therefore, logically, the maintainability term should be described and explained before the availability term. Nonetheless, the availability term is presented first due to the chronological order of the RAMS acronyms.

2.2. RAMS in the Railway Industry

Reliability, availability, maintainability, safety and cost -optimisations are critical topics in the present global railway industry, since the complexity of the railway systems is continuously increasing. Therefore, in order to meet the requirements of having a railway system, able to reach high levels of safety, availability and cost effectiveness, railway organisations have introduced engineering guidelines to perform railway system analysis and railway development projects more successfully. These started with the application of RAMS guidelines with the US railways in the early 1980s, being established in the European railways in the early 1990s with the modification and introduction of systems engineering in railway projects [33], becoming a meaningful decision making element in the global railway industry.

The goal of a railway system is to achieve a defined level of traffic in a given time under safe conditions. Consequently, the RAMS standards and guidelines help to achieve this goal by providing guidance and confidence that a particular railway system is going to achieve its goals, safely. Moreover, it describes benchmarks on how to establish targets to assure reliability, availability, maintainability and safety of railway systems, influencing the systems functionality, regularity of service and the frequency of service, thus increasing the quality of service delivered to the customer. This is accomplished with the use of the British and European standard BS EN 50126 "*Railway Applications: The Specification and Demonstration of Reliability, Availability, Maintainability and Safety (RAMS)"* [34], which provides a common process throughout the European Union (EU) for the specification and demonstration of the RAMS requirements. This European standard supports railway operators, maintainers or suppliers with a method which enables the implementations of systematic paths to address railway RAMS. The BS EN 50126 standard helps to identify key aspects that influence the RAMS characteristics and manage these key aspects by evaluating these at each phase of the system life cycle with risk assessment techniques. To guarantee a reliable, safe, cost-effective, and enhanced quality of railway systems, the standard recommends a system life cycle, composed by sequences of tasks and feedback loops that go from initial concepts in design through to decommissioning and conclusion [32], which are extremely relevant in design phases of railway systems. This life cycle approach comprises three main areas which are applicable to any railroad system or component and can be simplified depending on the appropriate project phase. Moreover, railway organisations have continuously focused on the introduction of railway RAMS to improve its railway operational effectiveness (last phase of the life cycle approach). According to Park [33], railway organizations have generally applied three aspects to properly conduct a RAMS analysis:

1) The definition of the RAMS characteristics, namely: Reliability, Availability, Maintainability and Safety, which belong to the analysis requirements and are extremely relevant in the operational context of the organization;
2) Assessment and control of risks, such as failures, errors or faults that impact the quality and safety of the rail traffic service;
3) The arrangement of controlling the risks, such as failure prevention, fault tolerances and fault predictions.

These aspects are embedded in the European railway standard BS EN 50126 and are taken into consideration for this work. In railway RAMS, safety and availability are strong correlated since a mismanagement of one can result in a sub-optimal performance of the system. Both are highly dependent on the reliability and maintainability of the system, which are influenced by three main influence factors, namely: the system conditions, such as inherent weaknesses or errors in requirements of the system, the operating conditions, like environmental conditions or human factors, and the maintenance conditions, such as preventive or predictive maintenances. Figure 2.3 illustrates the system lifecycle process embed in the RAMS management process (a), as well as a diagram of the influencing factors in railway RAMS (b).

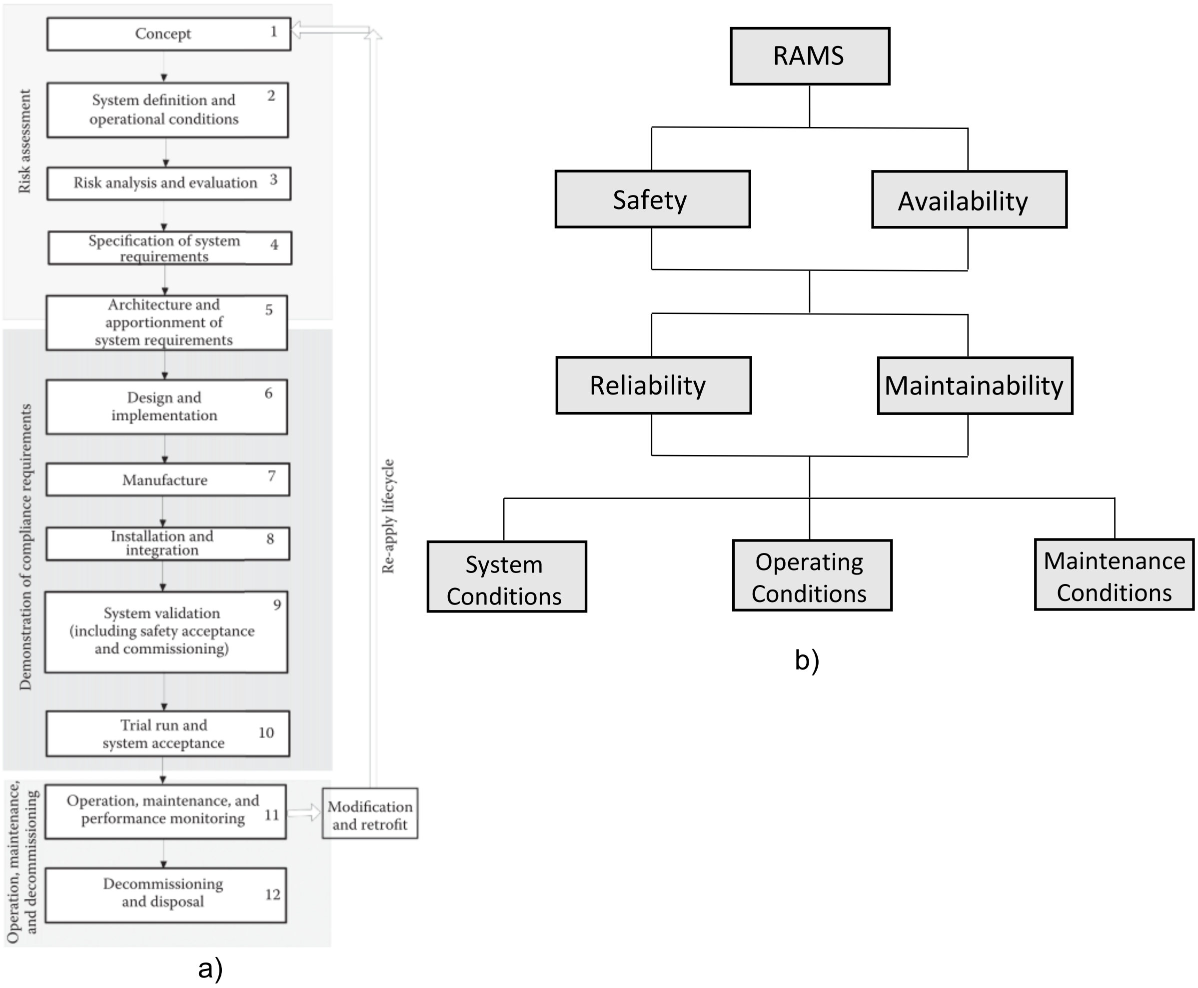


Figure 2.3 – a) System life cycle applicable for RAMS management process [32] b) Diagram of the influencing factors of railway RAMS (adopted from [34])

From a mathematical point of view, the analytical concepts, definitions and terminologies related to a railway RAMS analysis defined in the BS EN 50126 [34] standard go according to IEC 61703:2016 [32] international standard, which are defined in section 2.1.

2.3. FMEA Analysis

As part of a RAMS analysis recommended in the railway standard BS EN 50126 [34] to define the factors which will affect the successful operation of a railway system, the *failure mode and effect analysis* (FMEA) is a methodology employed to determine potential failure modes (FM), failure effects, failure mechanisms and failure causes that affect a system to operate successfully and that mitigates a system reliability, availability, maintainability and safety [29]. In a FMEA analysis it is extremely relevant to fully correlate its acronyms to have a good risk assessment. A failure mode (FM) is defined as an undesired state or function of a system or item, which is implicit or caused, and is the explanations of the inability of a system or item to perform its function. A FM can lead to a failure effect. A failure effect is the result of a FM on the higher levels of a system, which can bring the system to fail or reach an unacceptable high probability of failure. A failure mechanism is a physical result of an origin cause that leads to a FM.

A failure cause is a situation or condition which explains the fundamental causes of a problem that lead to a failure mechanism. Figure 2.4 illustrates a flowchart of the FM and effects relationship.

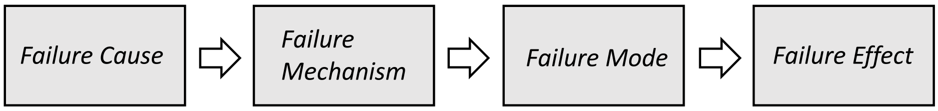


Figure 2.4 – Flowchart of the failure modes and effects relation (adapted from [29])

The FMEA analysis was one of the first engineering techniques introduced in reliability and safety engineering. It was first implemented by the US Military in the 1950s with the *MIL-STD-1629A* [35] guideline to improve and verify the reliability of space program hardware, and afterwards, it was developed in industries such as the automotive industry, food processing industry, and electronic equipment industry [36][37]. As one of well-used safety and reliability assessment technique, FMEA provides a framework that defines, identifies, prioritizes and controls all potential FM that may include in the system design, manufacture phases, or functional process of a system [33]. In the railway industry, the FMEA analysis was first introduced with the RAMS Guideline standard "*BS EN:50126 Railway Applications - The Specification and Demonstration of Reliability, Availability, Maintainability and Safety (RAMS) - Part 1: Generic RAMS Process*" [34] and has since been developed. In the railway industry the most common standard to apply a FMEA analysis is the BS EN 60812 standard, which defines a general procedure to perform a FMEA analysis and gives guidance as to how the methodology may be applied to achieve various RAMS objectives. This is an international standard, which not only is applicable in the railway industry, but also in other major industries.

In this section, the qualitative and quantitative background of the FMEA analysis in accordance with the railway standards is demonstrated, as well as the criticality analysis, which prioritizes the most critical subsystems, components and its associated failure modes.

2.3.1. Risk Priority Number

The procedure for performing a FMEA in the railway industry is recommended in the RAMS Guideline standard [34] and shown in Figure 2.5:

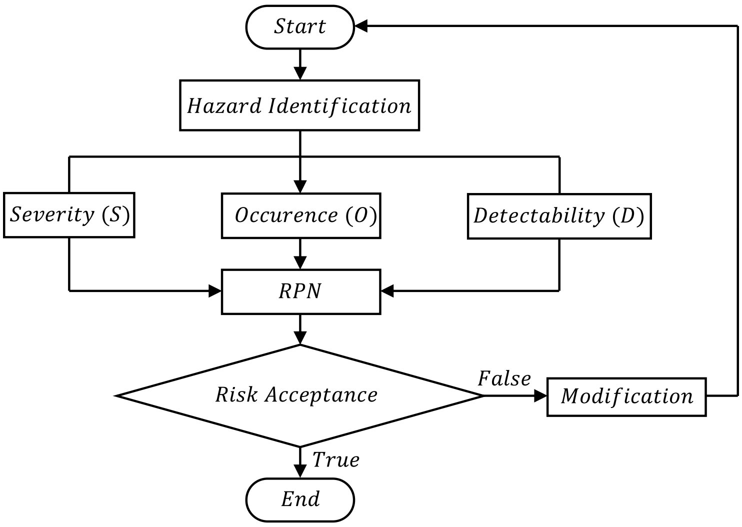


Figure 2.5 – Procedure for implementing a FMEA in the rail industry [34]

As recommended in the RAMS Guideline standard [34] procedure and in the general FMEA procedure standard BS EN 60812 [38], the importance of risks associated with a hazard in a railway system can be prioritised by using an index, named as the Risk Priority Number (RPN). The Risk Priority Number takes three global indicators into account, namely:

1. Severity, S : a risk indicator corresponding to the consequences of the failure mode;
2. Occurrence, O: a risk indicator corresponding to the probability of occurrence of the failure mode;
3. Detectability, D: a risk indicator corresponding to the probability that a failure mode is detected (in an early stage).

These indicators can be assessed on a scale from one to ten and the RPN is obtained as a product of these.

$$RPN = S \times O \times D \tag{2.12}$$

Therefore, the RPN takes values from 1 to 1000.

The criteria to define each of the global indicators goes by the guidelines provided in the *BS EN 60812* [38] standard. For the Severity (S), the criteria to define the indicator can be verified in Figure 2.6.

Rank	Impact	Criteria	Example
1	no impact	No recognisable effect.	
2	very little	Error is noticed by few passengers. Minor changes in structure and dimensions which are below limits.	
3	Little	Error is noticed by few passengers and there are impacts on rolling stock and infrastructure on long term	
4	very low	Error is noticed by many passengers. Due to the failure there is an impact on the quality of rolling stock and on the infrastructure in long term.	
5	Low	Error is noticed by all passengers. Due to the failure there is an impact on the quality of rolling stock and on the infrastructure in mid-term.	less comfort, minor damages on transported goods, eventually higher noise level, increase maintenance cost
6	moderate	Due to the failure there is an impact on the quality of rolling stock and on the infrastructure in short term. Error is noticed by all passengers. Loaded goods can get damaged.	
7	high	Risk of very few light injured people and risk of significant impact on environment and operation. Operation on the line is closed or the line capacity is declined for hours. The loaded goods can get damaged.	small derailment in a shunting yard
8	very high	Risk of few injured people and severe impact on environment. Operation on the line is closed for weeks. Part of the train is destroyed.	major derailment in a shunting yard
9	unsafe with warning	Risk of multiple injured people and few dead people. The impact on environment is very high. Operation on the line is closed for weeks. Large parts of the train are destroyed.	
10	unsafe without warning	Risk of many dead and numerous injured people or the impact on environment is catastrophic. Operation on the line is closed for weeks. The train is destroyed.	derailment ("Viareggio")

Figure 2.6 – Definition of the Severity, *S* in the UIC guideline [38]

As can be seen, the Severity (*S*) criteria is established concerning financial losses and human fatalities, whereas its lowest score can have no recognizable impact on the functionality of the system and its highest score can bring human losses and a destructive impact in the operation of the system.

For the Occurrence (*O*), the criteria is presented in Figure 2.7, established by the UIC guidelines [38]:

Rank	Impact	Probability number of failures per operating-h "vehicle is in use"
1	little - failure is implausible	< 10-9
2	very low: relative very few failures	=< 10-9 till < 3 * 10-8
3	low: relative few failures	=< 3 * 10-8 till < 8 * 10-7
4	moderate: seldom there are failures	=< 8 * 10-7 till < 2 * 10-6
5	moderate: sometimes there are failures	=< 2 * 10-6 till < 5 * 10-6
6	moderate: often there are failures	=< 5 * 10-6 till < 10-5
7	high: repeating failures	=< 10-5 till < 2 * 10-5
8	high: repeating failures in short cycle	=< 2 * 10-5 till < 4 * 10-4
9	very high: Failures in short cycle are nearly not nearly avoidable	=< 4 * 10-4 till < 8 * 10-3
10	very high: Failures in very short cycle which are not avoidable	more than 8 * 10-3 per year

Figure 2.7 – Definition of the Occurrence, *O* in the UIC Guideline [38]

The score criteria of the Occurrence (*O*) is dependent on the failure rate of the identified hazard. For low failure rates, where the probability of the event to happen is relatively small, lower scores are given. Contrarily, for high failure rates, where the probability of the event to happen is high, the scores are higher.

For the Detectability (*D*), the criteria is presented in Figure 2.8, established by the UIC guidelines.

Rank	Detection	Criteria
1	nearly certain	With a very high probability a failure will be detected in a very early initial stage.
2	very high	With a high probability a failure will be detected in a very early initial stage.
3	high	With a high probability a failure will be detected in an early initial stage.
4	moderate high	With a high probability a failure will be detected after initial stage.
5	moderate	With a moderate probability a failure will be detected while existing a short while before getting critical.
6	low	A failure will be detected while existing a while just before getting critical.
7	very low	A failure will be detected while existing for a long while just before getting critical.
8	little	A failure will be hardly detected in a very late stage.
9	uncertain	The detection of a failure before becoming critical is uncertain.
10	nearly uncertain	The detection of a failure nearly is not possible

Figure 2.8 – Definition of the Detectability, *D* in the UIC Guideline [38]

The Detectability (D) criteria is mainly based on expert judgment, where low scores mean the failure can be easily detected in early initial stages and high scores mean the failure can be hardly detected.

2.3.2. Criticality Analysis - FMECA

Failure Mode, Effects and Criticality analysis (FMECA) is an analysis identical with the FMEA, with the addition of including a criticality analysis. According to its definition, criticality is a relative measure of the consequences of a failure mode and the frequency of its occurrence. By means of equations, this quantitative analysis calculates the criticality of each FM, allowing to rank the failures and establish critical FM, components, or systems relative to criticality thresholds or benchmarks. As a result, the criticality analysis is very useful for prioritizing maintenance actions or design improvements, to mitigate risks embed in a system.

Quantitatively, the criticality C_m of a FM (also known as the Modal Criticality) and the criticality of an item C_i is given as follows [[39,40]]:

$$C_m = \beta_m \times \alpha \times \lambda_p \times t \tag{2.13}$$

$$C_i = \sum_{m=1}^{M} C_m \tag{2.14}$$

Where: β_m is the failure effect probability of each FM, α is the failure mode ratio, λ_p is the failure rate of each FM, t the operating hours of each failure mode and M the number of FMs associated to each component i. In fact, for FMs with a specific and assumingly constant failure rate, $\alpha \times \lambda_p = \lambda_m$, where λ_m is the constant failure rate of the FM. The failure effect probability can be defined as the probability of a failure mode to happen, regarding its severity $\beta = S \times O$, where S is the severity of each failure mode and O is the occurrence.

2.4. Assessing uncertainties using Expert Judgment Techniques

For systems that are already built and in operation, reliability analysis, where a FMEA and FMECA analysis are incorporated, should be performed using the existing operation data, e.g. failure rate or warning rate, in order to have a more rigorous real case scenario and reduce uncertainties, since the operating conditions tend to differ for different use-cases, resulting in different component degradation. Considering that the usual data obtained in service is mainly collected during maintenance and inspection activities, research studies have demonstrated that the use of survival analysis [41] generates appropriate statistical models to assess failure uncertainties in components, which support the assessment of the reliability of the overall system [42]. In these studies, parametric and nonparametric approaches are used to fit the most appropriate reliability curves or function. The choice of each approach relies on many details of the failure data set. Nevertheless, when studying components that are designed to have a very long life cycle, despite facing all kinds of extreme operating conditions, the data obtained from maintenance and inspection activities is often scarce and is almost always censored since it is very likely that no failure has actually occurred. Consequently, survival analysis with available information will not be fruitful, and thus maintenance or inspection actions are often performed based on experience or expert knowledge. This idea leads to expert judgment to assess uncertainties.

Expert Judgment (also known as expert elicitation) is an effective tool to explore the sources of uncertainty and to quantify them , when data is scarce or expensive to obtain [43]. According to Taylor et al. [44], elicitation is the procedure of developing the expertise of a person about one or more uncertain quantities into a probability distribution. Consequently, the success of such elicitations depends not only on the type and format of the questions but also on the personality, experience, and technical background of each expert [45]. Therefore, the definition of an expert is not only based on great knowledge of the subject matter but, according to Wood and Ford [46], on someone who represents problems in terms of formal principles and solves them with acknowledged strategies. Once the elicitation process is completed, and assuming the Decision Maker (DM) has access to more than one expert, it makes sense to aggregate/weight the different judgments for each expert. This weighting process of each expert can follow a mathematical or a behavioural approach, in order to produce a single aggregated distribution. Mathematical aggregation methods create single evaluations per variable by applying analytical models to each assessment, such as the Bayesian methods, Opinion pooling, or the Cooke's Method. Behavioural aggregation methods, on the other hand, comprise a synergy of the experts to accomplish a homogeneity on the assessment of the variable of interest [47]. A typical behavioural method is the Delphi method, which implicates various rounds of experts providing their assessments, sharing that information with all the other experts, and then allowing them to review their assessment to move towards a general opinion. This is commonly known as group elicitation [48].

From the mathematical models mentioned, the Opinion Pool method is the most widely used technique due to its simplicity. The simplest decision-making process is seen as the linear opinion pool, where the aggregated distribution is obtained through an equal-weighted average of the individual

distributions. Nevertheless, this method is not perfect, since the weighting process does not contemplate the experts who are recognized to be better and to have more expertise in the required field.
Consequently, a more refined method of the linear Opinion Pool was developed by Roger M. Cooke called the Structured Expert Judgment (also known as the Cooke Method), which has been validated over the years as a more accurate and informative assessment than the equal weighting of experts [49]. In the present study, a mathematical model was used to estimate the weight of each expert, and the associated Structured Expert Judgment (SEJ) was selected as the elicitation method.

2.4.1. The Cooke Method

The Cooke Method is an approach for eliciting and mathematically aggregate expert judgments based on the principle of objective calibration scoring and hypothesis testing in classical statistics [13]. The model elicits judgments from experts in a field of interest to develop probability distributions. The method consists of two types of questions: i) target questions and ii) calibration questions.

Target questions are, as Cooke describes, the variables of interest, i.e. those variables that one wants to quantify and that cannot be assessed with other methods. Calibration questions are questions that are either known to the expert at the time of the elicitation, or will be known during the analysis period, and provide the experts' know-how on the specific topic. Experts are then scored based on their performance on the calibration questions, and their assessments are weighted (according to their scores) and combined. This subsection will explore the basic concepts of the model. An illustrative example is provided in the following subsection.

In the Cooke Method, each expert quantifies his/her uncertainty for each calibration question, whereas his/her score is based on two variables: i) the calibration score, which measures the statistical accuracy of the expert, and ii) the information score, which measures the informativeness of the experts' assessments.

The uncertainty quantification can take many forms, nevertheless, it tends to take a common structure due to application purposes, which was first presented in Cooke's initial study [13]: the experts commonly specify their fifth (5%), fiftieth (50%) or median and ninety-fifth (95%) percentiles for the estimate of each uncertain quantity of interest, and thus each expert provide a 90% confidence interval. Note that with the 5% percentile, the expert is assessing a lower bound, meaning the expert believes that the true value (also known as realization) has a 5% chance of being below that value and a 95% chance of being above. Similarly, with the 95% percentile, the expert is assessing the upper bound, and thus he/she believes that there is a 95% chance that the true value lies below that value (or a 5% chance of being above). The experts' best guess, the 50% percentile (or median value) specifies that there is an equal chance that the true value is lower or higher than the value given. Consequently, there is a 90% confidence (from the expert) that the true value lies between the lower and the upper bounds. This inter-quantile structure was described in Cooke's initial studies, where formula (2.15) specifies a probability vector $p(x) = (v_1, v_2, v_3, v_4)$:

$$p(x) = \begin{cases} v_1, & x \in [0, 0.05[\\ v_2, & x \in [0.05, 0.5[\\ v_3, & x \in [0.5, 0.95[\\ v_4, & x \in [0.95, 1] \end{cases} \tag{2.15}$$

Where $v_\mathrm{i}, i = 1, \ldots, n$, represents each inter-quantile probability (with $n = 4$), x each realization in each inter-quantile, and $p(x)$ the total inter-quantile vector that describes the probabilities for each interval.

These three percentile assessments (5%, 50%, and 95%) define four intervals or inter-quantile ranges: i) one from 0% up to the 5%, which is described by v_1; ii) one from the 5% up to the 50%, which is described by v_2; iii) one from the 50% up to the 95%, which is described by v_3; and finally iv) one from the 95% up to 100%, which is described by v_4. This leads to the theoretical probability vector:

$$p = (p_1, p_2, p_3, p_4) = (0.05, 0.45, 0.45, 0.05) \tag{2.16}$$

Where $p_\mathrm{i}, i = 1, \ldots, n$ is the absolute value of each inter-quantile probability (with $n = 4$), which gives the expected proportion of realizations in each interval. In practice, the inter-quantile ranges of the expert do not usually capture the true realizations at the expected frequency. If N quantities are assessed, where N are the number of seed questions, each expert may be regarded as a statistical hypothesis, namely, each realization falls in one of the four inter-quantile intervals with probability vector p.

Assuming $x_1, \ldots, x_N$ realizations of these quantities are available, one may then form the sample distribution of the expert's inter-quantile intervals as:

$$\begin{gathered} s_1(e) = \frac{1}{N} \textstyle\sum_{i=1}^{N} \mathbf{1}_{\{x_i \leq q_{5\%}\}} \\ s_2(e) = \frac{1}{N} \textstyle\sum_{i=1}^{N} \mathbf{1}_{\{q_{5\%} < x_i \leq q_{50\%}\}} \\ s_3(e) = \frac{1}{N} \textstyle\sum_{i=1}^{N} \mathbf{1}_{\{q_{50\%} < x_i \leq q_{95\%}\}} \\ s_4(e) = \frac{1}{N} \textstyle\sum_{i=1}^{N} \mathbf{1}_{\{q_{95\%} \leq x_i\}} \\ s(e) = \big(s_1(e), \ldots, s_4(e)\big) = (s_1, \ldots, s_4) \end{gathered} \tag{2.17}$$

Where $\mathbf{1}_{\{\ \}}$ is the indicator function and vector $s(e)$ is the empirical probability vector of an expert e.

To measure how different the empirical vector $s(e)$ is from the theoretical vector p, one can apply the relative information measure of vector $s(e)$ with respect to vector p, also known as the Kullback-Leibler (K-L) divergence or distance, which measures the difference between two distributions. This divergence is given by:

$$I(s(e) \mid p) = \sum_{i=1}^{n} s_i \ln\left(\frac{s_i}{p_i}\right) \tag{2.18}$$

Where n is the number of inter-quantile ranges (e.g. $n = 4$). Note that the divergence is equal to 0 if $s_i = p_i$ for all i, otherwise, it is positive. If the realizations are indeed drawn independently from a distribution with quantiles as stated by the expert, then:

$$T = 2 \times N \times I(s\ (e) \mid p) \sim \chi^2_{(3)} \tag{2.19}$$

is asymptotically following a Chi-square distribution variable with 3 degrees of freedom, where N is the number of seeding variables (calibration questions) and $n - 1$ are the degrees of freedom (dof) of the Chi-square distribution. Based on this result, the calibration score for each expert e is given by:

$$C(e) = 1 - F_{\chi_3^2}(t) \tag{2.20}$$

where F is the cumulative distribution function of the Chi-square probability distribution [50], and thus the calibration score can vary from 0 to 1. The greater the calibration score, the more statistically accurate is the expert.

Unlike the calibration score, the information score is calculated for each calibration question separately. To determine the information score for each expert in each question, one first needs to determine the intrinsic range, i.e. one needs to obtain bounds that are determined by expert assessments and the realizations. For this, one first takes the minimum between all the 5% percentiles of each expert $q_{5\%_e}$ and the realization itself $q_{5\%}$, i.e. $\min\{\min_e(q_{5\%_e}), q_{5\%}\} = L$, which is considered as the lower bound L. Likewise, the maximum between all the 95% percentiles of each expert and the realization is assumed as the upper bound U. The intrinsic range in each seed variable (calibration question) i is then given by:

$$[L_i, U_i] = [L, U] \tag{2.21}$$

The intrinsic range is then determined by extending the interval by an overshoot k, with $k > 0$. The extended intrinsic range is then given by:

$$[L_i^*, U_i^*] = [L - k(U - L), U + k(U - L)] \tag{2.22}$$

A typical value for the overshoot is $k = 0.10$. Hence, the information score including all assessments (for N seeding variables or calibration questions), for each expert e and for the three quantiles is calculated by the following formula:

$$\mathrm{Inf}(e) = \frac{1}{N}\sum_{i=1}^{N}\left[\ln(U_i^* - L_i^*) + 0.05 \times ln\frac{0.05}{q_{5\%} - L_i^*} + 0.45 \times ln\frac{0.45}{q_{50\%} - q_{5\%}} + 0.05 \times ln\frac{0.05}{U_i^* - q_{95\%}}\right] \tag{2.23}$$

Where $\mathrm{Inf}(e)$ is the information score of each expert e.

The combined score of an expert e will serve as an (unnormalized) weight for each expert. It is based on both the calibration score $C(e)$ and the information score $\mathrm{Inf}(e)$, and is obtained by the following formula:

$$w'_{e,\alpha} = C(e) \times \mathrm{Inf}(e) \times \mathbf{1}_{\{C(e) \geq \alpha\}} \tag{2.24}$$

Where $\mathbf{1}_{\{\ \}}$ is the indicator function, i.e. $\mathbf{1}_{\{C(e)\geq\alpha\}} = 1$ if $C(e) \geq \alpha$, and 0 otherwise. The use of a cut-off threshold α is imposed by the requirement that the weights w'_e should be an asymptotically strictly proper scoring rule, meaning that the long-run expected weights should correspond to the expert's true beliefs.

Finally, the (unnormalized) weights w'_e are then normalized across all experts to get the normalized weights w_e:

$$w_e = \frac{w'_e}{\sum_e w'_e} \tag{2.25}$$

2.4.1.1. An illustrative example

This subsection explores an illustrative example to provide a better understanding of how the calibration and information scores are obtained.

Taking an example of 2 expert assessments for 10 calibration questions on the failure of different Bogie components (e.g. the primary suspension or the wheelset before an inspection of the bogie is performed). The three quantile assessments of the experts are provided and the realizations of the number of failures of each component are also taken into account. For the first expert, in 3 out of the 10 calibration questions, he/she overestimated the quantity of interest, i.e. in three questions the realization of the assessment is below the 5% percentile. In addition, in one calibration question, the expert underestimated the realization, i.e. the realization was above its 95% percentile. For the remaining six questions: four questions had the realizations between the 5% and the 50% percentiles, while two questions had the realizations between 50% and 95% percentiles. For the second expert, one question had the realization under the 5% percentile, six questions had the realization between 5% and 50% percentiles, two questions between 50% and 95% percentiles, and one question above the 95% percentile. These assessments lead to the following vectors of observed frequencies for each expert:

$$s_{e_1} = (s_1, s_2, s_3, s_4) = \left(\frac{3}{10}, \frac{4}{10}, \frac{2}{10}, \frac{1}{10}\right) = (0.3, 0.4, 0.2, 0.1)$$

$$s_{e_2} = (s_1, s_2, s_3, s_4) = \left(\frac{1}{10}, \frac{6}{10}, \frac{2}{10}, \frac{1}{10}\right) = (0.1, 0.6, 0.2, 0.1)$$

The Kullback-Leibler (K-L) divergence (computed with equation (2.18)) for both experts is then obtained as:

$$I_{e_1}(s,p) = 0.3\, ln\left(\frac{0.3}{0.05}\right) + 0.4\, ln\left(\frac{0.4}{0.45}\right) + 0.2\, ln\left(\frac{0.2}{0.45}\right) + 0.1\, ln\left(\frac{0.1}{0.05}\right) = 0.3975$$

$$I_{e_2}(s,p) = 0.1\, ln\left(\frac{0.1}{0.05}\right) + 0.6\, ln\left(\frac{0.6}{0.45}\right) + 0.2\, ln\left(\frac{0.2}{0.45}\right) + 0.1\, ln\left(\frac{0.1}{0.05}\right) = 0.1491$$

With the K-L divergence, it is possible to calculate the calibration score for each expert. The calibration score is then obtained with equation (2.20):

$$C(e_1) = 1 - F_{\chi^2_{(3)}}(2 \times 10 \times 0.3975) = 1 - F_{\chi^2_{(3)}}(7.95) = 0.047$$

$$C(e_2) = 1 - F_{\chi^2_{(3)}}(2 \times 10 \times 0.1491) = 1 - F_{\chi^2_{(3)}}(2.98) = 0.394$$

Therefore, the calibration score of expert 2 is higher than the calibration score of expert 1, i.e. the assessment of expert 2 was statistically more accurate than the assessment of expert 1. In other words, the higher the calibration score, the more accurate the expert is.

For the same two experts and the respective assessments, let us consider that for one specific calibration question (e.g. the question on the number of failures of the wheels due to cavities), the realization is 16 failures and the experts' assessments were the following:

Table 2.2 – Experts assessment for one seed variable as an illustrative example

Expert	5%	50%	95%
Expert 1	7	10	15
Expert 2	6	7	10

Table 2.2 provides an example of the expert's assessment for one seed variable. Note that the 90% confidence interval for expert 1 lies between 7 failures and 15 failures, whereas for expert 2 the 90% confidence interval lies between 6 failures and 10. The accuracy of both assessments is poor since the realization of the seed question was 16 failures. Nevertheless, if one would compute the associated calibration score, expert 1 would get a higher score, due to its closeness to the realization.

To calculate the information score of each expert for this calibration question, one first needs to determine the intrinsic range. For this specific case, the intrinsic range is given by:

$$[L_i, U_i] = \left[min\{min_e(q_{5\%_e}), q_{5\%}\}, max\{max(q_{95\%_e}), q_{95\%}\}\right] = [6,16]$$

By extending the interval with a 10% overshoot, the intrinsic range for the following seed variable is:

$$[L_i^*, U_i^*] = [6 - 0.1(16-6), 16 + 0.1(16-6)] = [5,17]$$

Consequently, for each expert the information score is the following:

$$I(e_1) = 0.05 \times ln\frac{0.05}{7-5} + 0.45 \times ln\frac{0.45}{10-5} + 0.45 \times ln\frac{0.45}{15-10} + 0.05 \times ln\frac{0.05}{17-15} + \ln(17-5) = 0.179$$

$$I(e_2) = 0.05 \times ln\frac{0.05}{6-5} + 0.45 \times ln\frac{0.45}{7-6} + 0.45 \times ln\frac{0.45}{10-7} + 0.05 \times ln\frac{0.05}{17-10} + ln(17-5) = 0.875$$

As we can verify intuitively, the distribution of expert 2 is more concentrated than the distribution of expert 1. Hence, expert 2 is more informative than expert 1 and, therefore, expert 2 has a higher information score. For all the calibration questions, one information score is obtained for each expert, whereas the final information score is obtained through an average of all information scores of each expert in each question, using equation (2.23).

Finally, the unnormalized weights of each expert are obtained with equation (2.24) and divided by the sum of each expert's unnormalized weight to obtain each final weight of each expert using equation (2.25). Considering the calibration score for both experts, along with the information score for one seed variable, the unnormalized weights, as well as the normalized for this illustrative example, can be visualized in Table 2.3:

Table 2.3 – Experts weights for the illustrative example

Expert	Unnormalized Weight	Normalized Weight
Expert 1	0.008414	0.0238
Expert 2	0.34475	0.9762

2.5. Reliability Assessment Method

This section explores a methodology to quantify failure rates of long service-life components using expert judgment techniques. The model assumes that if experts are able to assess quantities and specific standard measures of related components and subsystems, which are commonly published and shared in the industry by annual reports or standards from regional or national authorities, through seed questions, then they are able to assess failure estimates of the component of interest.

The framework for this method is inspired by Berg et al. [14] guideline, whereas some changes are presented in the structure and the type of target questions to adjust to a reliability assessment, and new items are added to conduct the assessment. The steps are the following:

1. Seed and Target Questions
2. Selection of experts
3. Experts weighting process
4. Fitting Reliability Curves

These steps are presented in the following subsections.

2.5.1. Seed and Target Variables

The design of seed questions is usually based on failure quantities, standards, and annual reports that have been published by authorities in the interested industry. The seed questions need to be addressed to critical known information of the component of interest or a subsystem associated with it, in order to assess the know-how of the expert in the topic under analysis. The life cycle of the asset of interest, which is usually provided by the manufacturer and based on quality control studies, and the respective failure modes and causes should be included in the information around the questions.

Target questions, where the reliability assessment is performed, are based on the histogram technique, which was first introduced to expert judgment by Van Noortwijk et. al [15]. The histogram technique is a simple technique, where experts specify their subjective probability of failure for the component in equidistant intervals. From a practical point of view, the experts use a discretised version of a continuous probability density function (PDF), in such a way that the concept of the probability density, which is used in the seed variables, is replaced by the concept of probability of failure in a fixed interval. Each target question should be based on the inspection or maintenance intervals of the component of interest and on the content the analyst is looking for. The last interval is defined as an open interval since an open interval is motivated by the fact that maintenance engineers have experienced only with the first part of a component life cycle considering that most components are replaced before failing. The assessment asks the expert to imagine that there are *n* components of the same type installed at interval *i* and requests the expert to estimate the expected number of components which would fail within interval *i* ($n_{i,e}$). It is then possible to calculate experts e's (subjective) probability of failure within interval *i* as: $p_{i,e} = \frac{n_{i,e}}{n}$, $i = 1,..,m$, where m is the number of intervals proposed. To have a more precise probability, *n* is assumed to be a large number (e.g. 1000), and the sum of all failures is equal to *n,* i.e. $\sum_{i=1}^{m} n_{i,e} = n$.

In order to guarantee a more robust analysis, more than one component should be targeted, especially an asset where failure data is abundant, to compare the analysis and consequently, reduce the uncertainty associated with the component of interest. Moreover, the questionnaire should start with a brief clarification about the methods used and the types of questions presented in the study, followed by the seed and target questions. Testing the questionnaire with experts not belonging to the expert pool before the actual pool happens, can bring improvements to the questions used and is therefore recommended. Formulating extra seeding variables, in order to pick the preferred ones, is also recommended, since the complexity of some questions might confuse the expert, causing potential biases.

2.5.2. Selection of experts

The creation of a list of experts should be based on individuals that have a verifiable knowledge on the topic. Since the target questions are directed to operation, maintenance, and quality data, reliability engineers are recommended as potential experts, not only due to their experience on different real case scenarios of the operation of the component but also due to their understanding of the variables. A practical way to determine such a list of experts is to search in regulatory agencies (in the industry of interest) and to look for individuals who are members of special interest groups or have participated in committees relevant to the topic.

2.5.3. Experts weighting process

The weighting process is conducted as explained in section 2.4. In fact, various software applications have been developed to calculate the performance measures and combine the expert opinion to a virtual DM. Two of these software are EXCALIBUR, which was developed by Cooke and his students, and ANDURIL, which was developed at the technical university of Delft by Leontaris and Morales-Nápoles in 2018 [51]. Combining expert opinion results in an improved assessment of the target variables.

2.5.4. Fitting Reliability Curves

After obtaining the weights of each expert, two approaches for the analysis of the target variables should be considered:

i) the first approach consists of considering each expert's assessment as a whole and fit each expert opinion (each assessment on the histogram) on a distribution function. Then, a performance-based opinion is obtained by multiplying each expert's weight by the cumulative distribution function of each expert. A performance-based reliability curve is then calculated as:

$$R_{PW} = 1 - \sum_{e=1}^{E} w_e F_e \tag{2.26}$$

Where R_{PW} is the performance-based reliability curve, w_e each expert weight, E the total number of experts and F_e the best fitted cumulative distribution function from each expert e.

ii) the second approach consists of determining first a performance-based opinion (on the histogram) with each expert weight:

$$f_{PW_i} = \sum_{e=1}^{E} w_e \, f_{e,i} \quad (2.27)$$

Where f_{PW_i} is the performance-based opinion on each period i of the histogram, w_e each expert weight and $f_{e,i}$ each expert's assessment on each period i of the histogram. After defining a performance-based opinion on the Histogram, a distribution function is fitted to the aggregated opinion.

For both approaches, fitting reliability curves using parametric distributions to the subjective probabilities from the target variables is needed. Such fitting is performed with the maximum likelihood estimator method [50], where the likelihood function depends on the distribution parameters θ, and assumes the existence of censored data, as defined in [52]:

$$L(\theta) = \prod_{i=1}^{N_{nonC}} f(x_i|\theta) \times \prod_{j=1}^{N_{leftC}} F\left(x_j^{upper}|\theta\right) \times \prod_{k=1}^{N_{rightC}} \left[1 - F\left(x_k^{lower}|\theta\right)\right] \times \prod_{m=1}^{N_{intC}} \left[F\left(x_m^{upper}|\theta\right) - F(x_m^{lower}|\theta)\right] \quad (2.28)$$

Where x_i are the non-censored observations (N_{nonC}), x_j^{upper} are the upper values defining the left-censored observations (N_{leftC}), x_k^{lower} are the lower values defining the right-censored observations (N_{rightC}), $[x_m^{upper}, x_m^{lower}]$ are the intervals defining the interval-censored observations (N_{intC}), and f and F are the density and cumulative distributions functions, respectively, from a parametric distribution [33,34]. Since the histogram technique is an interval-based assessment, the latter products of equation (2.28) are used. For the parametric distribution, typical choices are the following distributions: the Weibull distribution, the Normal distribution, the Lognormal distribution, the Gamma distribution, and the Exponential distribution, which are mentioned in section 2.1 and mathematically explained in chapter 3. From a practical point of view, the *Fitdistcens* function from the *Fitdistrplus* package [52] in *R* software is used to fit the reliability curves.

Moreover, a goodness-of-fit test is performed to select the statistical distribution that best fits the failure assessments. Delignette-Muller and Dutang [52] state that computations of goodness-of-fit statistics have not yet been developed for fits using censored data, though the comparison between different parametric distributions can be made by using the Akaike Information Criteria (AIC). The AIC provides a criterion to compare different models, in which the preferred model is the one with the lowest AIC value. After selecting the best model, an estimate for the failure rate can be obtained by computing the expected mean from the fitted distribution.

Finally, both approaches should be compared, and the most conservative reliability curve should be considered. The reader who is interested to know more about the fitting modelling and the computation behind the functions of interest is directed to Delignette-Muller and Dutang study [52]. Note that the outcome of the described steps will consist of reliability curves for the assets of interest, which are derived by combining different expert judgments.

3. Discrete Event Simulation

Modelling the reliability and availability of complex systems can be often hard and unrealistic with analytical methods, which represent the system by a mathematical model, evaluating it with mathematical solutions. Therefore, the model used in such analysis is often simplified, where the output is limited to expected values. When considering simple systems, where only the failure characteristics are considered, analytical approaches are typically used [55]. Nevertheless, when considering modern engineering systems with complex environments, repairable systems and multiple events, analytical models are impossible to solve analytically, bringing the need for simulation models, which can incorporate any system characteristic that is recognized as crucial in the system's behaviour.

In this chapter, Discrete-event Simulation (DES) is explained, as well as the algorithm behind the simulation approach. Further on, the Reliability Block Diagram (RBD) is clarified, and the mathematical background of the Monte Carlo Simulation (MCS) method is exposed. Distribution functions of interest for the DES, which are relevant in a reliability analysis, are analytically exposed as well as stochastic modelling of repairs and correlated failures.

3.1. General principles of discrete simulation and modelling

Simulation modelling has become a very important mechanism for sophisticated system analysis and decision-making [56]. Simulation, which is defined as an approximate reproduction of the operation of a process or a system, is a family of computational-based methods to study the operational behaviour of a system in its real time condition. It has been applied in many contexts, such as computer experiments, scientific modelling or safety engineering. In the latter, some argue that the simulation of maintenance functions is the best technique, than most of the traditional analytical modelling, mostly due to the complexities of the maintenance operations and the uncertainties that are intrinsic in the parameters that define the operation [57].

In system theory, a system can be described as a group of interacting entities that depend on each other in order to fulfil a task or function. Defining a dynamic system in terms of a state variable can take three forms: continuous, discrete and quantum. Systems, in which state changes are mostly progressive and smooth, are called continuous systems. Systems, in which changes are mostly discontinuous, are called discrete systems. Systems, in which state changes occur due to interactions among components in the subatomic or cosmological level, are quantum systems [58]. Nevertheless, when considering middle level system (between the subatomic and cosmological level), such as manufacturing systems (e.g. factories), transportation systems (e.g. traffic networks), service systems (e.g. hospitals) and/or communications systems (e.g. wireless networks), the most typical system type to model its state change is the discrete-event system (DES) [59]. Indeed, according to Jahangirian et. al. [60], a DES is the most suitable technique to model any type of manufacturing system and its maintenance operations.

Within the discrete systems, there are models that can be further distinguished from traditional dynamic system models. These are defined by how the models treat the passage of time, on this case time-driven or event-based, and how they treat interdependencies of component elements, on this case synchronous or asynchronous [61]. A Discrete time-driven simulation model refers to a model which considers equal periods of time during its simulation, thus changing its state according to each time step. Alternatively, a discrete-event simulation model can be defined as one in which the state variable only changes when events in specific discrete points of time occur. In both approaches, a clock recording the simulation time is used. While in time-driven systems, the state changes of the system are synchronized by the system clock, in event-based systems the event occurs asynchronously, meaning that several events can occur simultaneously. The advantage of using an event-based approach, is that periods of inactivity are excluded, resulting in a simulation time improvement. Moreover, time-driven approaches need to use smaller simulation time steps to obtain more accurate results [22].

3.1.1. Modelling a DES

To produce a reliable operational behaviour, a DES model is typically defined with a progressive procedure, in which the problem is defined, the mathematical model that best relates to the problem is chosen and the required input information is gathered. In discrete-event simulations, the analysis of the simulation is performed by numerical methods rather than analytical methods, where models are simulated instead of being solved. Typically, discrete-event systems have stochastic elements incorporated in the activity of the system, since the exact outcome of an activity at any point of time is unknown. To model a successful simulation analysis, a close match between the input data and the fundamental probabilistic mechanism of the system is required. Therefore, the definition of a discrete-event simulation model is a complex task, which typically includes the following activity blocks [61]:

- Clock: simulation time, which skips to the next event as the simulation proceeds;
- Events List: The events are created as a series of events giving the starting time and ending time of the discrete events T, which can be interpreted as a queue;
- Random Number Generator: generates random numbers, linked to a stochastic event, to perform an event;
- Statistics: quantifies the aspects of interest;
- Ending Condition: the condition to end the simulation, which is typically the simulation time T;

To perform a good simulation, a simulation algorithm is needed to correctly implement the operation of the case study of interest. A typical DES algorithm is described in Figure 3.1 flowchart.

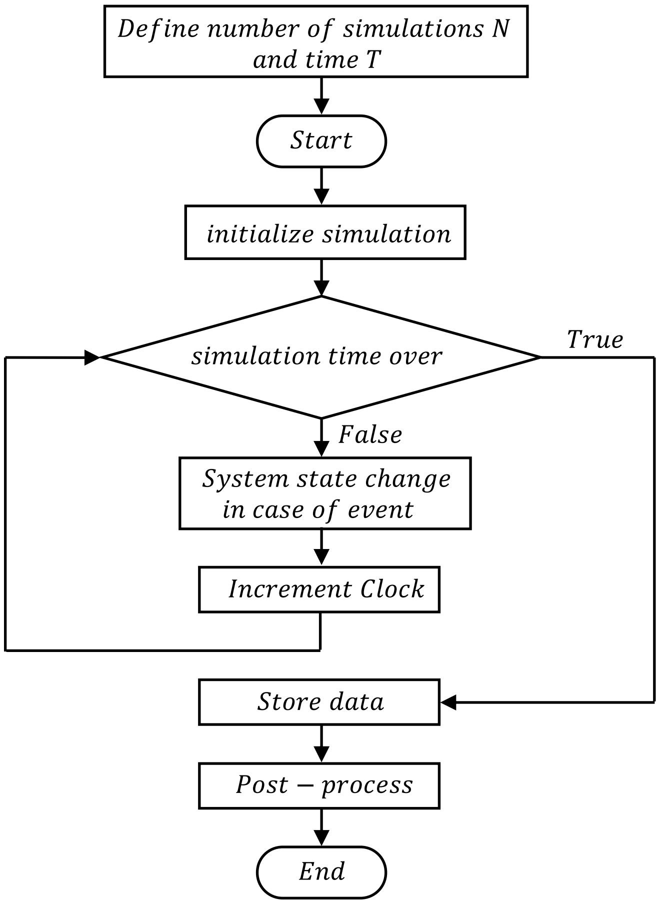


Figure 3.1 – Flowchart of the DES algorithm (adapted from [61])

The algorithm starts by defining the number of simulations N and simulation time T. The number of simulations N desired should be associated with the confidence interval the user aims, in order to have a more rigorous analysis of the behaviour of the system (to see convergence or not, mathematically described in the next section). The simulation starts by allocating each information of the system in its desired workflow and generates stochastic events, which go according to the input data that entered the system. The generated events create state changes to the system, which increment the simulation clock with a time step Δt. After the simulation time has reached its limit, the operational behaviour data of the system is stored to quantify the aspects of interest and the simulation is finished.

3.2. Reliability Block Diagram (RBD)

With the guidance of the progressive procedure definition, explained in the previous section, one needs to define first the problem in which the DES will be built, e.g. the components of interest, their interconnections and functions, as well as the maintenance tasks associated with these. Therefore, many reliability, availability, maintainability and safety (RAMS) methods have been established to model the interdependencies of complex systems, thus guaranteeing the reliability, availability, maintainability and safety (RAMS) of such systems. The methods created can be divided into two groups: inductive methods and deductive methods. An inductive method performs an analysis from a specific case to a general outcome. It is generally recognized as a bottom-up approach, where a specific fault is considered and the possible outcome and effect on the system is deducted. The best known inductive analysis methods are FMEA and FMECA (explained in section 2.3), Event Tree Analysis and Dynamic Event Trees [22]. Alternatively, a deductive method performs an analysis from a general case to a more specific. It is therefore considered a top-down approach, where a system failure is assumed and the causes to the failure are analysed, looking to subsystems, components, and failure modes, and how they interact and perform in the system. The most used methods are Fault Tree Analysis (FTA) and Reliability Block Diagrams (RBD). Both approaches are good representations of complex systems. However, the RBD approach has several limitations when considering combinations of failure, repair and priority of events. Nonetheless, for systems which only have “AND” and “OR” gates, which define the logical behaviour of the system, the RBD is a simpler and intuitively representation of a system [4,55].

A Reliability Block Diagram (RBD) is a success-oriented graphical representation of a system, which uses blocks with logical connections to model the function of components. Each function is individually described by one block, where each block gathers information of a particular function of the system. Therefore, it represents the relationship and hierarchy between functions and their components. In order to build a reliable RBD, it is necessary to reflect the logical behaviour of the system so that each block is statistically independent. The logical behaviour represents therefore the connection of the blocks to form a diagram of a success path. The structure of an RBD can take three forms:

3.2.1. Series Configuration

A system structure is referred as a series structure (‘AND’ gate for FTA) when it only operates if each and every component and their associated functions are operational, i.e. the failure of one single function brings the system to failure. The RBD configuration of a series system with n components can be visualized in Figure 3.2.

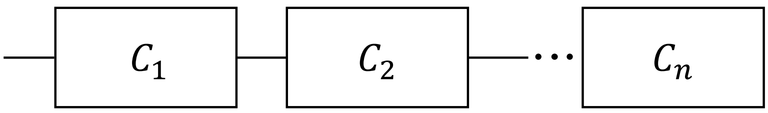


Figure 3.2 – RBD of a series configuration with n components

Assuming independent events, i.e. the failure and repair processes are independent, the reliability and the instantaneous availability of a system of independent components in series can be mathematically expressed by the following equations [62]:

$$R_S(t) = \prod_{i}^{n} R_i(t) \quad (3.1)$$

$$A_S(t) = \prod_{i}^{n} A_i(t) \quad (3.2)$$

Where $R_S(t)$ is the reliability of the system in series with n components, $R_i(t)$ is the reliability of a single component or failure mode/function i, $A_S(t)$ is the instantaneous availability of the system in series with n components and $A_i(t)$ is the instantaneous availability of a single component or failure mode/function

i. Since $R_i(t) < 1$, the reliability of a system in series $R_S(t)$ is always inferior to the reliability of its least reliable element.

3.2.2. Parallel Configuration

A system structure is referred as a parallel structure ('OR' Gate in FTA) when it operates if at least one of its components is operational, i.e. when a component or function fails it does not cause the system to fail. This is typically referred as a system with redundancy, where only one component operating is sufficient to guarantee the system performance. The RBD configuration of a parallel system with n components can be visualized in Figure 3.3.

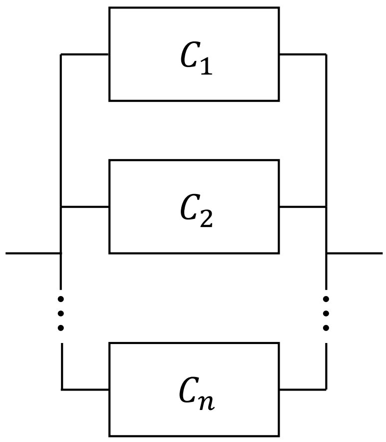


Figure 3.3 – RBD of a parallel configuration with n components

Again, assuming independent events, the reliability, and the instantaneous availability of a system of independent components in parallel is given by the following equations:

$$R_P(t) = 1 - \prod_i^n [1 - R_i(t)] \tag{3.3}$$

$$A_P(t) = 1 - \prod_i^n [1 - A_i(t)] \tag{3.4}$$

Where $R_P(t)$ is the reliability of the system in parallel with n components, $R_i(t)$ is the reliability of a single component or failure mode/function i, $A_P(t)$ is the instantaneous availability of the system in parallel with n components and $A_i(t)$ is the instantaneous availability of a single component or failure mode/function i. It is simple to identify, that the reliability and availability projections for a parallel system are greater than the reliability and availability of a single component, conducting to greater reliabilities and availabilities than a system in series.

3.2.3. $k - out - of - n$ configuration

A system that cannot be described by either a series configuration or a parallel configuration is typically portrayed by a combination of both, which is known as a $k - out - of - n$ system. Such a system requires that $k\ (< n)$ or more components out of n operate correctly, in order to guarantee the performance of the total system. If $k = 1$, the configuration can be transformed into a parallel system. If

$k = n$, the configuration can be transformed into a series system. In fact, such a configuration is a better representation of complex systems, where functionalities are difficult to describe and model. Figure 3.4 exhibits the RBD representation of a $k - out - of - n$ system.

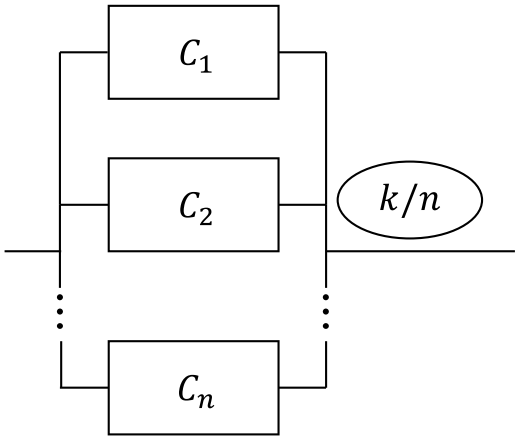


Figure 3.4 – RBD representation of a $k - out - of - n$ system with n components

Mathematically, the reliability and the instantaneous availability of a system of n statistically identical and functionally independent components with a $k - out - of - n$ configuration is given by:

$$R_{k/n}(t) = \sum_{i=k}^{n} \binom{n}{i} R^i (1 - R)^{n-i} \tag{3.5}$$

$$A_{k/n}(t) = \sum_{i=k}^{n} \binom{n}{i} A^i (1 - A)^{n-i} \tag{3.6}$$

Where the binomial coefficient $\binom{n}{i} = \frac{n!}{i!(n-i)!}$ expresses the number of possible combinations to choose i components from a set of n components.

3.3. Monte Carlo Simulation

Monte Carlo Simulation (MCS) technique is a very relevant method for the analysis of real engineering problems in many areas, such as in the automotive industry, health care, military, aviation or service systems. The method consists of obtaining estimates, by generating random numbers for the system inputs, of analytical problems [22]. A MCS is applied by running a model a considerable amount of times in order to produce a large number of simulations and get a precise result. A DES algorithm conducts the progress of the stochastic model in each simulation of the MCS. In each simulation, a random failure or repair time for each component is generated, where a system component is characterized by a probability density function of failure and/or repair. These failures or repairs are then linked in accordance with the relationship and hierarchy between functions and components of the system, which is defined by the RBD. Therefore, this simulation approach samples for each component the next state change event (failure and/or repair) with the use of random numbers and the inverse of the cumulative density function (CDF). Each simulation reproduces the evolution of the system until the simulation time T is over. The complete results after each simulation are then analysed to determine the behaviour of the system. The overall procedure to build a MCS algorithm within a DES goes in accordance with Figure 3.5.

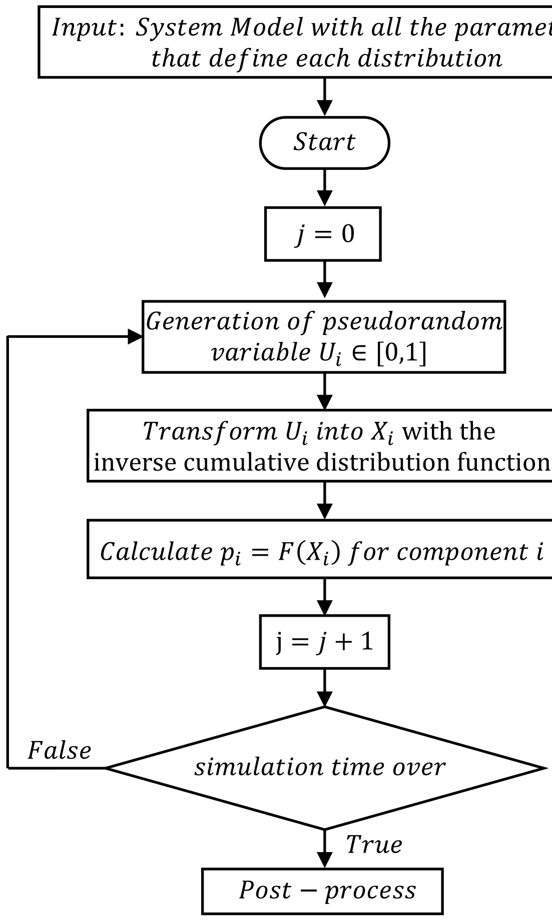


Figure 3.5 – MCS algorithm

The first step is to obtain the required data to model adequately the system of interest. This includes the distribution functions and the associated parameters that model the stochastic behaviour of the failure and/or repair from the components that characterize the system.

The second step consists of generating uniformly pseudo random numbers $U_i \in [0,1]$ for each failure and/or repair distribution function. A uniform random number is a variable that can take, with equal probabilities, any value between 0 and 1. When the algorithm that generates the uniform random number is processed computationally, the value generated is referred to as a pseudo random number. The most typical computational algorithm used to generate pseudo random numbers is the Lehmer's Algorithm, which is a type of Linear Congruential Generator (LCG), a simple generator which uses seed variables to generate uniform random numbers [63]. The computational implementation of the Lehmer's algorithm can go according to [64].

After generating $U_i \in [0,1]$, the conversion from a pseudo random number to a random variable X_i is conducted by using appropriate mathematical transformations. There are many approaches for converting random numbers into random variables, nevertheless, if one wants to guarantee uncorrelated random variables from a distribution of interest, the inverse cumulative distribution function (CDF) $F_X^{-1}(x)$

should be used [63]. The inverse CDF depends on the distribution function type and its associated parameters, therefore the determination of the inverse CDF is obtained differently according to each distribution function type. The inverse CDF determination of each distribution function is explained further in the next subsection. One of the major advantages of the MCS method in comparison, for example, with a Markov-based method, is that the simulation approach can handle any type of distribution functions, whereas in the latter only exponential distribution functions can be considered [22].

Finally, the random variables X_i are introduced in the CDFs of interest, to study the behaviour of the system. To finish the MCS, a number of iterations N is defined before the simulation, which coincides with the number of iterations chosen for the DES. In order to produce reliable representations of the systems behaviour, it is recommended to choose a large sample size and iteratively observe if the results converge to determined values. Nonetheless, a good technique to determine the order of magnitude of the number of simulations N is based on the confidence interval that is desired. The confidence interval for the mean values of the sample $\bar{Y}$ is obtained by the normal distribution function as follows [65]:

$$(\bar{Y} - z_{1-\frac{\alpha}{2}}\frac{\sigma}{\sqrt{N}}, \bar{Y} + z_{1-\frac{\alpha}{2}}\frac{\sigma}{\sqrt{N}}) \quad (3.7)$$

Where α is the significance level considered for the test, z_i the i-th quantile of the $\mathcal{N}(0,1)$ distribution, σ the standard deviation of the sample and N the number of simulations or iterations.

3.4. Distribution Functions of interest

The stochastic failure and/or repair behaviour of components is typically represented by different probability distribution functions which are characterized by parameters. As mentioned in section 2.1 and section 2.5, the most typical distributions to describe the reliability and availability of complex systems are: the Exponential distribution, the Normal distribution, the Weibull distribution, the Lognormal distribution and the Gamma distribution. In this section, the noticed distribution functions are explained, emphasizing the equations which are commonly implemented in studying the reliability and availability of systems. The latter distribution was not considered, mainly due to the mathematical complexity of modelling it. The definitions of each distribution function go according to [4,55,65,66].

3.4.1. Exponential distribution

The exponential distribution is the most used distribution to model the reliability, availability, maintainability, and safety (RAMS) of complex systems, mainly due to its mathematical simplicity. It is characterized for having a constant hazard rate, which indicates the accuracy to model realistic life distributions for an element in its useful life period. With a constant hazard rate $h(t)$, the probability density function (PDF) of an exponential distribution is defined as follows (for $t \geq 0$):

$$f(t) = \lambda e^{-\lambda t} \quad (3.8)$$

$$h(t) = \lambda \quad (3.9)$$

Where λ is the exponential distribution parameter, which is constant. The exponential cumulative distribution function (CDF) $F(t)$ and the reliability function $R(t)$ are both derived from the exponential PDF, as explained in section 2.1, and are defined as follows:

$$F(t) = 1 - e^{-\lambda t} \tag{3.10}$$

$$R(t) = e^{-\lambda t} \tag{3.11}$$

By having a constant hazard rate $h(t)$, the exponential distribution has a memoryless property, which means that the probability of a failure in a particular time interval is the same regardless of the original starting point of the time period. Considering the definition of the $MTTF$, discussed in section 2.1, the $MTTF$ is defined as follows:

$$E(T) = MTTF = \int_0^{+\infty} R(t)dt = \int_0^{+\infty} e^{-\lambda t} dt = \frac{1}{\lambda} \tag{3.12}$$

With the failure function $F(t)$ it is possible to generate random times to failure (TTF) by applying the inverse transformation, also known as the quantile of one probability distribution function. For an exponential distribution, the resulting transformation is given by:

$$TTF = -\frac{1}{\lambda}\ln(1-p), \qquad p \in (0,1) \tag{3.13}$$

Where $p = U_i \in [0,1]$ is generated randomly. It is important to emphasize that the TTF is a pseudorandom variable, since it is obtained via a computational random generator algorithm, whereas the $MTTF$ is the expected value of the distributions.

3.4.2. Normal Distribution

The normal distribution is the most used distribution in the field of statistics and probability, which is also referred as a Gaussian distribution. A random variable T is normally distributed with mean μ and variance σ^2, $T \sim \mathcal{N}(\mu, \sigma^2)$ when the probability density function of T is defined as:

$$f(t) = \frac{1}{\sqrt{2\pi} \times \sigma} e^{-(t-\mu)^2/2\sigma^2}, \quad -\infty \leq t \leq \infty \tag{3.14}$$

When a Normal distribution is characterized with a mean $\mu = 0$ and variance $\sigma^2 = 1$, it is referred to as a Standard Normal distribution. In fact, in terms of application, the Standard Normal distribution is the most widely used, since that if a behaviour can be modelled with the Standard Normal distribution in terms of quantiles and distribution function, then it can be modelled with a generic normal variable [67] For a specific random variable t from a Normal distributed random variable $T \sim \mathcal{N}(\mu, \sigma^2)$, the equivalent random number z of a standardized Normal random variable $Z \sim \mathcal{N}(0,1)$ is given by the following transformation:

$$z = \frac{t - \mu}{\sigma} \tag{3.15}$$

The cumulative distribution function of z, the transformed CDF of t and the reliability function are the following:

$$\Phi_Z(z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz = F_Z(z) \tag{3.16}$$

$$F_T(t) = F_Z\left(\frac{t-\mu}{\sigma}\right) = \Phi_Z\left(\frac{t-\mu}{\sigma}\right) \tag{3.17}$$

$$R(t) = 1 - F_T(t) = 1 - \Phi_Z\left(\frac{t-\mu}{\sigma}\right) \tag{3.18}$$

The hazard rate $h(t)$ of a Normal distribution can be expressed as:

$$h(t) = \frac{f(t)}{R(t)} = \frac{f(t)}{1 - \Phi_Z\left(\frac{t-\mu}{\sigma}\right)} \tag{3.19}$$

The mean of the Normal distribution is:

$$E(t) = MTTF = \mu \tag{3.20}$$

The quantile of a Normal distribution function can also be obtained with the inverse transformation algorithm, by applying $F^{-1}(t)$. The quantile function of the standardized Normal distribution with random number z and the quantile function of the Normal distribution function with mean μ and variance σ^2 can be expressed in terms of the error function as follows:

$$z_p = {\Phi^{-1}}_Z(p) = \sqrt{2}\,\mathrm{erf}^{-1}(2p-1), \qquad p \in (0,1) \tag{3.21}$$

$$TTF = \mu + \sigma \times \sqrt{2}\,\mathrm{erf}^{-1}(2p-1), \qquad p \in (0,1) \tag{3.22}$$

Where $\mathrm{erf}(z) = \frac{2}{\sqrt{\pi}} \int_0^z e^{-t^2}$ and $p = U_i \in [0,1]$ is generated randomly.

3.4.3. Weibull Distribution

The Weibull distribution is one of the most used distributions in reliability analysis since the aging modelling of components is accurately represented by the distribution. In reliability analysis, it has many application ranges due to its flexibility in modelling distribution shapes. The Weibull distribution was first introduced by the Swedish mathematician Waloddi Weibull (1887-1979), who established this distribution when studying material sciences. The two-parameter Weibull distribution is defined for $t \geq 0$ and is described by the following probability density function (PDF) $f(t)$, failure function $F(t)$, reliability function $R(t)$ and hazard rate function $h(t)$:

$$f(t) = \frac{\beta}{\eta} \times \left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{3.23}$$

$$F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{3.24}$$

$$R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{3.25}$$

$$h(t) = \frac{f(t)}{R(t)} = \frac{\beta}{\eta} \times \left(\frac{t}{\eta}\right)^{\beta-1} \tag{3.26}$$

Where $\eta > 0$ is the scale parameter, which establishes the position of the PDF on the time axis, and $\beta > 0$ the shape parameter, which determines the shape of the PDF. Increasing the value of the scale parameter η while holding the value of β as a constant stretches the PDF curve in the abscissa axis. In fact, when $\beta = 1$, the failure rate is constant (useful life period) becoming an exponential distribution, when $0 < \beta < 1$ the failure rate is decreasing (burn-in period) and when $\beta > 1$ the failure rate is increasing (wear-out period). Indeed, this shape flexibility is the reason why the Weibull distribution is overly applied in the interpretation and analysis of components failure phenomena.

The mean of the Weibull distribution can be derived as follows:

$$E(T) = MTTF = \int_0^\infty t \times f(t)\, dt = \eta.\Gamma\left(1 + \frac{1}{\beta}\right) \tag{3.27}$$

Where $\Gamma(\cdot)$ is the gamma function.

The quantile (inverse cumulative distribution function) of the Weibull distribution is for $0 \leq p < 1$ the following:

$$TTF = \eta(-\ln(1-p))^{\frac{1}{\beta}} \tag{3.28}$$

Where $p = U_i \in [0,1]$is generated randomly.

3.4.4. Lognormal Distribution

The Lognormal distribution is a distribution where its continuous positive random variable T is characterized by a mean μ and variance σ^2 such that $T \sim lognormal(\mu, \sigma^2)$, if $Y = ln(T)$ is normally distributed with mean μ and variance σ^2 such that $Y \sim \mathcal{N}(\mu, \sigma^2)$. The lognormal distribution is commonly used to model the wear out of materials, specially metals, and repair times of components. Its probability density function is given by:

$$f(t) = \frac{1}{\sigma t\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{\ln t - \mu}{\sigma}\right)^2} \tag{3.29}$$

The shape of the distribution is largely dependent with σ. The parameters μ and σ refer to the mean and variance of $\ln T$.

The lognormal failure function $F(t)$ and reliability function $R(t)$ are defined as follows:

$$F(t) = \Phi\left[\frac{\ln t - \mu}{\sigma}\right] \tag{3.30}$$

$$R(t) = 1 - \Phi\left[\frac{\ln t - \mu}{\sigma}\right] \tag{3.31}$$

Where Φ is the CDF of the standard normal distribution.

The hazard rate function $h(t)$ for the lognormal distribution is given as:

$$h(t) = \frac{f(t)}{R(t)} = \frac{f(t)}{1 - \Phi\left[\frac{\ln t - \mu}{\sigma}\right]} \tag{3.32}$$

The hazard rate has no simple mathematical expression, nevertheless, for $t = 0$ the hazard rate is $h(t) = 0$ and for $t \to \infty$ the hazard rate $h(t) \to 0$ with a single maximum.

The mean $E(T)$ of the lognormal distribution is:

$$E(T) = MTTF = e^{\mu + \frac{\sigma^2}{2}} \tag{3.33}$$

The quantile of the lognormal distribution function is obtained with the inverse CDF algorithm and is defined as follows:

$$TTF = e^{\left(\mu+\sqrt{2\sigma^2}\operatorname{erf}^{-1}(2p-1)\right)} \quad (3.34)$$

Where $\operatorname{erf}(\cdot)$ is the error function and $p = U_i \in [0,1]$is generated randomly

3.5. Uncertain Maintenance Durations

Maintenance durations, usually referred as repair times, can assume a deterministic behaviour, where the duration of the repair is constant and known in advance, or can assume a stochastic behaviour, where the repair is modelled as a random variable by assigning a probability distribution function to consider uncertainty embedded in the repair duration. A maintenance duration with a stochastic behaviour is commonly modelled when studying the reliability and availability of complex systems.

To model the uncertainty in the repair durations, the PERT distribution is considered, which is based on [68] implementation of uncertain maintenance durations. Although in Maintainability (M), the most used distribution functions to model the stochastic behaviour of the repair times are the exponential and the lognormal distribution, these are only applicable if enough data is gathered [27]. Motivated by the Project Evaluation Research Technique (PERT), the PERT distribution is a continuous distribution function, which is a transformation of the four-parameter Beta distribution with an expected value μ assumed as [69]:

$$\mu = \frac{a + 4b + c}{6} \quad (3.35)$$

Where a is the minimum value, b is the most likely value (mode) and c is the maximum value. The three parameters are referred to as the PERT parameters and serve as input to the function. To generate a random time to repair (TTR), it is essential to derive the quantile of the CDF of a PERT distribution. The CDF of a PERT distribution is based on the regularized incomplete Beta function $B(x|\alpha,\beta)$ and the complete Beta function $B(\alpha,\beta)$ which are defined as:

$$B(x|\alpha,\beta) = \int_0^x t^{\alpha-1}(1-t)^{\beta-1}dt \quad (3.36)$$

$$B(\alpha,\beta) = \int_0^1 t^{\alpha-1}(1-t)^{\beta-1}dt = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)} \quad (3.37)$$

$$F_z(\alpha,\beta) = \mathrm{I}_z\,(\alpha,\beta) = \frac{B(z|\alpha,\beta)}{B(\alpha,\beta)} \quad (3.38)$$

Where $B(\cdot)$ is the Beta function and Γ the gamma function. In order to obtain the CDF, some transformations have to be obtained, namely:

$$\alpha = 1 + 4\frac{b-a}{c-a} \quad (3.39)$$

$$\beta = 1 + 4\frac{c-b}{c-a} \quad (3.40)$$

$$z = \frac{(x-a)}{(c-a)} \tag{3.41}$$

The quantile (TTR) of the PERT distribution is obtained with $TTR = x = z(c-a) + a$, where $z = F^{-1}(p|\alpha, \beta)$ and with $p = U_i[0,1]$ randomly generated.

3.6. Correlated Failure Modes - Multivariate Normal Random Numbers

When modelling complex systems, with strong interdependencies, the failure of some components can either bring an abrupt wear-out to other components or bring no effect to function-related components. Therefore, to better model a system, one can consider correlation of the interdependencies of each subsystem, component or the associated failure modes. This can be modelled with the use of a multivariate Gaussian process (MGP) model, which applies multivariate normal random numbers to generate correlated failures [70].

The multivariate normal distribution is an extension of the univariate normal distribution (or Gaussian) by assuming two or more variables. It is based on two parameters, the mean vector $\vec{\mu}$ and the covariance matrix $\sum$, which are related to the mean and the variance of the univariate normal distribution. The covariance matrix $\sum$ measures the dependency of each specific proportion and is defined as [71]:

$$\sum = \mathrm{E}[(\mathrm{X} - \vec{\mu})(X - \vec{\mu})^T] = \begin{pmatrix} \sigma_{1,1}\, \sigma_{1,2} \cdots \sigma_{1,d} \\ \sigma_{2,1}\, \sigma_{2,2} \cdots \sigma_{2,d} \\ \cdots \;\; \cdots \; \cdots \; \cdots \\ \sigma_{d,1} \sigma_{d,2} \cdots \sigma_{d,d} \end{pmatrix} \tag{3.42}$$

Where d is the dimension of the proportions being analysed. The covariance $\sigma_{i,j}$ of proportions i and j is defined as:

$$\sigma_{i,j} = \mathrm{E}[(x_i - \overrightarrow{\mu_i})(x_j - \overrightarrow{\mu_j})^T] \tag{3.43}$$

Considering that $\sigma_{i,j} = \sigma_{j,i}$, $\sigma_{i,j} \geq 0$ for $\forall i, j$ and that $\sigma_{i,j} = \sigma^2$ for $i = j$ the covariance matrix $\sum$ is positive semi-definitive.

The probability density function of a multivariate normal distribution with d-dimensions is defined as follows:

$$f(x, \mu, \sum) = \frac{1}{\sqrt{|\sum|(2\pi)^d}} e^{(-\frac{1}{2}(x-\mu)\sum^{-1}(x-\mu)')} \tag{3.44}$$

Where μ and x are 1-by-d vectors. The generation of multivariate normal random numbers is defined in [72], which is mathematically based on the Central Limit Theorem. After generating normally distributed random numbers X, the multivariate normal probabilities are obtained by applying X to the Standard Normal Distribution CDF $\Phi_Z(z)$ defined with equation (3.16). Then, the normal correlated random probability is introduced to a quantile of interest. For each correlation scenario, a mean vector $\vec{\mu}$ and a covariance matrix $\sum$ is needed.

4. Case Study - FGC Freight Locomotive

After discussing the principles of a RAMS analysis, where emphasis is put on the FMEA/FMECA risk assessment technique, and after proposing a reliability assessment method (in chapter 2), the simulation model background, on which the RAMS analysis of this work is based, was explained (in chapter 3). In this fourth chapter, the case study is explained and described, as well as FGC, the train operating company on which the resulting models of this work are implemented. The functional breakdown of the bogie of interest is explored and the methodologies presented in chapter 2 are applied to it.

4.1. Project Context

The LOCATE project, which stands *for Locomotive bOgie Condition mAinTEnance*, is a 24-month *Shift2Rail* joint undertaking project that started in November 2019, which aims to create a set of tools to assess the condition of freight locomotive bogies in order to implement a condition-based maintenance program. Consequently, the project will contribute to the development of standard predictive maintenance programs, with the ambition of replacing current preventive and scheduled maintenance programs of freight locomotives in the European Union. The consortium of the project is made by 6 entities, namely: Ferrocarrils de la Generalitat de Catalunya (FGC), EVOLEO Technologies, Vibratec, Instituto Superior Técnico (IST), University of Huddersfield and *Union Internationale des Chemins de Fer* (UIC), with a total budget of 1.5 Million €, financed by the Horizon 2020 research and innovation fund. The project is divided into seven work packages (WP), where each entity performs and aids the execution of each task inside a WP. WP1 is the leading WP of the project and is responsible for the project management activities, aiming that the effectiveness of the project plan is fulfilled. WP2 is focused on the requirements and specifications of the end user needs, in order to ensure that the research and development of the project is directed to the end user. WP3 aims on the project development of the observed measured behaviour, selecting and implementing the right sensor technology and processing the obtained data from the critical components. WP4 is focused on modelling digital twins, which will be used for comparison with the actual measured behaviour (strong related to the result obtained in WP3). This will enable to predict the degradation of the system and the need for maintenance. WP5 is responsible for defining the maintenance schedule procedures for the future generations of condition-based maintenance programs, where focus is put on the safety of the framework. The framework developed will be applied to FGC locomotive bogie. Consequently, an additional WP6 serves as a leading WP by establishing a demonstrator on which the project's results are validated. This will include a validation process on which the developed algorithms as well as the information is analysed. Lastly, the dissemination, communication and exploitation of the project is gathered and exposed in WP7. To have a better perception of the entire project, Figure 4.1 presents the flowchart of the project, where the main work packages of the project are demonstrated.

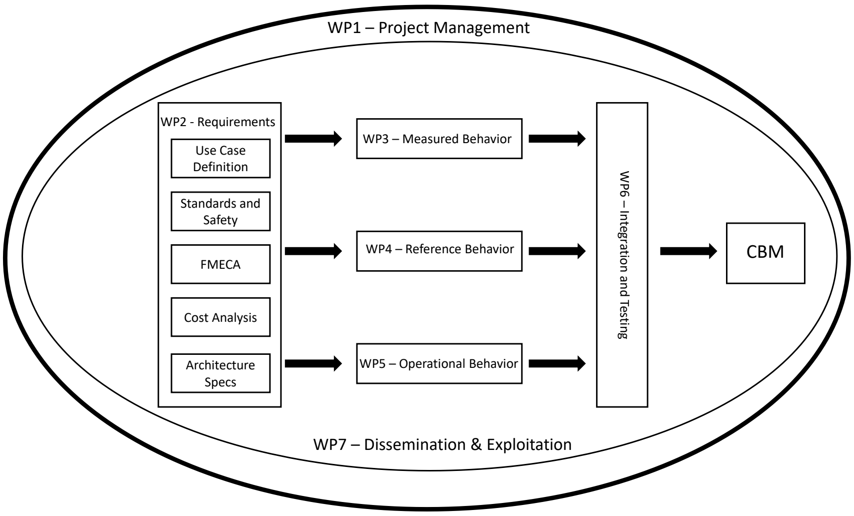


Figure 4.1 – Flowchart of the project

The purpose of the present case study is to contribute to WP2 and WP5 by performing a FMEA and FMECA analysis, in order to support the selection of "use cases" of the project as a diagnosis and by studying and testing the real time reliability and availability of the bogie of interest with different simulations models, respectively, to support the maintenance planning and scheduling as a prognosis model.

4.2. General Characteristics of the Freight Locomotive

As mentioned in the previous section, the LOCATE Project framework is applied and studied with FGC, a Spanish train operating company. FGC is a state-owned train operating company from Catalunya, Spain, that operates both freight and passengers' trains, transports approximately 90 million people a year, employees a workforce of 2000 people and manages 300km of railway tracks.

In the freight transport, FGC is responsible for managing the transport of minerals, such as salt and potash, as well as containers of goods and cars (Seat). It has a freight fleet of approximately 81 wagons and 7 locomotives. The freight locomotive involved in the project, the 254 class locomotive, is used for the transportation of the cars and potash and is shown in Figure 4.2.

Figure 4.2 – FGC Series 254 Class Locomotive

In total, FGC operates 3 units of the Series 254 Class locomotives. Each of these is equipped with a supercharged two-stroke diesel engine, which provides the power that generates the direct current needed in the traction system. The traction engine, which supplies motion to the wheelsets, is assembled in the bogie structure. The global locomotive structure is made up by the locomotive box and the running gear, which in the case of interest is the bogie vehicle. There are 2 bogies per locomotive, 3 wheelsets per bogie and 1 electric traction engine per wheelset. Each traction engine is directly employed to an axle. The summarized technical details comprised by each Series 254 Class locomotive are presented in Table 4.1.

Table 4.1 – Series 254 Class Locomotives [73]

TECHNICAL DETAILS	
Locomotive type	Co' Co'
Max Speed	90 km/h
MWater for cooling	568 l
Fuel capacity	3.000 l
Sand capacity	400 l
Total weight	81000 kg
Electric Traction Engine	
Traction Power	1500 HP 118,568 kW
Nº of engines	6
Model	D29CCT
Current Type	DC
Intensity in DC	450 A
Weight	2002 kg
Wheelset	
Distance between Wheels	924 mm
Wheels diameter initial	914 mm
Wheels diameter final	854 mm
Brake shoes	Free of asbetos
Axle Box	TIMKEN 6x11"
Weight	1991kg

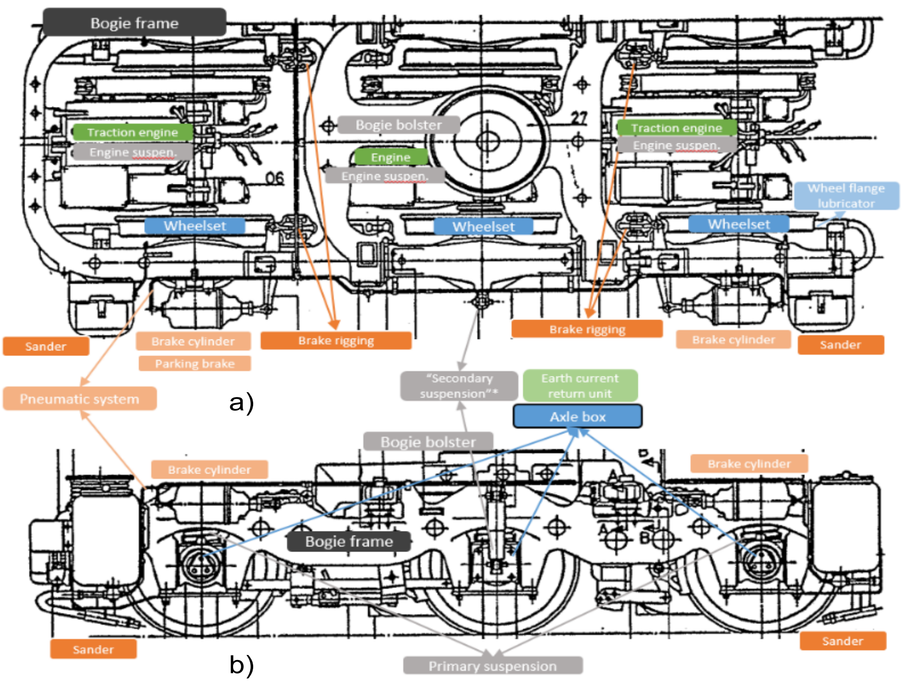
4.3. The Series 254 Class Bogie – Functional Breakdown

Each locomotive of the Series 254 Class is supported by two *Flexicoil GLC* type bogies. The bogie is designed to support the rail vehicle body and to distribute its weight through the locomotive wheels. Not only does it provide stability to the locomotive, by absorbing vibration and minimizing the impact of centrifugal forces when the locomotive runs, but it also houses several subsystems which are critical to the execution of the locomotives function, such as the electric traction engine.

In order to study the bogie system, a functional analysis was completed to identify the functions performed by the system, its subsystems and the components associated with these. In Figure 4.3, the bogie subsystems are identified and, according to the Handbook of railway dynamics [74], the definition of each subsystems function is as follows:

- Bogie bolster: responsible for the vehicle body weight transfer to the bogie frame;
- Wheelset: provides the necessary distance between the vehicle and the track, provides the vertical support, provides the guiding role to negotiate curves on the track, transmits traction and braking forces to the rails;

- Axlebox: allows the wheelset to rotate, providing the bearing housing and the mountings for the primary suspension to attach the wheelset to the bogie frame;
- Wheel flange lubricator: lubricator system to reduce friction between the wheel flanges and the inner sides of the rail;
- Primary suspension: connects the wheelsets to the bogie frame, guides the wheelsets and aims at absorbing the high-frequency wheel-rail contact loads;
- Secondary suspension: connects the bogie frame to the vehicle body, deals with the low-frequency loads;
- Traction engine suspension: connects the traction engine to the bogie frame;
- Electric traction engine: provides motion to the axle and therefore to the wheels;
- Brake rigging: distributes the braking forces from the brake cylinder to the various brake shoes interacting with the wheels of the vehicle;
- Brake cylinder: responsible for creating the breaking force when air is introduced;
- Parking brake: blocks the wheel motion when the train unit is parked;
- Sander: projects sand on the wheel-rail interface to improve adhesion in both traction and braking;
- Pneumatic equipment: responsible for activating the braking and sander system;
- Earth current return unit (in the axlebox): directs the path of the current away from the bearings through the wheels or axles;



	Braking and adherence related subsystems
	Stability related subsystems
	Rotation related subsystems
	Electricity related subsystems
Soft	Non selected subsystem

Figure 4.3 – Subsystem identification and Bogie drawings a) Top View and b) Side View [73]

It is worth mentioning that the identification of the subsystems presented above was also based on the maintenance plan of FGC, which was provided in the project and discussed in the project Deliverable [73].

4.4. FMEA Analysis

4.4.1. Selection of components and identification of their failure modes

Following the identification of the bogie configuration and the respective functionalities, FMEA requires the identification of potential component and interface failure modes and their effects to the system and ultimately to the bogie (the system-of-interest). Therefore, in order to proceed to the analysis, a comprised configuration of the bogie was established, which not only embraces the use case of interest mentioned in the previous section, but it also relates to other general freight locomotive bogies. Consequently, the subsystems selected to the case study are the following:

1) Wheelset;
2) Axlebox;
3) Bogie frame;
4) Brake system;
5) Suspension system/ elements;
6) Electric traction engine.

According to the MIL-STD-1629A standard [75], a failure mode should describe the manner a component fails to fulfil its defined function. The key requirements for defining a failure mode can be summarised as follows:

- relates to how the failure is observed:
- describes the manner the failure occurs;
- describes the impact/effect of the failure on the component;
- relates to performance measurement of the component.

However, due to limited information on the case studies being analysed, the FMEA analysis was conducted by referring to the findings from the previous EU Project INNOWAG [76], a project focused on lightweight cargo wagons bogies which shares a number of commonalities with the case study. For example, in the bogie of interest and the lightweight cargo bogie, many similarities can be found on the functional breakdown of both systems, as well as typical failure modes and their effects on the system. It is worth mentioning that the findings from the INNOWAG project are summarized, not including any inspection or maintenance sheets where the failure causes, failure effects and failure mechanism are mentioned.

The INNOWAG project comprised its study with three different sets of data, all based in three different subsystems of the bogie, namely: the wheelset, the braking system, and the suspension system. Although the different datasets belong to three different operating wagon companies, which have different maintenance policies, a combined FMEA analysis spreadsheet was created to list the most critical components and their failure modes since all the wagons operate in accordance with the *General Contract of use for Wagons* [77].

Using the methodology described in section 2.3, an evaluation of the RPN number was performed for all failure modes identified. In accordance with the UIC Guidelines [38], a threshold limit value of $RPN_i = 250$ was set and all the failure modes with a higher value than this acceptable threshold were identified as critical. In addition to this threshold limit value, and to guarantee that all critical failure modes were identified, all failure modes whose Severity (S) number is $S = 10$ are also considered as critical.

The results of the FMEA analysis of the three systems are shown in Table 4.2.

Table 4.2 – FMEA Analysis based on the findings of the INNOWAG Project [76]

Subsystem	Component	Failure Mode	Failure Rate 1/h	Severity, S		Occurrence, O		Detectability, D		RPN
Wheelset	Axle	Axle crack	1.31E-06	unsafe, without warning	10	low, relative few failures	3	moderate	5	150
	Wheel	Wheel out of round	6.04E-06	very high	8	moderate, often some failures	6	very low	7	336
		Wheel cracks and notches	4.80E-05	very high	8	high, repeating failures in short cycle	8	very low	7	448
		Wheel flat	9.60E-05	very high	8	high, repeating failures in short cycle	8	very low	7	448
		Wheel thermomechanical crack	3.50E-07	very high	8	low, relative few failures	3	very low	7	168
		Wheel build-up material	6.00E-05	very high	8	high, repeating failures in short cycle	8	very low	7	448
		Wheel profile under threshold limit	8.40E-04	unsafe, without warning	10	very high, many failures in short cycles	9	low	6	540
	Axlebox	Absence of the cover box screw	6.00E-05	very high	8	high, repeating failures in short cycle	8	moderate	5	320
		Housing not watertight	1.20E-04	very high	8	high, repeating failures in short cycle	8	moderate	5	320
		Bearing Failure	2.12E-06	unsafe, without warning	10	moderate, sometimes some failure	5	very very low	8	400
Braking System	Brake	Parts of brake rigging hanging	2.01E-05	very high	8	high, repeating failures in short cycle	8	moderate	5	320
		Brake isolating cock	2.01E-05	very high	8	high, repeating failures in short cycle	8	uncertain	9	576
		Cast iron Brake Block	1.08E-04	moderate	6	high, repeating failures in short cycle	8	very low	7	336
		Composite Brake Block	3.12E-05	moderate	6	high, repeating failures in short cycle	8	very low	7	336
		Brake coupling missing	1.20E-04	moderate	6	high, repeating failures in short cycle	8	very high	2	96
	Pneumatic System	Front air valve damaged	6.00E-05	unsafe, without warning	10	high, repeating failures in short cycle	8	moderate	5	400
		Brake cylinder damaged	6.00E-05	moderate	6	high, repeating failures in short cycle	8	very very low	8	384
		Air distributor damaged	3.00E-04	moderate	6	high, repeating failures in short cycle	8	uncertain	9	432
		Slack adjuster damaged	2.40E-04	very high	8	high, repeating failures in short cycle	8	low	6	384
Suspension System	Spring Buckle	Spring Buckle Fracture	6.00E-05	unsafe, without warning	10	high, repeating failures in short cycle	8	very very low	8	640
	Helical Spring	Helical Spring broken	6.00E-05	unsafe, without warning	10	high, repeating failures in short cycle	8	moderate	5	400
	other suspension elements	Bottoming between Axlebox housing and bogie frame	1.44E-06	unsafe, without warning	10	low, relative few failures	3	moderate	5	150

In order to highlight the most critical failure modes that resulted from the FMEA analysis, the cells corresponding to an RPN higher than the threshold limit (250) and/or with a severity (S) indicator equal to 10, were highlighted and presented in bold.

From the FMEA analysis results, the critical components of three main subsystems of the bogie were identified. Nevertheless, and considering that FGC has also major problems regarding maintenance, number of failures or warnings and times to repair, with other types of subsystems, such as the bogie frame and the electric traction engine, there is a need to address additional statistical references, to model the failure behaviour of other critical systems and prioritize the ones identified as most critical, taking in mind the lack of useful data provided by FGC. This was possible with two reference articles, namely [78] and [79], where:

- In [78], a reliability and availability analysis of a Polish diesel locomotive is conducted to identify the components which present greater impact on the downtime of the operation;
- In [79], a reliability analysis of a Chinese high-speed train bogie is performed, where different distribution functions are tested and modelled to represent each critical component embedded in the functional behaviour of the bogie;

Although both articles comprise a different case study than FGC, some bogie components perform identical purposes, resulting in similar statistical behaviours. Therefore, a proposal was created that is aligned with the interests and research opportunities of the present case study, which is based on the FMEA analysis results and these additional references. Following the definition of the subsystems, the critical components and their failure modes were defined again, with the guidance of the FMEA analysis results and with the additional references [78,79].

Table 4.3 – Components and Failure Modes identified as critical

Subsystem ID	Subsystem	Component ID	Component	Failure Mode	Source
1	Wheelset	1.1	Axle	Axle Crack	FMEA
		1.2	Wheels	Wheel out of round	FMEA
		1.2	Wheels	Wheel Cracks and notches	FMEA
		1.2	Wheels	Wheel Build-up Material	FMEA
		1.2	Wheels	wheel flat	FMEA
		1.2	Wheels	Profile under the threshold limit	FMEA
2	Axle Box	2.1	Axle Box	Absence of the cover box screw	FMEA
		2.1	Axle Box	Housing not watertight	FMEA
		2.1	Axle Box	Bearing Failure	Literature [78]
3	Bogie Frame	3.1	Frame	-	Literature [78]
4	Brake System	4.1	Brake	parts of brake rigging hanging	FMEA
		4.1	Brake	Brake isolating cock	FMEA
		4.1	Brake	Cast Iron Brake Block	FMEA
		4.1	Brake	Composite Brake Block	FMEA
		4.2	Pneumatic Braking system	Front air valve damaged	FMEA
		4.2	Pneumatic Braking system	Brake cylinder damaged	FMEA
		4.2	Pneumatic Braking system	Air distributor damaged	FMEA
		4.2	Pneumatic Braking system	Slack adjuster damaged	FMEA
		4.2	Master/Auxiliary Compressor	-	Literature [78]
		4.3	Master/Auxiliary Compressor Driving Motor	-	Literature [78]
		4.5	Servo-motor in the braking system	-	Literature [78]
		4.6	Other Elements of the pneumatic braking system	-	Literature [78]
		4.7	Other Elements of the braking system (pins, sleeves,…,)	-	Literature [78]
5	Suspension Elements	5.1	Spring Buckle	Spring Buckle Fracture	FMEA
		5.2	Helical Spring	Helical Spring broken	FMEA
		5.4	Other Suspension elements	Bottoming between Axlebox housing and bogie frame	FMEA
6	Electric Traction Module	6.1	Power transmission system	-	Literature [79]
		6.2	Shaft Coupling	-	Literature [79]
		6.3	Traction Motor	-	Literature [79]

As it can be verified from Table 4.3, the failure modes that comprise the braking system and bogie frame were obtained from [78], whereas the failure modes from the electric traction engine were obtained from [79]. Some components, especially the ones which were adopted from the literature review, are not disaggregated in its failure modes, mostly due to lack of information, which is implicit in both reference analysis.

4.5. Assessing Uncertainty – Application of the Reliability Assessment Method

There are some challenges when applying an adaptation of a classic method to the real-world scenarios. In the case study, one of the main challenges is the uncertainty embedded in the decision-making process, due to the availability of reliable information from FGC of the real-life behaviour of some subsystems and components. To mitigate the impact of the uncertainty and to gain more confidence in our analysis in order to accomplish a more realistic assessment aligned with the real case study of FGC freight locomotives, a survey was conducted to experts and expert judgment techniques were used to quantify survival curves and failure curves of the most critical subsystem of the bogie: the wheelset subsystem.

Therefore, in order to build the reliability assessment method proposed in section 2.5, one needs to disaggregate the wheelset subsystem in its components, to try to understand which of these might be the most desirable for the project and select those for further analysis. As a result, and based on what FGC considered critical for the analysis, the following wheelset components were identified as target variables:

i. Axles
ii. Wheels

In order to obtain a robust result, one had to construct the target questions, calibration questions, and a list of experts that would benefit the project. The following subsections 4.5.1-4.5.4 apply each step of the Reliability Assessment Method previously described in subsections 2.5.1-2.5.4.

4.5.1. Seed Questions

The seed questions were formulated with the guidance of two European Railway Agency (ERA) annual reports from the past 3 years, namely the ERA report on Railway Safety and Interoperability in the EU from 2018 [80] and 2019 [81], and also from the European Standards available for the wheelset components. Therefore, a total of 13 questions were formulated, whereas 4 questions out of 13 were used for the survey (see Appendix A1). All questions were specific to the components topic and all questions were based on the reliable data published, and thus all questions had their actual realizations.

The target questions were formulated with the histogram technique (as explained in subsection 2.5.1). Typical mean distances between inspections for both components were used, to have a better reference of the real case scenario. The defined intervals were the following:

i. Axles: seven equally spaced intervals with a range of 300,000 km each. Starting at zero, the first interval was [0; 300,000 km], the second [300,000 km; 600,000 km], and so on until the seventh interval, which was defined from [1,800,000 km; +∞];
ii. Wheels: seven equally distant intervals with a range of 15,000 km each. Starting at zero, the first interval was [0; 15,000 km], the second [15,000 km; 30,000 km], and so on until the seventh interval, which was defined from [90,000 km; +∞].

The sum of all failures in all intervals is the amount of the batch, which was set equal to 1,000 components. For the axle, the chosen failure mode was the “axle crack” since it is the most known failure mode of this component. It is worth mentioning, that commonly there is plentiful of data for the wheel’s component, regarding the typical failure modes linked to the failure of the component. This enables us to analyse the adequacy of the reliability assessment methodology since the reliability curves can be easily compared with the operation data of each user-case. Therefore, each expert assessed a typical mean distance between failure (MDBF) for the wheel component after each assessment.

4.5.2. List of Experts

In order to obtain reasonable results, which would reflect the real case scenario as much as possible, a list of experts in wheelset components was established. This list was built with the support of *Union Internationale des Chemins de Fer* (UIC) Experts list, namely the *List of recognized UIC experts to elaborate expertise on braking components 2019* [82] and the *List of experts recognized by UIC and relative expertise of wheels 2012* [83]. In addition to the UIC lists, the list of experts had also the support of the network of researchers involved in the Shift2Rail Joint undertaking. It should be noted that the list of experts was composed of wheelset experts, not only of freight locomotives but also of passenger locomotives.

The survey was designed using the public platform Google Forms. It contained a brief introduction to the research project, a brief illustrative example to explain the reader on the format of the elicitation, the seed questions and finally the target questions. The survey was held anonymously and from the entire list of experts, 6 experts completed the survey.

4.5.3. Experts Weighting Process

This subsection comprises the results of the expert judgment performed to assess the uncertainty associated with failure rates of the wheels and axle component. A total of 6 experts completed the survey, namely the calibration and target questions (which are available in the Appendix A1). The results are also presented below. Table 4.4 summarizes the expert's performance in the four calibration questions (CQ1-CQ4).

Table 4.4 – Experts assessment on the four Calibration Questions (CQ1- CQ4)

Expert	CQ1			CQ2			CQ3			CQ4		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
Expert 1	40	50	80	10	50	90	50	60	80	40	50	60
Expert 2	1800	2074	2400	5	20	35	200	500	800	50	100	150
Expert 3	1500	2000	2500	20	30	40	300	600	900	50	100	150
Expert 4	270	346	422	15	30	45	10	25	40	800	1700	2600
Expert 5	1700	1900	2100	2	8	10	50	75	100	100	200	300
Expert 6	1500	1750	2000	60	70	80	40	90	200	30	50	200
Realization	**1789**			**58**			**104**			**18**		

After assessing the results of the expert's calibration questions, the expert weights were obtained, with the support of the free software EXCALIBUR. By introducing the expert's assessments, as well as the realizations for each calibration question, a summarized table with all the relevant scores is obtained.

Each expert's calibration score, information score, unnormalized and final weights can be observed in Table 4.5.

Table 4.5 – Experts calibration score, information score, unnormalized and normalized weight

Expert	Calibration Score	Information Score	Unnormalized weight	Normalized weight
Expert 1	0.01043	2.76600	0.02885	**0.28400**
Expert 2	0.00022	1.28500	0.00028	**0.00277**
Expert 3	0.01043	1.26300	0.01318	**0.12970**
Expert 4	0.00022	1.61300	0.00035	**0.00348**
Expert 5	0.01043	2.09000	0.02180	**0.21460**
Expert 6	0.02197	1.69100	0.03714	**0.36550**

As shown in Table 4.5 , Expert 6 has the largest weight, due to his/her good performance in accurately replying to the calibration questions. Concerning the other experts, Expert 6 was statistically more accurate. Despite not being the most informative, since its information is not the narrowest one (check experts' assessments in Table 4.4), his/her accuracy stands out in comparison with the remaining experts. On the other hand, Expert 2 is the least accurate, as well as one of the least informative experts in the poll. Therefore, his/her opinion on the target variable will have a relatively poor impact on the result of the analysis. Having computed the weights for each expert, after analysing their performance on the calibration questions, it is now time to assess their responses to the target variables. In this case, the target questions are related to the failure rates of each component being analysed. For each target variable, the weight of the expert is taken into account, and the following list is a ranking of the most impactful expert in each assessment on the target variables: Expert 6, Expert 1, Expert 5, Expert 3, Expert 4 and Expert 2. Both assessments are summarized in Table 4.6, where each expert evaluated the number of failures in each interval. For the wheels, the experts additionally assessed the mean distances between failures (MDBF), in order to compare with the final MDBF of the analysis.

Table 4.6 – Experts assessments on the axle and on the wheels (with MDBF) for each interval

Axle									
	[0; 300] 10^3 km	**[300; 600] 10^3 km**	**[600; 900] 10^3 km**	**[900; 1200] 10^3 km**	**[1200; 1500] 10^3 km**	**[1500; 1800] 10^3 km**	**[1800; +∞] 10^3 km**	**Sum**	**MDBF**
Expert 1	0	0	5	5	5	10	975	1000	-
Expert 2	0	2	4	6	8	10	970	1000	-
Expert 3	0	2	5	10	15	20	948	1000	-
Expert 4	20	80	150	250	300	150	50	1000	-
Expert 5	10	50	150	250	400	100	40	1000	-
Expert 6	2	18	40	100	120	150	570	1000	-
Wheels									
	[0; 15] 10^3 km	**[15; 30] 10^3 km**	**[30; 45] 10^3 km**	**[45; 60] 10^3 km**	**[60; 75] 10^3 km**	**[75; 90] 10^3 km**	**[90; +∞] 10^3 km**	**Sum**	**MDBF**
Expert 1	10	70	125	150	150	200	295	1000	75000
Expert 2	10	40	50	100	100	100	600	1000	100000
Expert 3	10	50	100	150	150	200	340	1000	80000
Expert 4	2	8	20	40	70	90	770	1000	150000
Expert 5	10	30	70	100	300	400	90	1000	70000
Expert 6	10	20	70	100	150	200	450	1000	90000

The next subsection estimates the reliability curves following the two basic approaches (see subsection 2.5.4).

4.5.4. Fitting Reliability Curves

4.5.4.1. Approach 1: "Fit first, combine later"

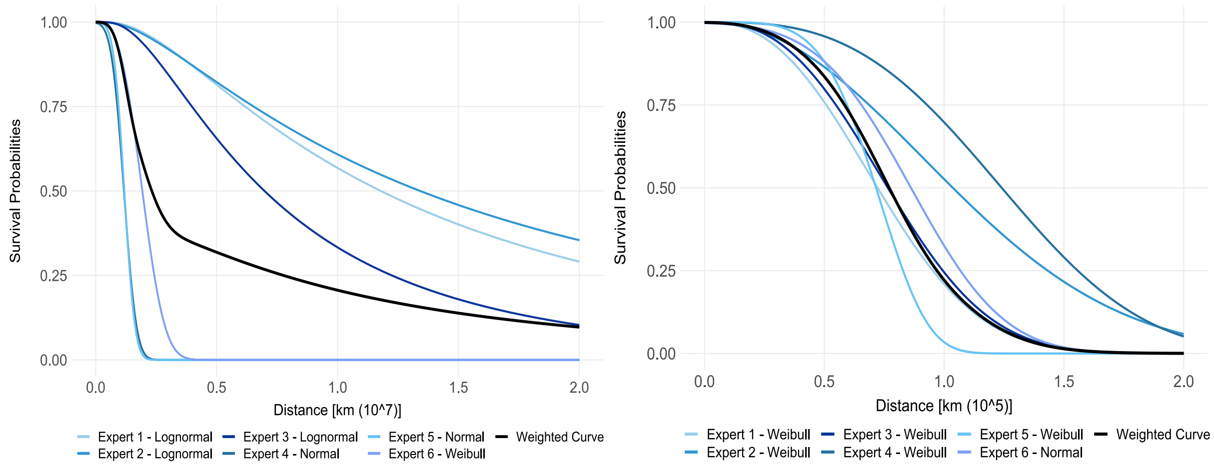
For this first approach, a survival analysis on the opinion of each expert is performed. For each expert, five probability distributions were considered, namely: Weibull, Normal, Lognormal, Gamma, and Exponential. The AIC values for each fitting for both components can be verified in Table A.1 and Table A.2 (see Appendix A2), where the parameters from each fitted distribution, which presented the lowest AIC values, can be visualized in Table 4.7.

Table 4.7 – Distribution parameters for each expert opinion fit – Axle and Wheels

Axle												
Expert	**Expert 1**		**Expert 2**		**Expert 3**		**Expert 4**		**Expert 5**		**Expert 6**	
Distribution	**Lognormal**		**Lognormal**		**Lognormal**		**Normal**		**Normal**		**Weibull**	
Estimates for the parameters	**Meanlog**	**SDlog**	**Meanlog**	**SDlog**	**Meanlog**	**SDlog**	**Mean**	**SD**	**Mean**	**SD**	**Shape**	**Scale**
	0.16467	0.95948	0.2939	1.06807	0.35963	0.83351	0.11669	0.040669	0.11669	0.04067	3.02929	0.21748
Wheels												
Expert	**Expert 1**		**Expert 2**		**Expert 3**		**Expert 4**		**Expert 5**		**Expert 6**	
Distribution	**Weibull**		**Weibull**		**Weibull**		**Weibull**		**Weibull**		**Normal**	
Estimates for the parameters	**Shape**	**Scale**	**Shape**	**Scale**	**Shape**	**Scale**	**Shape**	**Scale**	**Shape**	**Scale**	**Shape**	**Scale**
	2.49365	0.83719	2.14123	1.22972	2.64162	0.8788	2.49365	0.83719	2.14123	1.22972	2.64162	0.21748

All the scale variables are in 10^7 km for the axles and in 10^5 km for the wheels. For the Normal and Lognormal distribution in Table 4.7, the parameters are the mean and the standard deviation (SD).

Considering the axle assessments, for experts 1, 2, and 3, the Lognormal distribution is the distribution that best fits each expert's opinion, according to the AIC criterion. For experts 4 and 5, the Normal distribution is the most suitable. Finally, for expert 6 the best distribution is the Weibull distribution. For the wheel assessment, for experts 1 to 5, the distribution that best fits the data is the Weibull distribution, due to the low AIC values. For expert 6, the best distribution is the Normal distribution. Having fitted firstly a distribution to each expert opinion, a final curve is needed that could represent the know-how of each expert combined. Therefore, in order to create a final curve, each weight of each expert is multiplied by the corresponding distribution function. The final fitted expert opinions as well as the weighted expert opinion for both components are demonstrated in Figure 4.4



a) b)

Figure 4.4 – Each experts opinion fitted and the weighted curve after fitting expert opinion for a) the axle and b) the wheels component

For the axle, since the expert's opinions diverge a lot, the final weighted curve is formed by a combination of expert 6, expert 1, and expert 5 slopes. Here, we can confirm the impact of a high weighted expert. For the wheels, one can identify that the experts with the highest weights have the most impact in the final curve, like experts 5 and 6, where the values and slopes of the final curve are very similar to these experts' opinions.

4.5.4.2. Approach 2: "Combine first, fit later"

For the second approach, a combined weighted opinion was first obtained, following a survival analysis of the combined opinion. The combined weighted opinion is obtained by multiplying each expert's weight to each opinion in every interval. The combined expert opinion can be verified in Table 4.8, for the axle and the wheels, respectively.

Table 4.8 – Combined weighted expert opinion: axle and wheels

				Axle				
	[0, 300] 10^3 km	**[300, 600] 10^3 km**	**[600, 900] 10^3 km**	**[900, 1200] 10^3 km**	**[1200, 1500] 10^3 km**	**[1500, 1800] 10^3 km**	**[1800, +∞] 10^3 km**	**Sum**
Combined Expert	3	18	49	94	134	82	620	1000
				Wheels				
	[0 , 15] 10^3 km	**[15 , 30] 10^3 km**	**[30 , 45] 10^3 km**	**[45 , 60] 10^3 km**	**[60 , 75] 10^3 km**	**[75 , 90] 10^3 km**	**[90 , +∞] 10^3 km**	**Sum**
Combined Expert	10	40	89	121	182	242	316	1000

After combining the judgments of each expert, the reliability curves are fitted/estimated for both the axle and the wheels, and the five statistical distributions are compared based on the AIC value. In Table A.3 (see Appendix A2), the AIC values for the goodness-of-fit can be verified, while the parameters of the resulting distribution (lowest AIC value) are demonstrated in Table 4.9.

Table 4.9 – distribution parameters for the combined weighted expert opinion: axle and wheels

Axle		**Wheels**	
Parameters of the Distribution		**Parameters of the Distribution**	
Lognormal		**Normal**	
Meanlog	**SDlog**	**Mean**	**SD**
-1.5219	0.63316	0.774	0.277

4.5.4.3. Fitting Comparison - Decision

Finally, a comparison is made between the two approaches, concerning the distribution that best describes the component failure in real case scenarios. Both reliability curves for each component are represented in Figure 4.5, to identify and compare the similarities or divergences. Having assessed both statistical distributions for both approaches, a comparison is made to determine which of the distributions is more conservative.

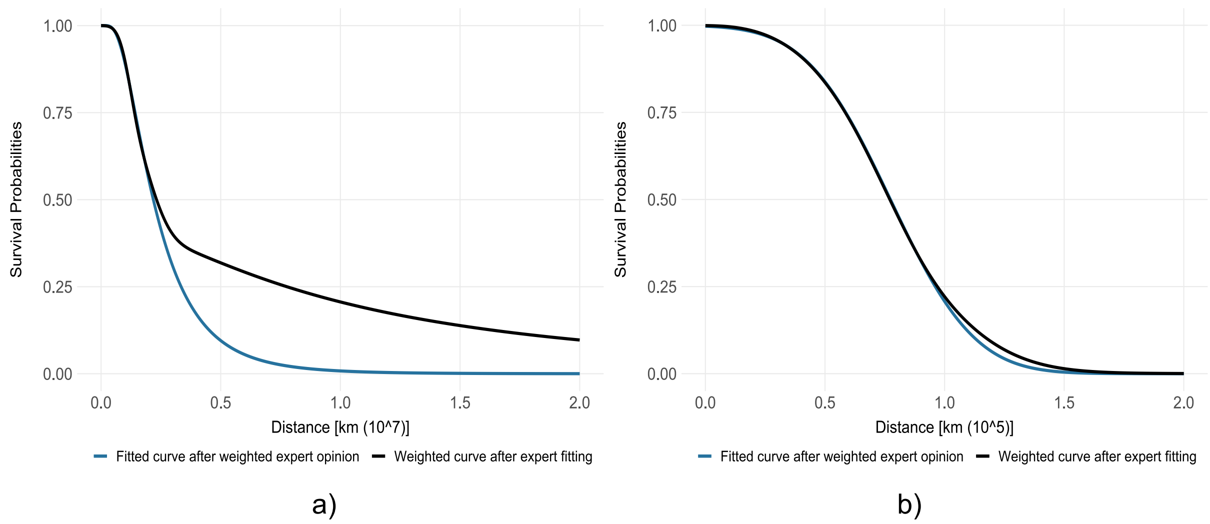


Figure 4.5 – Comparison between approach 1 (black) and approach 2 (blue) results for a) the axle and b) the wheels component

For the axle, the blue curve (approach 2) shows lower survival probabilities for high values of travelled distances. This means that the probability of the component not to fail for a high value of kilometres is lower than the probability given by the black curve. As a result, the blue curve is considered more conservative and is selected to be the most appropriate to represent the real-life degradation of the component, since it is safer in terms of maintenance to think a component is going to fail earlier.

For the wheels, though the curves are very similar, once again the blue curve (Approach 2) is more conservative, i.e. for higher values of kilometres, the wheels have lower survival probabilities than the black curve. Consequently, the blue curve is assumed to be the final distribution function chosen to best describe the case study under analysis, as it is more conservative.

Finally, one can estimate the associated failure rates for the components of interest. For the case study, failure rates of the axle and the wheels were obtained with the use of the mean estimate of each cumulative distribution function, using the following formulas:

1. Lognormal Distribution (Axle):

$$mean = \exp\left(\mu + \frac{\sigma^2}{2}\right)$$

Where μ is the meanlog and σ the sdlog from Table 4.9. The mean value is:

$$mean = \exp\left(-1.5219 + \frac{0.63316^2}{2}\right) = 0.266748\ x10^7\ km = MDTF_{A,Lognormal}$$

Finally, the failure rate is obtained with the $MDTF$:

$$\lambda_1 = \frac{1}{MDTF_{A,Lognormal}} = 3.749\ x\ 10^{-7}\ km^{-1}$$

2. Normal Distribution (Wheels):

$$\hat{\mu} = 0.77375x10^5\ km = MDTF_{W,Normal}$$

With the $MDTF$, which is obtained with the mean $\hat{\mu}$ from Table 4.9, the failure rate is calculated with:

$$\lambda_2 = \frac{1}{MDTF_{W,Normal}} = 1.2924\ x\ 10^{-5}\ km^{-1}$$

As mentioned in section 2.5, in order to guarantee a robust methodology, the failure rate of the wheels was compared to typical failure rates in operation, with the help of the experts, where after the expert elicitation, the $MDTF$ of the operation was requested. With the use of the expert weights, a performance-based $MDTF$ for the wheels was calculated and a comparison between both failure rates was performed:

$$MDTF_{W,Global} = \sum_{e=1}^{E} w_e \times MDTF_{wheels,e} = 80394.25\ km$$

$$\lambda_{wheels,global} = \frac{1}{MDTF_{W,Global}} = 1.244\ x\ 10^{-5} km^{-1}$$

$$\% = \left|\frac{\lambda_2 - \lambda_{wheels,global}}{\lambda_{wheels,global}}\right| = 3.902\%$$

Indeed, the failure rate λ_2 did not diverge with the failure rate of the component in operation $\lambda_{wheels,global}$, thus giving more confidence and accuracy to the estimated failure rate and survival curve of the long service-life component, the axle.

4.6. FMECA Analysis (consolidating FMEA with Expert Judgment)

After performing a FMEA analysis, in order to identify and prioritise the most relevant subsystems and components of the bogie system, and after conducting an expert judgment to obtain failure rates of two components, this subsection combines these two analyses to have a better assessment of a real case scenario and perform a criticality analysis, to rank the most critical components and subsystems.

Nevertheless, to combine these two analyses, one must first modify the failure rate units that resulted from the expert judgment. The average cargo locomotive speed was assumed to be equal to 40km/h. Therefore, with a given $MDTF$ the units conversion to Mean Time to Failure ($MTTF$) is obtained with the following formula:

i. $$\mathrm{MTTF_1} = \frac{\mathrm{MDTF_1}}{\frac{40\ \mathrm{km}}{\mathrm{h}}} = 66687h \rightarrow \lambda_1 = \frac{1}{\mathrm{MTTF_1}} = 1.5x10^{-5}\frac{1}{h}$$

ii. $$\mathrm{MTTF_2} = \frac{\mathrm{MDTF_2}}{\frac{40\ \mathrm{km}}{\mathrm{h}}} = 1933.93h \rightarrow \lambda_2 = \frac{1}{\mathrm{MTTF_2}} = 5.171x10^{-4}\frac{1}{h}$$

Considering the occurrence of the FMEA analysis in Table 4.2, one can verify that for component 2 (wheels), the impact would be ranked with number 8, meaning the occurrence is high with repeating failures in a short cycle. Therefore, and having in mind that every wheel failure mode is ranked with an 8 or higher in terms of severity and detectability, one can assume that the component is critical. For the axle (component 1), the occurrence with the new failure rate would be ranked with a 7, also high. Bearing in mind that the axle has a severity of 10, this component should always be considered critical, since a failure could bring possible fatalities. In order to perform a criticality analysis, one has to calculate first the modal criticality and then the items criticality. In the latter, the items considered are the assumed critical subsystems analysed. For this purpose, the formulas (2.13) and (2.14) were utilized. Considering that in this case study the failure rate of the effect was not assumed due to lack of information on the failure modes effects and that the operating hours are the same for each component and therefore for each failure mode, β and t of equation (2.13) are assumed to be 1. Following this and considering the critical subsystems, with its critical components and the associated failure modes that resulted from the FMEA analysis (see subsection 4.4), one can adapt Table 4.3 and insert the new failure rates estimated using the expert judgment techniques, the severity numbers and the occurrences (Table 4.2). It is important to emphasize that the severity numbers linked to the components and failure modes not mentioned in the FMEA analysis, were obtained from the reference articles [78] and [79] and from expert judgment. The additional occurrences are linked to the failure rate and were established with the UIC Guidelines [38] (see Figure 2.7). Table A.4 in Appendix A3 summarizes the new critical components, where emphasises is put on the updated wheelset subsystem. As can be verified, all failure modes from the wheels were aggregated to a general failure mode. This general failure mode has a higher combined failure rate than the failure modes themselves. Therefore, a more conservative and realistic scenario was analysed, which leads to a better criticality assessment of the bogie.

After performing the criticality calculations, Table 4.10 was obtained.

Table 4.10 – Criticality Analysis

Subsystem ID	Subsystem	Component ID	Component	Failure Mode	C_m	C_i	Ranking
1	Wheelset	1.1	Axle	Axle Crack	4.50E-04	**3.77E-02**	**2**
		1.2	Wheels	(Wheel out of round, Wheel cracks and notches, wheel build up material, wheel flat, profile under threshold)	3.72E-02		
2	Axle Box	2.1	Axle Box	Absence of the cover box screw	3.84E-03	**1.16E-02**	**4**
		2.1	Axle Box	Housing not watertight	7.68E-03		
		2.1	Axle Box	Bearing Failure	1.06E-04		
3	Bogie Frame	3.1	Frame	-	7.43E-04	**7.43E-04**	**6**
4	Brake System	4.1	Brake	parts of brake rigging hanging	1.29E-03	**7.99E-02**	**1**
		4.1	Brake	Brake isolating cock	1.29E-03		
		4.1	Brake	Cast Iron Brake Block	5.18E-03		
		4.1	Brake	Composite Brake Block	1.50E-03		
		4.2	Pneumatic Braking system	Front air valve damaged	4.80E-03		
		4.2	Pneumatic Braking system	Brake cylinder damaged	2.88E-03		
		4.2	Pneumatic Braking system	Air distributor damaged	1.44E-02		
		4.2	Pneumatic Braking system	Slack adjuster damaged	1.54E-02		
		4.2	Master/Auxiliary Compressor	-	7.85E-03		
		4.3	Master/Auxiliary Compressor Driving Motor	-	1.87E-03		
		4.5	Servo-motor in braking system	-	4.73E-04		
		4.6	Other Elements of the pneumatic braking system	-	1.38E-02		
		4.7	Other Elements of the braking system (pins, sleeves,….)	-	9.22E-03		
5	Suspension Elements	5.1	Spring Buckle	Spring Buckle Fracture	4.80E-03	**9.64E-03**	**5**
		5.2	Helical Spring	Helical Spring broken	4.80E-03		
		5.4	Other Suspension elements	Bottoming between Axle-box housing and bogie frame	4.32E-05		
6	Electric Traction Module	6.1	Power transmission system	-	2.87E-02	**3.35E-02**	**3**
		6.2	Shaft Coupling	-	4.40E-03		
		6.3	Traction Motor	-	4.22E-04		

Based on the criticality analysis, a consolidated ranking of the most critical subsystems is obtained by ordering the subsystem with the highest combined C_i score. The following list ranks the most critical subsystems:

1. Brake System
2. Wheelset components
3. Electric Traction Module
4. Axle Box
5. Suspension System
6. Bogie Frame

Intuitively, it can be verified that one of the main reasons the braking system is considered to be the most critical subsystem is due to excessive failure modes linked to its components and the information obtained for this subsystem.

4.7. Discussion – Risk Mitigation Actions

By identifying the most critical subsystems, it is possible to implement risk mitigation strategies, to optimize the operation and the cost associated with the maintenance of the bogie. The common risk mitigation strategies to decrease severity and occurrence, and increase detectability are the following:

1. Implement redundancy to reduce the risk of losing the function (decrease Occurrence);
2. Apply specific test in simulated operating conditions to check the reliability of a component (decrease Occurrence and increase detectability);
    i. Creation of a functional simulation model that simulates the real-time condition of the components and subsystems combined, according to the operation of FGC;
3. Increase the frequency of inspections (decrease Occurrence and increase detectability);
4. Change the maintenance type to predictive maintenance, monitoring the condition of the components (decrease Occurrence and increase detectability) – by implementing sensors:
    i. Monitoring of bogie stability through the implementation of sensors (e.g. accelerometers) that are able to monitor the movement of each bogie and identify situations/conditions which might increase the risk of derailment;
    ii. Axlebox monitoring using vibration and temperature sensors to detect any unusual behaviour;
    iii. Vibrations and temperature sensors for monitoring any unusual behaviour of the electric traction engines;
5. Apply specific test to ensure maintainability of components that require a long time to repair (decrease Severity);
    i. Control with sensors the real-time of failure of the most critical components;
6. Prepare specific training and procedures to allow falling back to a safe degraded mode in an emergency (decrease Severity)
    i. providing intermediate system repair to the most critical subsystems;
7. Keep spares on-site so that time to repair is shortened (decrease Severity).

A summary of all the previous strategies and their impact on the three indexes mentioned in section 2.3 are presented in
Table 4.11.

Table 4.11 – Risk Mitigation Strategies and their impact on the Severity, Occurrence, and Detectability

	Decrease Severity	Decrease Occurrence	Increase Detectability
Strategy 1		X	
Strategy 2		X	X
Strategy 3		X	X
Strategy 4		X	X
Strategy 5	X		
Strategy 6	X		
Strategy 7	X		

After extensive analysis to decide which strategy one needs to implement in the case study, regarding the structure and the objectives of the project, a combination of some of these was obtained in order to follow the path of the project of providing a continuous monitoring system.

By starting at strategy 1, one can assume that this strategy is not appropriate in an already operating cargo locomotive since this strategy is usually implemented in a design phase of a product. Strategy 2, which mentions the implementation of specific tests in order to monitor the reliability of the system in real-time, provides a good continuous monitoring system. Therefore, this strategy is aligned with the case study and taken into consideration. Strategies 3 and 6, which focus on an increasing frequency of inspections and intermediate repairs, are exactly one of the key tasks to eradicate in the case study, since FGC wants to reduce the number of (potentially unnecessary) inspections and intermediate system repairs for each cargo locomotive. In fact, such strategies are considered to be an output of a continuous monitoring system. By implementing a predictive maintenance type, as it is specified in strategy 4 and taken into consideration for the case study, the inspection frequency is increased by introducing sensors, which will trigger unusual behaviours on real-time conditions of the most critical components. Concisely, a continuous monitoring system provides a remote real-time inspection frequency and therefore one can predict when is suitable to provide a system repair regarding the condition of the component or subsystem. In addition to strategy 4, strategy 5 ensures the maintainability of the components with high severity numbers by employing sensors. Once again, this strategy is aligned with the goal of having a continuous monitoring system. Finally, strategy 7 is associated with strategies 3 and 6 since this strategy is an output of a continuous monitoring system. With a continuous monitoring system, it is possible to predict the failure of a component and therefore plan beforehand the number of spare parts to have on-site.

Finally, a continuous monitoring system, which is the goal to be implemented in the case study, is obtained with a combination of strategies 2 to 5. This enables to reduce the occurrence of several failure modes, since these are being monitored and one can predict the most advantageous time to replace or repair the component, increase the detectability of critical failure modes, by increasing the probability of detecting the failure mode before it turns critical with abnormal behaviours, and to decrease the severity, by providing condition-based repairs to the most critical components.

5. Simulation Model of FGC

This chapter illustrates the simulation model that was developed to study the availability and the reliability of the different components of the system, regarding the stochastic behaviour of the occurrence of failure and repair, and its impact on the system. The reliability block diagram of the bogie system is described, and the analytical model and its results are demonstrated. Following this, the algorithm of the proposed DES model is explained, and several potential simulation scenarios for the reliability and availability are considered and described. Finally, the results of these models are discussed and compared.

5.1. Reliability Block Diagram (RBD)

Following the functional breakdown and the FMECA analysis of the bogie discussed in section 4 and where each subsystems function was described and the critical subsystems, components and the associated failure modes were identified (Table 4.10), the RBD for the present case study was built with the guidance of Table 5.1 reliability and maintenance data and Figure 5.1 configuration of the bogie. For the analysis, the failure data and part of the repair data were obtained from the previous studies [78,79], while the additional repair data was obtained from previous maintenance experiences using expert judgment techniques. The reliability-wise relationships, which link each block, were also based in the FTA analysis performed in [78] (article analysis described in section 4.4). Moreover, the number of elements were not only based on FGC's technical drawings (in fact, some technical drawing of the bogie were provided to the case study, nevertheless, the scarce information embedded in these drawings was impractical to process), but also on KTH Railway Book [84], a reference handbook of railway systems and vehicles composition and configuration.

Table 5.1 – Components reliability and maintainability input data for the RBD

Subsystem	Component	# of components	Failure Mode	Failure Distribution	Failure rate (1/h))	MTBF (h)	Distribution Parameters	MTTR (h)
Wheelset	Axle	3	Axle Crack	Lognormal	1.5E-05	66666.7	σ_{log} = 0.633, μ_{log} = 10.91	10
	Wheels	6	(Wheel out of round, Wheel cracks and notches, wheel build up material, wheel flat, profile under threshold)	Normal	5.171E-04	1933.9	σ = 693.52, μ = 1933.86	2
Axlebox	Axlebox	6	Absence of the cover box screw	Exponential	6.00E-05	16666.7	λ = 6.00E-05	10
		6	Housing not watertight	Exponential	1.20E-04	8333.3	λ = 1.20E-04	10
	Bearings	12	Bearing failure	Weibull	2.12E-06	5711.3	β = 1.5193, η = 6336.1	12
Bogie Frame	Frame	1	-	Weibull	1.18E-05	85083.3	β = 0.8422, η = 77751.2	8
Brake System	Brake	4	Brake Rigging - parts of brake rigging hanging	Exponential	2.01E-05	49751.2	λ = 2.01E-05	12
		4	Brake Rigging - Brake isolating cock	Exponential	2.01E-05	49751.2	λ = 2.01E-05	12
		6	Cast Iron Brake Block	Exponential	1.08E-04	9259.3	λ = 1.08E-04	12
		6	Composite Brake Block	Exponential	3.12E-05	32051.3	λ = 3.12E-05	12
	Pneumatic Braking system	6	Front air valve damaged	Exponential	6.00E-05	16666.7	λ = 6.00E-05	4
		2	Brake cylinder damaged	Exponential	6.00E-05	16666.7	λ = 6.00E-05	12
		6	Air distributor damaged	Exponential	3.00E-04	3333.3	λ = 3.00E-04	4
		6	Slack adjuster damaged	Exponential	2.40E-04	4166.7	λ = 2.40E-04	4
	Master/Auxiliary Compressor	3	-	Weibull	1.09E-04	9204.0	β = 1.1252, η = 9607.99	12
	Master/Auxiliary Compressor Driving Motor	3	-	Weibull	2.60E-05	38484.1	β = 1.2142, η = 41034.1	8
	Servo-motor in braking system	3	-	Weibull	8.76E-06	114211.6	β = 1.0221, η = 115243	6
	Other Elements of the pneumatic braking system	2	-	Weibull	1.92E-04	5221.5	β = 1.7743, η = 5867.3	2.5
	Other Elements of the braking system (pins, sleeves,…,)	2	-	Weibull	1.28E-04	7809.6	β = 2.4482, η = 8806.18	12
Suspension Elements	Helical Spring	12	Spring Buckle Fracture	Exponential	6.00E-05	16666.7	λ = 6.00E-05	10
	Helical Spring	12	Helical Spring broken	Exponential	6.00E-05	16666.7	λ = 6.00E-05	10
	Other Suspension elements	2	Bottoming between Axle-box housing and bogie frame	Exponential	1.44E-06	694444.4	λ = 1.44E-06	10
Electric Traction Module	Power transmission system	3	-	Weibull	3.99E-04	2507.9	β = 1.7098, η = 2811.91	10
	Shaft Coupling	3	-	Weibull	6.98E-05	14320.9	β = 326.203, η = 14346.2	10
	Traction Motor	3	-	Weibull	7.82E-06	127904.8	β = 0.87826, η = 119878	10
Number of elements		122						

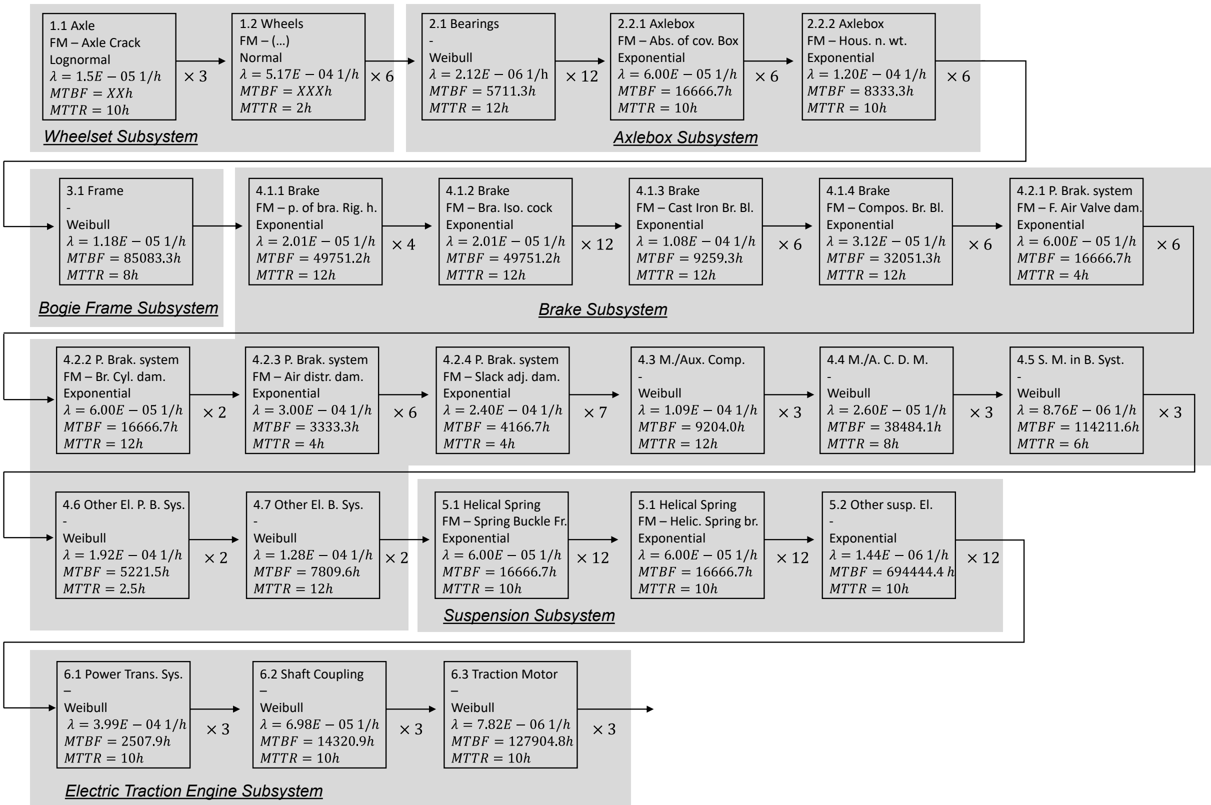


Figure 5.1 – RBD configuration of the 254 Class Locomotive Bogie

As one can verify from Figure 5.1, the RBD of the bogie is considered to be in series, which indicates that an item's or associated FM failure, will bring the system down i.e. the system will fail, which will consequently lead to the systems repair. Note that each block is characterized by: i) the item or FM ID, ii) the failure distribution function, iii) its failure rate, iv) its $MTBF$ v) each distribution function parameters and vi) its $MTTR$. Since the maintainability of the system is considered (by considering a repair time), the $MTBF$ is used and not the $MTTF$. The number of elements is exposed after each block and following the RBDs logical path.

5.2. Analytical Approach

To first comprehend the possible results of a reliability and availability simulation analysis of FGC's bogie, to identify key subsystems, components or the associated FMs and to validate any simulation model, an analytical approach was developed. Considering Figure 5.1 RBD configuration of the bogie and each block's reliability and maintainability parameters (failure and repair data, respectively), the analytical reliability and availability is obtained with the use of equations (3.1) and (3.2), since the bogie's functional breakdown and relationship-wise interdependencies is considered to be in series. Table 5.2 summarizes both analytical reliability and availability calculations performed to obtain the analytical reliability and availability of the total system. For each block, the failure and repair events are considered independent and the failure rate is considered to be constant (useful life period). Each failure event goes in accordance with each block's failure function distribution, while each repair assumes a deterministic value.

Table 5.2 – Analytical reliability and availability calculations considering the bogie's RBD

		Reliability	Availability
1.	**Wheelset System:**	$\boldsymbol{R_1 = \prod_{n=1}^{N} R_{1,n}\,,\ N = 2}$	$\boldsymbol{A_1 = \prod_{n=1}^{N} A_{1,n}\,,\ N = 2}$
i.	*Axle:*	$R_{1,1} = \prod_{n=1}^{N} R_{1,1,n}\,,\ N = 3$	$A_{1,1} = \prod_{n=1}^{N} A_{1,1,n}\,,\ N = 3$
ii.	*Wheels:*	$R_{1,2} = \prod_{n=1}^{N} R_{1,2,n}\,,\ N = 6$	$A_{1,2} = \prod_{n=1}^{N} A_{1,2,n}\,,\ N = 6$
2.	**Axlebox System:**	$\boldsymbol{R_2 = \prod_{n=1}^{N} R_{2,n}\,,\ N = 3}$	$\boldsymbol{A_2 = \prod_{n=1}^{N} A_{2,n}\,,\ N = 3}$
i.	*Bearings:*	$R_{2,1} = \prod_{n=1}^{N} R_{2,1,n}\,,\ N = 12$	$A_{2,1} = \prod_{n=1}^{N} A_{2,1,n}\,,\ N = 12$
ii.	*Axlebox FM1*	$R_{2,2} = \prod_{n=1}^{N} R_{2,2,n}\,,\ N = 6$	$A_{2,2} = \prod_{n=1}^{N} A_{2,2,n}\,,\ N = 6$
iii.	*Axlebox FM2*	$R_{2,3} = \prod_{n=1}^{N} R_{2,3,n}\,,\ N = 6$	$A_{2,3} = \prod_{n=1}^{N} A_{2,3,n}\,,\ N = 6$
3.	**Bogie Frame System:**	$\boldsymbol{R_3 = \prod_{n=1}^{N} R_{3,n}\,,\ N = 1}$	$\boldsymbol{A_3 = \prod_{n=1}^{N} A_{3,n}\,,\ N = 1}$
4.	**Brake System:**	$\boldsymbol{R_4 = \prod_{n=1}^{N} R_{4,n}\,,\ N = 13}$	$\boldsymbol{A_4 = \prod_{n=1}^{N} A_{4,n}\,,\ N = 13}$
i.	*Brake FM1:*	$R_{4,1} = \prod_{n=1}^{N} R_{4,1,n}\,,\ N = 4$	$A_{4,1} = \prod_{n=1}^{N} A_{4,1,n}\,,\ N = 4$
ii.	*Brake FM2:*	$R_{4,2} = \prod_{n=1}^{N} R_{4,2,n}\,,\ N = 4$	$A_{4,2} = \prod_{n=1}^{N} A_{4,2,n}\,,\ N = 4$
iii.	*Brake FM3:*	$R_{4,3} = \prod_{n=1}^{N} R_{4,3,n}\,,\ N = 6$	$A_{4,3} = \prod_{n=1}^{N} A_{4,3,n}\,,\ N = 6$
iv.	*Brake FM4:*	$R_{4,4} = \prod_{n=1}^{N} R_{4,4,n}\,,\ N = 6$	$A_{4,4} = \prod_{n=1}^{N} A_{4,4,n}\,,\ N = 6$
v.	*Pneumatic Braking System FM1:*	$R_{4,5} = \prod_{n=1}^{N} R_{4,5,n}\,,\ N = 6$	$A_{4,5} = \prod_{n=1}^{N} A_{4,5,n}\,,\ N = 6$
vi.	*Pneumatic Braking System FM2:*	$R_{4,6} = \prod_{n=1}^{N} R_{4,6,n}\,,\ N = 2$	$A_{4,6} = \prod_{n=1}^{N} A_{4,6,n}\,,\ N = 2$
vii.	*Pneumatic Braking System FM3:*	$R_{4,7} = \prod_{n=1}^{N} R_{4,7,n}\,,\ N = 6$	$A_{4,7} = \prod_{n=1}^{N} A_{4,7,n}\,,\ N = 6$
viii.	*Pneumatic Braking System FM4:*	$R_{4,8} = \prod_{n=1}^{N} R_{4,8,n}\,,\ N = 6$	$A_{4,8} = \prod_{1}^{N} A_{4,8,n}\,,\ N = 6$
ix.	*Master/aux. compressor:*	$R_{4,9} = \prod_{n=1}^{N} R_{4,9,n}\,,\ N = 3$	$A_{4,9} = \prod_{n=1}^{N} A_{4,9,n}\,,\ N = 3$
x.	*Master/au. Comp. driv. motor:*	$R_{4,10} = \prod_{n=1}^{N} R_{4,10,n}\,,\ N = 3$	$A_{4,10} = \prod_{n=1}^{N} A_{4,10,n}\,,\ N = 3$
xi.	*Servo motor braking system:*	$R_{4,11} = \prod_{n=1}^{N} R_{4,11,n}\,,\ N = 3$	$A_{4,11} = \prod_{n=1}^{N} A_{4,11,n}\,,\ N = 3$
xii.	*Other elements of pn. brak. sys.:*	$R_{4,12} = \prod_{n=1}^{N} R_{4,12,n}\,,\ N = 2$	$A_{4,12} = \prod_{n=1}^{N} A_{4,12,n}\,,\ N = 2$
xiii.	*Other elements of bra. Sys.:*	$R_{4,13} = \prod_{n=1}^{N} R_{4,13,n}\,,\ N = 2$	$A_{4,13} = \prod_{n=1}^{N} A_{4,13,n}\,,\ N = 2$
5.	**Suspension System:**	$\boldsymbol{R_5 = \prod_{n=1}^{N} R_{5,N}\,,\ N = 3}$	$\boldsymbol{A_5 = \prod_{n=1}^{N} A_{5,n}\,,\ N = 3}$
i.	*Helical Spring FM1:*	$R_{5,1} = \prod_{n=1}^{N} R_{5,1,n}\,,\ N = 12$	$A_{5,1} = \prod_{n=1}^{N} A_{5,1,n}\,,\ N = 12$
ii.	*Helical Spring FM2:*	$R_{5,2} = \prod_{n=1}^{N} R_{5,2,n}\,,\ N = 12$	$A_{5,2} = \prod_{n=1}^{N} A_{5,2,n}\,,\ N = 12$
iii.	*Other Suspension elements:*	$R_{5,3} = \prod_{n=1}^{N} R_{5,3,n}\,,\ N = 2$	$A_{5,3} = \prod_{n=1}^{N} A_{5,3,n}\,,\ N = 2$
6.	**Electric Traction Engine System:**	$\boldsymbol{R_6 = \prod_{n=1}^{N} R_{6,n}\,,\ N = 3}$	$\boldsymbol{A_6 = \prod_{n=1}^{N} A_{6,n}\,, N = 3}$
i.	*Power transmission system:*	$R_{6,1} = \prod_{n=1}^{N} R_{6,1,n}\,,\ N = 3$	$A_{6,1} = \prod_{n=1}^{N} A_{6,1,n}\,,\ N = 3$
ii.	*Shaft Coupling:*	$R_{6,2} = \prod_{n=1}^{N} R_{6,2,n}\,,\ N = 3$	$A_{6,2} = \prod_{n=1}^{N} A_{6,2,n}\,,\ N = 3$
iii.	*Traction Motor:*	$R_{6,3} = \prod_{n=1}^{N} R_{6,3,n}\,,\ N = 3$	$A_{6,3} = \prod_{n=1}^{N} A_{6,3,n}\,,\ N = 3$
	Total System	$\boldsymbol{R_s = \prod_{n=1}^{N} R_n\,, \qquad N = 6}$	$\boldsymbol{A_s = \prod_{n=1}^{N} A_n\,, \qquad N = 6}$

5.3. Discrete Event Simulation Model

A Discrete Event Simulation (DES) model is organized in a time interval, where the sequence of events is observed and analysed. In a RAMS analysis, tasks are modelled as discrete and the simulation is run with chronologically ordered steps. Consequently, simulations assess the importance of the time-dependent tasks, such as the failure or the repair of some component, over the operation of the system. By characterizing each task with its failure and/or repair time distribution function, the overall sequence of events is obtained, and the reliability and availability of the total system is gathered. From a practical perspective, a DES model starts by considering the total system operational until a failure of a component occurs. The event of failure switches the total system functionality to a down-state, until the repair event of the components failure is achieved, where the total system functionality reverts its state to an up-state. This sequence of events is chronologically ordered until a certain simulation time. All the performance measures, such as the downtime of the system or the time the system failed, are collected to produce the reliability and availability of the system. To guarantee a robust analysis, with relevant conclusions and statistically independent results, since the model makes use of random variables to describe the failure and/or the repair times, the number of simulations N, which are considered independent experiments, and the simulation time T must be previously defined. The implementation was done using an already under development program created by [85] and modelled in the commercial software package *Simulink* of *MATLAB*, for the reliability and availability analysis of an experimental tokamak nuclear fusion reactor that is being built in order to produce energy from thermonuclear fusion (ITER Project). Two distinctive models were created, a reliability model and an availability model, where in each model several scenarios were considered. Both are based on DES, where some activity blocks are identical.

5.3.1. Reliability Model

Considering that the reliability is defined as the probability that the system has not failed by time t, the reliability DES model is built with the ambition of producing failure events that contribute to the definition of the bogie system reliability. Therefore, a single simulation objective is to compute the first system's failure, which with an adequate number of simulations N, will lead to a histogram and, consequently, to a reliability curve. If no failure is observed in the system, then the simulation time is used as a right censored object/data. Figure 5.2 presents the flowchart algorithm of the reliability DES model for N simulations.

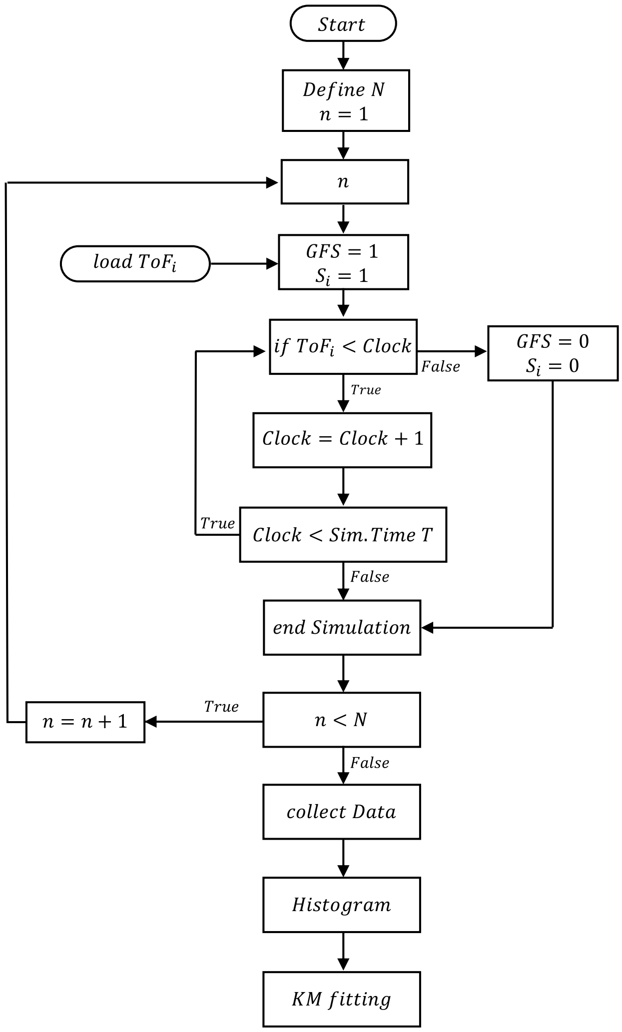


Figure 5.2 – Flowchart describing the algorithm of the reliability DES model

The reliability DES model starts by defining the number of simulations N and by creating a simulation variable n, which defines the simulation run on which the model is operating. In each simulation run, the model starts by creating a Global Final Signal (GFS) and a signal for component i (S_i)). At the same time, a random time of failure (ToF), which goes according to the distribution function of each block (component or FM), is generated, and allocated to each block. The random generation of ToF goes as explained in sections 3.3 and 3.4, which demonstrates the generation of a random quantile following a distribution function of interest and a Monte Carlo simulation approach. As part of a DES model, the first event happens (the lowest ToF, when in series) whenever the clock reaches its event time. Therefore, after reaching the first failure, the GFS is switched to 0, as well as the S_i for the component i responsible for the failure event. Note that only the S_i of the failed component or associated FM is switched to 0, in order to posteriorly collect the information on the impact of each component on the reliability of the total system. If no event happens, i.e. all random ToF are higher than the actual simulation time, the simulation ends, and the simulation time data is gathered as a right censored data. After all simulation runs are conducted, i.e. n is equal to N, the failure data is collected and a histogram of the number of failures is obtained. By using the non-parametric Kaplan-Meier estimator (KM), which is used to estimate survival curves from lifetime data, reliability curves are obtained from the failure data gathered from the simulation results. From a practical point of view, the functions *Surv* and *Survfit* from the *Survival* package [86] in *R* software are used to estimate the reliability curves of the total system and each subsystem. It is worth mentioning that the reliability DES model does not contemplate repairable systems, i.e. after a component fails, it is not repaired. Therefore, the maintainability parameter $MTTR$ is not taken into consideration.

To model the operational behaviour of the cargo locomotive bogie of FGC, there was the need to consider several assumptions. The assumptions for each block and for the simulation model go according to [85] and are the following:

- Each component starts the simulation in a state "As Good as New" (AGAN);
- Each component has its own activity-block that produces a Boolean signal (S_i):
  - 1 = the component is up and operating;
  - 0 = the component is down;
- Each component has its own unique reliability characteristics:
  - $MTBF_i$ and Failure rate λ_i;
- Each component has its own uniform ToF generator, which is based on the failure distribution function associated with each individual component;
- Failures correspond to state changes and occur instantaneously;
- The simulation ends at a predetermined time T.

Following the configuration and assumptions of the model and to test the robustness of the results of the model in the presence of uncertainty, five scenarios were created to study the reliability of the bogie system and each subsystem. Table 5.3 summarizes each individual scenario, where emphasis is put on the generation of the ToF, being this the only difference between each individual scenario.

Table 5.3 – Summary of the different scenarios considered for the reliability DES model of the cargo locomotive bogie

Scenarios	**Description**
Scenario 1	- each individual block has an independent $URNG$
Scenario 2	- all blocks (122) failures are correlated with a correlation factor $\rho_{i,j}$ of $\mathbf{0.2}$
Scenario 3	- all blocks (122) failures are correlated with a correlation factor $\rho_{i,j}$ of $\mathbf{0.5}$
Scenario 4	- within each subsystem (6), all failures are correlated with a correlation factor $\rho_{i,j}$ of $\mathbf{0.2}$
Scenario 5	- within each subsystem (6), all failures are correlated with a correlation factor $\rho_{i,j}$ of $\mathbf{0.5}$

As one can verify, scenario 1 is the already above described reliability DES model, were the ToF of each block (component or FM) is obtained with an independent uniform random number generator ($URNG$), which generates the probability $p = U_i \in [0,1]$ and produces a quantile of a distribution function of interest. Scenarios 2 and 3 control the correlation of failures in the bogies system level, meaning that all randomly generated probabilities $p_i \in [0,1], i \in [1,122]$ are correlated with a correlation factor $\rho_{i,j}$ of 0.2

and 0.5 in scenarios 2 and 3, respectively. Note that $\rho_{i,j} = \sigma_{i,j}$ when the standard normal distribution is considered. In each case, the covariance matrix is the following:

$$\sum_2 = \begin{pmatrix} 1 & 0.2 \cdots 0.2 \\ 0.2 & 1 \cdots 0.2 \\ \cdots & \cdots \dots \cdots \\ 0.2 0.2 \cdots & 1 \end{pmatrix}_{[122x122]} \qquad \sum_3 = \begin{pmatrix} 1 & 0.5 \cdots 0.5 \\ 0.5 & 1 \cdots 0.5 \\ \cdots & \cdots \dots \cdots \\ 0.5 0.5 \cdots & 1 \end{pmatrix}_{[122x122]}$$

Scenarios 4 and 5 focus on the correlation of failures in the bogie's subsystem level, meaning that each component or FM failure is correlated at the subsystem level and therefore both scenarios assume independence of each subsystem failure. For scenario 4, the correlation factor $\rho_{i,j}$ is assumed to be 0.2, corresponding to a low correlation between failures within each subsystem, while in scenario 5 the correlation factor $\rho_{i,j}$ is assumed to be 0.5, where the correlation between failures is stronger. In each case, the covariance matrix is similar to $\sum_2$ and $\sum_3$, just differing in the matrix dimensions. For both cases, each subsystem covariance matrix (total of six subsystems, therefore six covariance matrixes) has a dimension equal to the number of components or FMs comprising that same subsystem. Note that in an independent $URNG$, there is no correlation between failures, resulting in a correlation factor $\rho_{i,j}$ between failures of 0. In practical terms, the correlation of failures in scenarios 2 to 5 is obtained with the use of the *mvnrnd* and *normcdf* functions of the *Matlab* software, where the process for obtaining the multivariate normal probabilities is equal to the process explained in section 3.6. Moreover, to obtain the multivariate normal probabilities a mean vector $\vec{\mu}$ is needed. For the present case study, the standard normal distribution was considered, therefore the mean vector is equal to $\vec{\mu} = [0\ 0 \dots 0_n]_{[1xn]}$ where n is the number of components or FMs considered.

5.3.2. Availability Model

For the simulation of the availability of a complex system, a DES model can take many forms, nevertheless, two models and assumptions are typically considered. One is the synchronous model, which assumes that every component behaves independently, i.e. whenever a failure occurs to a component and the system goes down for its repair, the other components' clock keeps running, resulting in an abrupt wear of the system, with lower availability projections. Alternatively, the asynchronous model considers independence of components, meaning that when the system goes down due to a component failure, the operational working time of each component is not affected by modelling each component with an additional individual clock (internal clock) that delays its ToF according to the time needed for repair. In practice, Figure 5.3 demonstrates the difference between both simulation approaches, where a schematic of the state change in the signal of the component and of the system in both models is demonstrated. As one can verify from Figure 5.3, in an asynchronous model each component's clock is delayed by the TTR_i (Time To Repair of component i), meaning its ToF is expanded. It is worth mention that the difference between both modelling approaches can be overlooked when the order of magnitude of the $MTTR$ is small enough compared to the $MTBF$, which is the case being analysed. Nevertheless, in order to guarantee a robust analysis, the latter approach is considered for the case study.

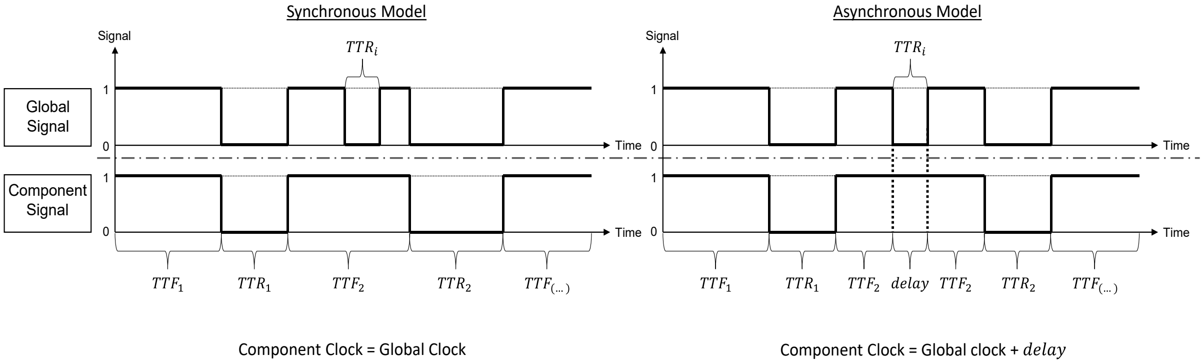


Figure 5.3 – Graphic Illustration of the global signal and the components signal with a) a synchronous Model and b) an asynchronous Model

Considering that in a given simulation, the availability is defined as the mean availability due to all downing events, i.e. the system is not operating, the availability DES model is constructed with the objective of defining all downtime events which contribute to the definition of the availability of the bogie system. Consequently, a single simulation objective is to compute all system's failures and its associated repairs, in order to gather the total downtime considering the simulation time T. Figure 5.4 presents the flowchart of the availability DES model for N simulations. The availability DES model starts by defining the number of simulations N and by creating a simulation variable n, which defines the simulation run on which the model is operating. In each simulation run, the model starts by creating a GFS, S_i, the global clock ($GClock$), each components clock ($Clock_i$) and the total component time of each component i (TCT_i). The TCT_i is defined as the cumulative time a component i has been operating until failure and has been down due to repair, and is described by the following equation:

$$TCT_i = ToF_{1,i} + TTR_{1,i} + ToF_{2,i} + TTR_{2,i} + \cdots + ToF_{f,i} + TTR_{f,i} - delay = \left[\sum_{f=1}^{Nf} (ToF_{f,i} + TTR_{f,i})\right] - delay$$

where Nf is the total number of failures and of repairs in one simulation N and $delay$ when the system is down to repair due to other components, which is comprised on each component $Clock_i$. At the same time, a random ToF, which goes according to the distribution function of each block (component or FM), is generated, and allocated to each block. In a simulation run, the GFS is the signal that rules the simulation. Consequently, within a time step there are three possible events that can either bring no change to the signal or trigger the signal. These are: i) there is no failure at all (**A**); ii) there is a failure but does not come from component i (**B**) and iii) there is a failure and it is due component i (**C**).

Starting with the first case (**A**), if there is no failure at all, the system is available which implicates that GFS is equal to 1. $Clock_i$ is compared with the sum of ToF_i and TCT_i. If $Clock_i$ is lower than the sum, meaning no failure is occurring, $Clock_i$ is incremented by one time-step and GFS is tested again. Otherwise $Clock_i$ is equal to the sum, which indicates that component i has failed, S_i is switched to 0, and, in case it is critical (which for the case study of interest is true, since all components are in series), GFS is changed to 0. Since component i has failed, its TTR_i is loaded and the repair process is started. The repair process only finishes if $Clock_i$ is equal to the sum of ToF_i, TCT_i and TTR_i. During this process, where the repair is ongoing, $Clock_i$ is incremented with one time-step. After the repair process is finished, TCT_i is equalized to the components clock, S_i and GFS are changed to 1, a new ToF_i is generated and the initial step, where GFS is evaluated, starts again. Considering both cases, where there has been a failure and GFS is equal to 0, a comparison between S_i and GFS is made. If S_i is not equal to GFS, i.e. component i has not failed and therefore the failure comes from another component (**B**), $Clock_i$ does not change. This enables to consider the $delay$ in ToF_i whenever another component fails and starts its repair. Otherwise, S_i and GFS are equal, meaning component i has failed (**C**). Here, $Clock_i$ is incremented since the repair process is ongoing. Both cases (**B)** and (**C)** are only achievable if there is a feedback in each time step of S_i. Each simulation run n only ends, if the $GClock$ equals the simulation time T Like the reliability model, after all simulation runs are conducted, i.e. n is equal to N, the data is collected.

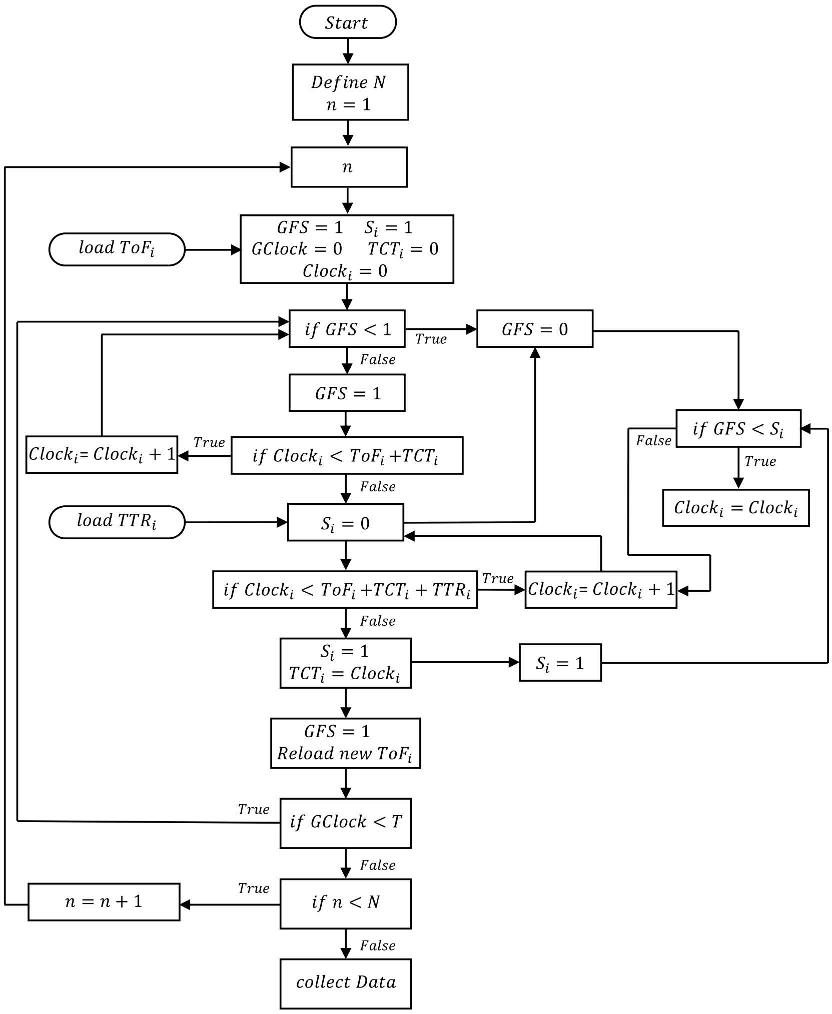


Figure 5.4 – Flowchart describing the algorithm of the availability DES model for one component

In addition to the reliability DES model assumptions for each block, the following assumptions were also considered for the availability DES model [85]:

- Each component is connected to two clocks: an individual clock and the system's clock (interdependency of each component with the system):
  - A failure of a component of the system, which brings the system down, generates a delay in the operational clock of other components clock (internal clock);
- Each component behaves with an operation – failure – maintenance and delay cycle;
- Each component has its unique maintainability characteristics (in addition to the reliability characteristics): $MTTR_i$;
- Each component has its own Time to Repair generator, which is a constant in some scenarios or a randomly generated number, based on a distribution function, in others;
- Whenever a failure occurs, maintenance starts immediately, and its duration is TTR_i;
- The model assumes idealized repairs, which restore a component to as good as new condition;
- Failures of other components, delay the internal clocks of other non-failing components by the same amount of time the system is not operational, which is the TTR_i of the failed component i;

Note that downtimes caused by preventive maintenance and inspections are not included in the model, only corrective repairs which restore the components reliability to an $AGAN$ state. Moreover, since the bogie system is considered to be in series, each component is critical, meaning its failure causes the system to fail. Following the configuration and assumptions of the model, ten scenarios were created to study the availability of the bogie system and each subsystem, and to perform a sensitivity analysis. Table 5.4 summarizes each individual scenario, where similarities can be verified which go according to the scenarios modelled for the reliability DES model.

Table 5.4 – Summary of the different scenarios considered for the availability DES model of the cargo locomotive bogie

Scenarios	**Description**
Scenario 1	- each individual block has an independent $URNG$ and the repair duration is deterministic
Scenario 2	- each individual block has an independent $URNG$ and the repair duration follows a PERT Dist.
Scenario 3	- Sc.1 where all blocks (122) failures are correlated with a correlation factor $\rho_{i,j}$of $\mathbf{0.2}$
Scenario 4	- Sc.1 where all blocks (122) failures are correlated with a correlation factor $\rho_{i,j}$ of $\mathbf{0.5}$
Scenario 5	- Sc.1 within each subsystem (6), all failures are correlated with a correlation factor $\rho_{i,j}$ of $\mathbf{0.2}$
Scenario 6	- Sc.1 within each subsystem (6), all failures are correlated with a correlation factor $\rho_{i,j}$ of $\mathbf{0.5}$
Scenario 7	- Sc.2 where all blocks (122) failures are correlated with a correlation factor $\rho_{i,j}$ of $\mathbf{0.2}$
Scenario 8	- Sc.2 where all blocks (122) failures are correlated with a correlation factor $\rho_{i,j}$ of $\mathbf{0.5}$
Scenario 9	- Sc.2 within each subsystem (6), all failures are correlated with a correlation factor $\rho_{i,j}$ of $\mathbf{0.2}$
Scenario 10	- Sc.2 within each subsystem (6), all failures are correlated with a correlation factor $\rho_{i,j}$ of $\mathbf{0.5}$

As Table 5.4 shows, scenario 1 is equal to the first scenario of the reliability DES model, with the addition of having the maintainability included, i.e. including the repair process, where repair durations are assumed to be deterministic. The repair durations are the $MTTR_i$ values of Table 5.1. Contrarily to scenario 1, scenario 2 assumes the repair durations as random variables, where the stochastic process is represented by a PERT distribution. The PERT parameters are the following:

$$a = 0.8 \times MTTR_i \qquad b = MTTR_i \qquad c = [1.5:2] \times MTTR_i$$

Where a is the minimum value the repair duration can take, b is the most likely value (mode) and c is the maximum value. For the maximum value c, a pseudorandom number between $[1.5:2]$ is generated to each block (122), in order to admit different repair durations. In scenarios 3 to 6, scenario 1 is used as basis, but applying the same ToF generators as in the reliability DES model. In scenarios 7 to 10, the same principles used in scenarios 3 to 6, are applied, respectively, nevertheless, these scenarios consider scenario 2 as a basis. The different random ToF generators are mentioned and explained in section 5.3.1 and go according to a MCS.

5.4. Results and concluding remarks

This section comprises all results from both the reliability and availability analytical models and the simulations models. The analytical results are compared with the simulations results, and further on, emphasis is put on the different simulation scenarios and its results. These are compared and discussed.

5.4.1. Analytical Results – Reliability and Availability

The analytical reliability results were calculated by considering an operation time of $t = 3000h$ and each distribution function characterizing the stochastic failure of each component or FM i with its parameters. The analytical reliability is graphically represented in Figure 5.5.

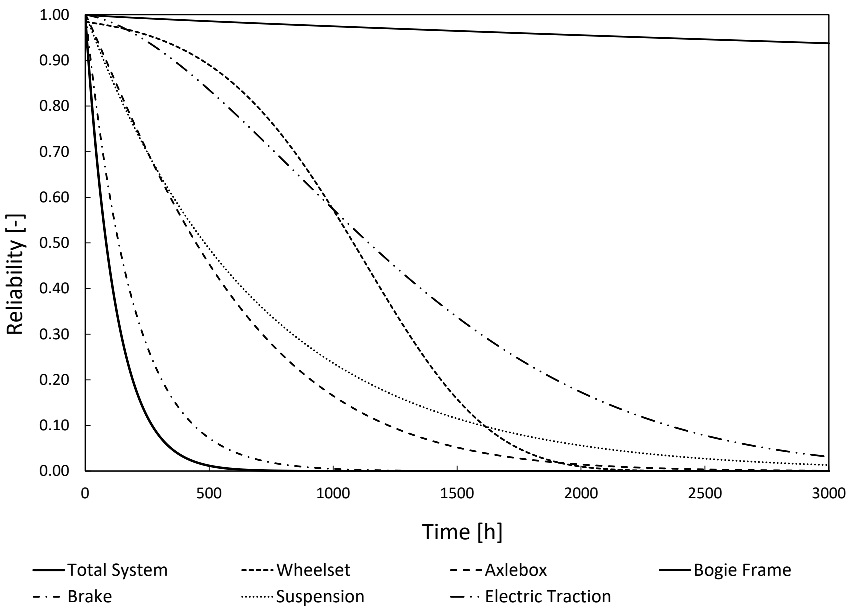


Figure 5.5 – Analytical reliability of the bogie system

Table B.1 (in Appendix B1) presents some analytical reliability values for key time units. From both Figure 5.5 and Table B.1, one can verify that the most impactful subsystems in the reliability of the total system are, indeed, the braking system, the suspension system and the axlebox system, respectively. This can be explained by the combination of the number of elements and each element low $MTBF_i$ comprising each subsystem of the bogie's configuration. Note that the lowest $MTBF_i$ comes from the wheelset (see Table 5.1). Nevertheless, since the number of elements comprising the wheelset system is much lower than other systems, e.g. braking system or the suspension system, the impact caused by the number of elements is greater than the $MTBF_i$ for each components/FM.

For the analytical availability, Table 5.5 presents the analytical availability of each subsystem and of the total bogie system. By combining the availability of every component accordingly to the reliability-wise relationships (in series), the analytical availability of each subsystem and of the total bogie system is obtained. Like in the analytical reliability results, the subsystem with the most considerable influence is the braking system ($A_4 = 96.416\%$), followed by the axlebox system ($A_2 = 96.466\%$) and the suspension system ($A_5 = 98.568\%$). The total system availability is projected to be $A_s = 89.771\%$. One should note that the analytical availability is just a possible projection of the availability of the bogie system, bearing in mind its reliability-wise relationship. Since the $MTTR_i$ are very small compared to the $MTBF_i$, the probability of having failures in other components when the system is down due to repair (i.e. when one component i fails and starts its repair), is low and therefore can be neglected. Nevertheless, when considering a high number of elements, such as the bogie of interest, this event can happen, resulting in lower availability projections and therefore showing the need to compare such results to simulation models.

Table 5.5 – Analytical Availability results

		Availability
1.	**Wheelset System:**	$A_1 = 99.337\%$
2.	**Axlebox System:**	$A_2 = 96.466\%$
3.	**Bogie Frame System:**	$A_3 = 99.991\%$
4.	**Brake System:**	$A_4 = 96.416\%$
5.	**Suspension System:**	$A_5 = 98.568\%$
6.	**Electric Traction Engine System:**	$A_6 = 98.583\%$
Total System		$A_s = 89.771\%$

5.4.2. Reliability Simulation results

Considering the reliability DES model algorithm, in each scenario a histogram of each subsystem and system failure is obtained, where a survival analysis is posteriorly performed to get each reliability curve. For scenario 1, a simulation time of $T = 50000h$ and $N = 1100$ simulations are considered, based on FGC's maintenance and average operating times. For the remaining scenarios (2 to 5), the same simulation time T is considered, but only $N = 250$, due to high computational efforts.

For scenario 1, Figure 5.6 shows the total system histogram (a), and each single subsystem histogram (b) which provokes the bogie to fail. As a matter of fact, in the initial time steps, the system which causes the bogie to fail most times is the wheelset system (above 10 failures). Nonetheless, in the long run, the braking system is clearly what persistently fails the most, followed by the axlebox system, the suspension system, electric traction engine system, wheelset system and, finally, the bogie frame system. Note that what defines the time range (x-axis) is the total system failures, which for the following scenario is lower than $700h$ for all failures of the bogie (from all $N = 1100$ simulations). Consequently, some system failures, like the failures from the bogie frame are not included in the total system since its failure occurs very rarely.

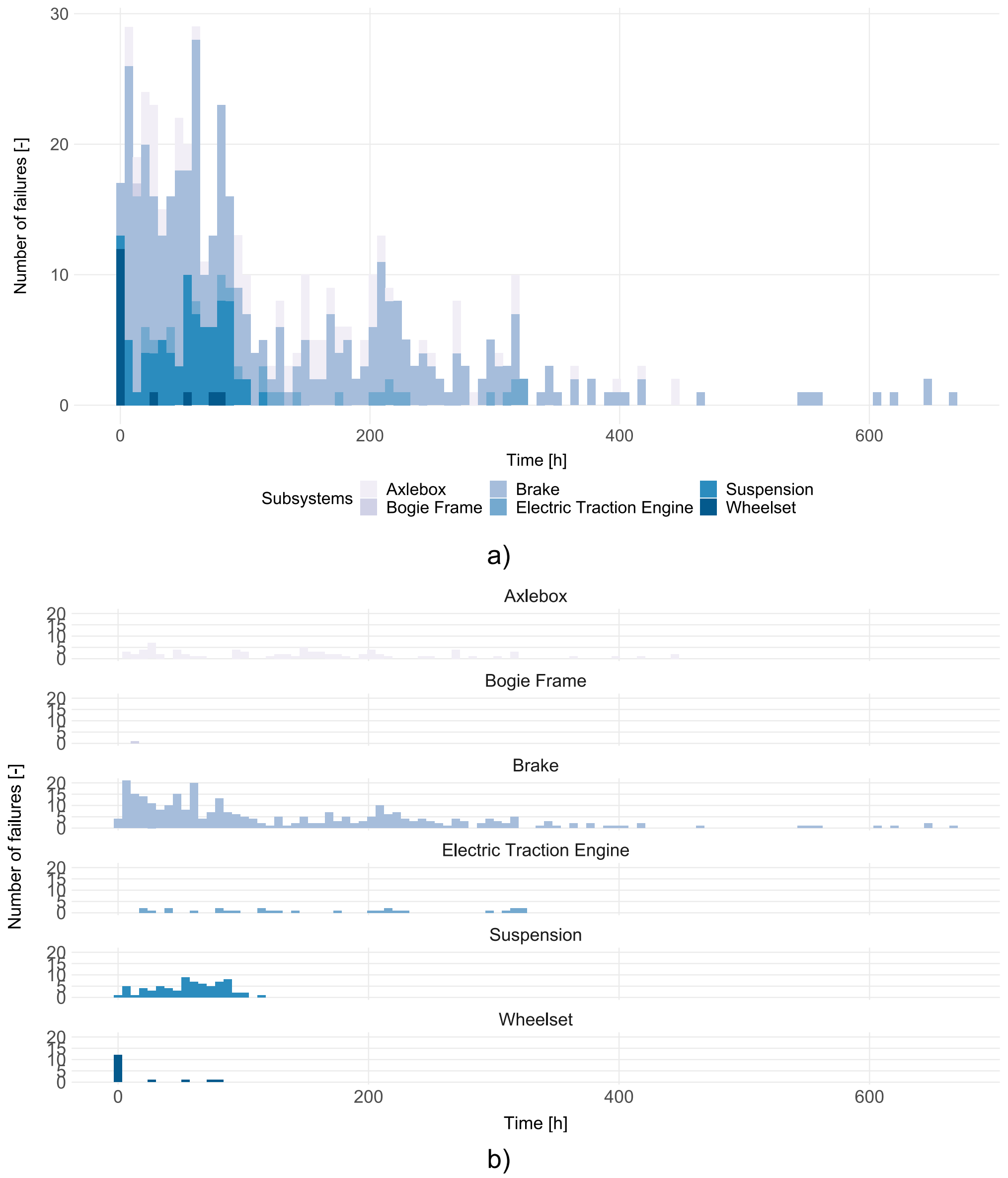


Figure 5.6 – Scenario 1 a) bogie total system histogram and b) each subsystems histogram

From these histograms, a survival analysis is performed in order to obtain the reliability curves of each subsystem and from the total bogie system. Figure 5.7 demonstrates the survival analysis performed to each subsystem and to the total system. In each graph, the KM-estimator and an empirical reliability is represented, which characterize the reliability of each individual subsystem and total system.

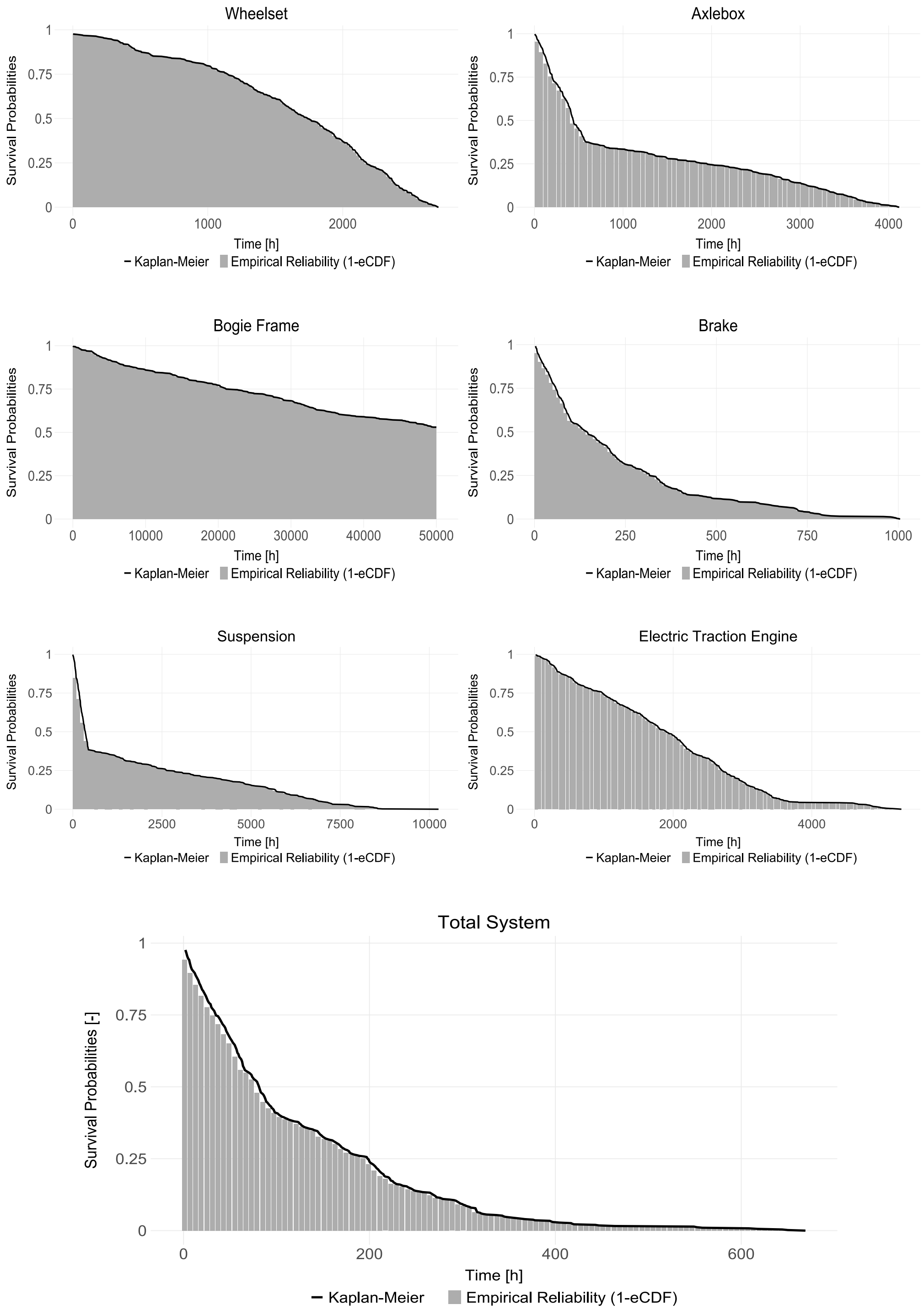


Figure 5.7 – Scenario 1 survival analysis of the Bogie's subsystems and total system

A summary of all reliability curves from scenario 1 is demonstrated in Figure 5.8. If compared with the analytical results obtained in Figure 5.5, one can verify that all reliability curves behave similarly. When comparing exact values from scenario 1 results with the analytical, for a reliability of $R_s = 0.8$ and $R_s = 0.5$, the system needs to operate $T_s \cong 26$ and $T_s \cong 82h$, respectively, as in the analytical model (see Table B.1) . As a result, this comparison verifies the reliability DES model and its algorithm. It should be noted that a comparison between the total bogie system reliability is sufficient since the reliability-wise relationship of the bogie is considered to be in series.

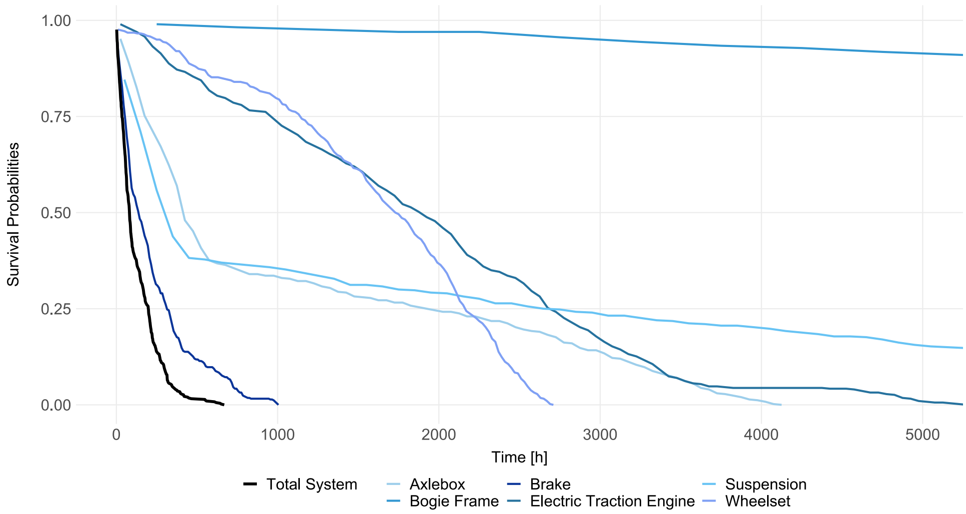


Figure 5.8 – Summary of all reliability curves of scenario 1

For the remaining scenarios, the same process and results were obtained and can be visualized for every scenario in Appendix B2. A summary of all scenarios is graphically exposed in Figure 5.9 where all the bogie total system reliability scenarios are represented.

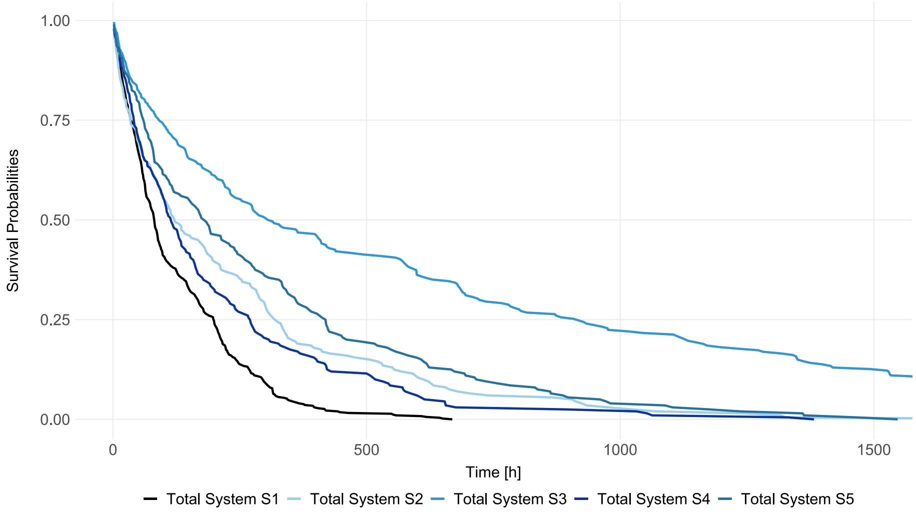


Figure 5.9 – Summary of the total bogie system reliability for scenarios S1 to S5

As expected, the bogie's reliability is higher in scenarios 2 to 5 than in the initial scenario 1 since a positive correlation of the failures is modelled in these scenarios. In addition, if one compares scenario 2 and scenario 3 with the bogie's reliability of scenario 4 and scenario 5, respectively, one can identify that by modelling a correlation of all failures within a system versus modelling the correlation of failures only in subsystems, results in higher reliabilities, with a histogram of failures more dispersed and with lower failures in each time bin (see scenario 2 to 5 histograms in Appendix B2). Moreover, the higher the correlation factor $\rho_{i,j}$ between failures, the higher the bogie's reliability (S2 vs. S3 and S4 vs. S5).

5.4.3. Availability Simulation results

For the simulation of the availability DES model for all availability DES model scenarios, a simulation time of $T = 50000h$ and $N = 50$ simulations were considered, based on FGC's maintenance, on the locomotive's lifecycle and on the confidence interval desired. Note that due to excessive computational efforts, the number of simulations N had to be retained low.

For scenario 1, Figure 5.10 shows the mean availability results for each simulation (a), the mean availability in function of the simulation time for one simulation, where the mean availability in one simulation is identical to the average availability obtained from all simulations (in this particular case $n = 22$) (b) and the mean availability results for all simulations of all subsystems represented in a Boxplot (c). The Boxplot is a measure of how distributed a data is from a data set. The Boxplot function represents (from bottom to top) the minimum, the first quartile, the median (2nd quartile), the third quartile and the maximum in the data set.

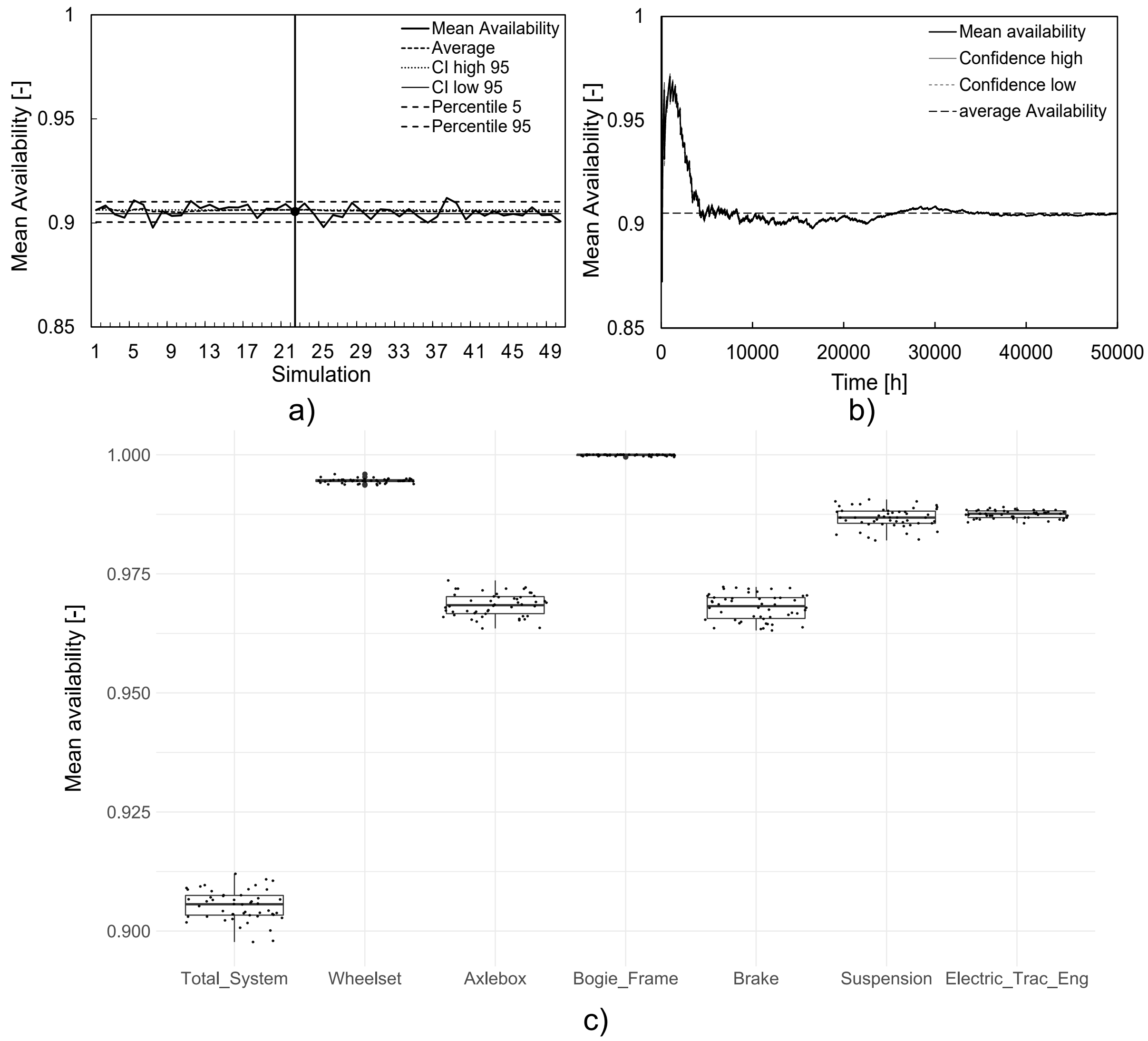


Figure 5.10 – Scenario 1 (a) mean availability results of the bogie system for each simulation, (b) mean availability in function of time for one simulation ($n = 22$) and (c) the mean availability results for all simulations of all subsystems

For scenario 1, the average availability of all simulations is $A_{S,1} = 90.53\%$. If compared with the analytical availability ($A_{S,A}$ = 89.77%), all availabilities, i.e. the bogie system and its subsystems, are higher, since in the analytical availability calculations, the failures of other components do not “delay” other components failures, resulting in lower availability projections. In addition, the most impactful systems as the braking system or the axlebox system, although they have a higher variability of mean availabilities for all the simulations, their lowest mean availability is higher than the analytical projections, resulting in a higher total system availability. For the remaining scenarios (2 to 10), the same graphical results were obtained and are illustrated in Appendix B3. A summary of the bogie’s system mean availability results for each scenario is presented in Figure 5.11.

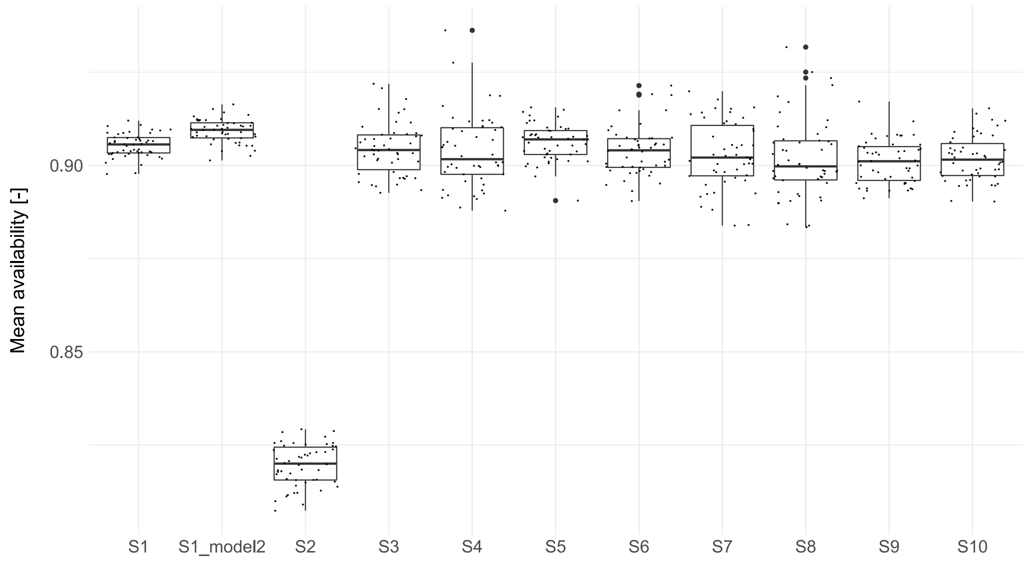


Figure 5.11 – Summary of the bogie’s mean availability for each scenario

Observe that an additional scenario ($S1\_model2$) was created, in order to model the acquisition of a new turning machine by FGC maintenance. The new turning machine reduces all wheelset repair durations to $MTTR_i = 0.5h$, resulting in a model equal to $S1$ but with the slight difference of having a new $MTTR_i$ for the wheelset (6 blocks). From Figure 5.11 it is possible to retrieve that the main difference between all scenarios is the variability of its results. Starting with $S1$ and $S1\_model2$ ($A_{S,1_{model2}}$ = 90.93%), it is clear that the new turning machine improves the availability projections (in this case by 0.44%), provoking less impact from the wheelset system to the total system availability. A major difference can be verified in $S2$ from the remaining scenarios (since $S2$ mean availability results differ very much from the remaining scenarios, an additional validation of $S2$ model is performed and is demonstrated in Appendix B3). What causes such low availability projections is the fact that the PERT distribution is considered to be a penalizing representation by assuming higher values of a random variable (in this case for the TTR_i), since its distribution function has a heavy tail, meaning the higher values are more widely distributed from the mode value than the minimum values. Indeed, the PERT parameters used for $S2$ penalize extremely the repair durations since the PERT parameter c is considered to be more far apart from b than a. By comparing the remaining scenarios ($S3 - S10$) with the initial scenario $S1$, one can confirm that assuming a correlation of failures does not have such an impact on the availability projections as one could expect. Especially, if one compares the scenarios availability projections with the results obtained from the reliability simulations projections. Nevertheless, the main difference to be identified in scenarios $S3$ to $S10$ is the variability of the results. First, the scenarios with correlation of failures in the component level (i.e. all blocks have correlated failures, $S3-S4$ and $S7-S8$) have a higher variability than the scenarios with correlation of failures in the subsystem level (i.e. only correlated failures within a subsystem, $S5-S6$ and $S9-S10$). Second, the scenarios with a low failure correlation, i.e. the correlation factor between failures is $\rho_{i,j}=0.2$ $(S3,S5,S7,S9)$, have a higher median availability than the scenarios with a higher correlation between failures, i.e. the correlation factor between failures is $\rho_{i,j}=0.5$ $(S4,S6,S8,S10)$. Nevertheless, the greater the correlation of failures, the greater the variability of the availability is. Third, the scenarios which consider deterministic repair durations $(S3-S6)$ have, as expected, higher availability projections and at the same time a lower variability of results than the scenarios which consider a stochastic repair duration $(S7-S10)$, respectively, due to having a stochastic behaviour in more than one variable (ToF_i and TTR_i) and due to the penalizing factor of the PERT distribution. Nonetheless, the scenarios with correlated failures and stochastic repair durations are not so penalized in terms of availability projections by the PERT distribution as $S2$.

5.4.4. Concluding remarks

In this chapter a reliability and availability DES model is built and implemented. With the aim of representing the real-case scenario of FGC, several scenarios are implemented and analysed. With the results obtained from the reliability and availability DES model, as well as with the development of the actual models and scenarios, a robust prognosis model is developed that can support decision-making in railway maintenance. For both models, the introduction of the variability of one or more parameters increases the reality of the operation in the model, therefore, allowing a greater flexibility in the estimation of possible scenarios that can represent a wider range of different circumstances in operation. As a result, these scenarios allow to identify the reliability and availability variations to that same variation of parameters. Special emphasis should be put on the availability results, since the variability of the results recognize where focus can be put on the uncertainty embedded in correlation of possible failures and/or in maintenance durations.

Finally, to mitigate risks of access to maintenance data, where detailed specifications can be scarce, the inclusion of several scenarios to project the reliability and availability of a bogie system is essential in order to model the sources of uncertainty which influence the most every estimate of the reliability and availability of a bogie system.

6. Conclusions and further research

6.1. Conclusions

This dissertation presents a reliability and availability assessment framework of a freight locomotive bogie, which follows a RAMS approach, with the objective of contributing to the maintenance decision-making in the railway industry as a diagnosis and prognosis model.

As part of the initial procedure of a RAMS analysis, the proposed framework starts by performing a Failure Mode and Effect Analysis (FMEA) in order to identify and prioritize the most critical components of the bogie system of interest. Due to limited information on the failure behaviour of some components and due to uncertainties associated with the long-term degradation process of key components, a reliability assessment method is also conducted. The proposed method combines the Cooke's Classical model (also known as Structured expert judgment) and the histogram technique with the aim of assessing performance-based lifetime distributions of long-service life components. To support the decision-making of the FMEA analysis, the proposed method is applied to the FGC's case study on the wheelset system of freight locomotive bogies to estimate the reliability/survival curves, and associated failure rates were obtained, resulting in the verification of the method. With the reference failure rates, a consolidated criticality analysis is performed and the most critical components in the bogie system are identified. Risk mitigation strategies are discussed, and focus is put on the strategies which follow the implementation of a predictive maintenance monitoring system.

After identifying the critical components and functional breakdown of the bogie, a Reliability Block diagram (RBD) of the bogie is obtained to identify the reliability-wise relationships of the bogie system. Based on the RBD, analytical and simulation models of both reliability and availability of the bogie of interest are modelled where emphasis is put on the variability of the stochastic parameters, which are modelled in alternative scenarios. The modelling approaches for each simulation model follow a Discrete Event Simulation (DES) approach. The verification of the simulation model is obtained by comparing the analytical results with the simulations results. The reliability simulation results show that a correlation of all failures in a component level compared to the correlation of failures in a sub-system level, as well as a higher correlation factor $\rho_{i,j}$ between failures, brings greater reliability projections. Most notably, and in opposition to the clear results obtained in the reliability model, the availability results show that the correlation of failure modes do not have significant impacts on the mean availability of the bogie system itself, but on its variability. Additionally, the results of the simulations show the penalizing impact of the PERT distribution, embedded in the repair durations, in the availability projections. The proposed simulation models confirm to be a useful solution to predict the reliability and the availability of a cargo locomotive bogie system. The simulation models might be extrapolated for more complex systems.

6.2. Limitations and Future Developments

Multiple limitations have characterized affected this work, nevertheless the main constraint is the lack of information provided by the case study operating train company FGC. A good starting point towards a good reliability and availability study is, obviously, reference maintenance sheets to identify and prioritize the uses cases being modelled (FMEA/FMECA). This was not possible, resulting in a generalized study based on results of several European studies results and not on the reference locomotive cargo bogie of FGC.

Extension of the present work can be done through several improvements and developments, such as:

1. Reliability Assessment Method:
   - the efficiency of the proposed method should be compared with real operation and maintenance data of the use-case of interest, or data obtained from computational models that can mimic the degradation behaviour or failure occurrences;
2. Reliability and Availability DES model:
   - Explore the application of repairs in the reliability DES model for a certain reliability value threshold to study the overall reliability curve of the bogie of interest;
   - Explore the application of downtimes caused by preventive maintenance and inspection tasks in the availability DES model to model a more real-case scenario, which replicates a train operating company day-to-day operation;
   - Implementation of imperfect maintenance tasks in the availability DES model i.e. maintenance tasks which do not restore the components reliability to an $AGAN$ state;
   - Study of the variability and of the variance of the availability results with an ANOVA test, Levene's test or Kruskal-Wallis test;
   - Study of negative correlation factors in the failure generation of components, i.e. negative correlation factors $\rho_{i,j}$ between failures and compare with the results obtained from the present work;
   - In case of sufficient data, explore the application of nonlinear-dependence measures to quantify component interdependencies [70] and therefore construct a real-case covariance matrix $\sum_{i,j}$;

Emphasis should be put on the application of the obtained results. These should support models that estimate real wear and failure occurrences and provide optimal maintenance and inspection intervals to reduce the lifecycle cost in the long-term of bogie components. Such results should also be integrated with maintenance planning and maintenance scheduling models, in order to improve the assets reliability, availability and the associated operational costs.

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Appendix A

A1 – Questionnaire: Seed and Target Questions

For the expert's assessment, in order to obtain the failure rates of the axle and the wheels, the following calibration questions and target questions were formulated:

Seed Questions:

1. Knowing that the average number per year of Railway Significant Accidents (i.e. accidents which include resulting fatalities and serious injuries) in Europe between 2010-2015 was 2074, how many significant accidents in Europe were there in 2016?

   5%__________ 50%__________ 95%____________

2. From the significant accidents in 2016, what was the percentage of fatalities and weighted serious injuries (FWSI) per significant accident? [%]

   5%__________ 50%__________ 95%____________

3. In 2017, there were 1908 significant accidents in Europe. How many of these accidents were caused by derailments of trains?

   5%__________ 50%__________ 95%____________

4. In 2017, there were in the 28 EU Countries 10026 total precursors. From these total precursors, how many belonged to the *"Broken Wheels and Broken Axles"* type?

   5%__________ 50%__________ 95%____________

Target Questions:

Axle:

Based on your experience and knowledge, from a sample of n=1000 locomotive axles, how many would fail in each interval?

1) 0 – 300,000 kms __________
2) 300,000kms – 600,000kms __________
3) 600,000kms – 900,000kms __________
4) 900,000kms – 1200,000kms __________
5) 1200,000kms – 1500,000km __________
6) 1500,000kms – 180,.000km __________
7) 1800,000kms – infinite __________

Wheels:

Based on your experience and knowledge, from a sample of n=1000 locomotive wheels, how many would fail in each interval?

1) 0 – 15,000 kms ___________
2) 15,000kms – 30,000kms ___________
3) 30,000kms – 45,000kms ___________
4) 45,000kms – 60,000kms ___________
5) 60.000kms – 75,000km ___________
6) 75,000kms – 90,000km ___________
7) 90,000kms – infinite ___________

For this batch, please present what could be a possible MDBF (in kms)? __________

A2 – Reliability Assessment Method: Fitting each expert's opinion

Table A.1 – AIC values for each probability distribution fit to each expert judgment on the axle failure

Distribution	AIC					
	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Weibull	309.44	363.81	558.39	3446.38	3176.37	**2614.10**
Normal	312.25	367.32	561.88	**3440.57**	**3173.73**	2624.91
Gamma	309.21	363.66	558.13	3553.26	3285.85	2616.32
Lognormal	**308.69**	**363.34**	**558.01**	3664.55	3385.31	2627.89
Exponential	325.68	379.35	598.35	4558.43	4618.45	3015.78

Table A.2 – AIC values for each probability distribution fit to each expert judgment on the wheel's failure

Distribution	AIC					
	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Weibull	**3509.07**	**2654.18**	**3380.18**	**1729.42**	**3192.99**	3030.61
Normal	3540.25	2687.15	3397.87	1732.75	3222.07	**3027.80**
Gamma	3522.01	2654.79	3398.06	1732.65	3448.87	3058.07
Lognormal	3554.52	2665.38	3434.54	1740.66	3602.68	3099.68
Exponential	4022.73	2844.47	3903.71	1933.19	4793.71	3537.13

Table A.3 – AIC values for the combined weighted expert opinion: axle and wheels

AIC - Axle		AIC - Wheels	
Distribution	**Combined Expert**	**Distribution**	**Combined Expert**
Weibull	2492.948	**Weibull**	3350.312
Normal	2520.536	**Normal**	**3348.156**
Gamma	2484.045	**Gamma**	3397.623
Lognormal	**2483.366**	**Lognormal**	3456.506
Exponential	2758.03	**Exponential**	4018.783

A3 – FMECA partial results

Table A.4 – Critical components based on the consolidated FMEA with Expert Judgment

Subsystem ID	Subsystem	Component ID	Component	Failure Mode	Severity	Occurrence	Failure rate (1/h))	Source
1	Wheelset	1.1	Axle	Axle Crack	**10**	3	1.5E-05	Expert Judgment
		1.2	Wheels	(Wheel out of round, Wheel cracks and notches, wheel build up material, wheel flat, profile under threshold)	8	9	5.171E-04	Expert Judgment
2	Axlebox	2.1	Axlebox	Absence of the cover box screw	8	8	6.00E-05	FMEA
				Housing not watertight	8	8	1.20E-04	FMEA
				Bearing Failure	**10**	5	2.12E-06	Literature [78]
3	Bogie Frame	3.1	Frame	-	9	7	1.18E-05	Literature [78]
4	Brake System	4.1	Brake	parts of brake rigging hanging	8	8	2.01E-05	FMEA
				Brake isolating cock	8	8	2.01E-05	FMEA
				Cast Iron Brake Block	6	8	1.08E-04	FMEA
				Composite Brake Block	6	8	3.12E-05	FMEA
		4.2	Pneumatic Braking system	Front air valve damaged	**10**	8	6.00E-05	FMEA
				Brake cylinder damaged	6	8	6.00E-05	FMEA
				Air distributor damaged	6	8	3.00E-04	FMEA
				Slack adjuster damaged	8	8	2.40E-04	FMEA
		4.3	Master/Auxiliary Compressor	-	9	8	1.09E-04	Literature [78]
		4.4	Master/Auxiliary Compressor Driving Motor	-	9	8	2.60E-05	Literature [78]
		4.5	Servo-motor in braking system	-	9	6	8.76E-06	Literature [78]
		4.6	Other Elements of the pneumatic braking system	-	9	8	1.92E-04	Literature [78]
		4.7	Other Elements of the braking system (pins, sleeves,…,)	-	9	8	1.28E-04	Literature [78]
5	Suspension Elements	5.1	Spring Buckle	Spring Buckle Fracture	**10**	8	6.00E-05	FMEA
		5.2	Helical Spring	Helical Spring broken	**10**	8	6.00E-05	FMEA
		5.4	Other Suspension elements	Bottoming between Axle-box housing and bogie frame	**10**	3	1.44E-06	FMEA
6	Electric Traction Module	6.1	Power transmission system	-	9	8	3.99E-04	Literature [79]
		6.2	Shaft Coupling	-	9	7	6.98E-05	Literature [79]
		6.3	Traction Motor	-	9	6	7.82E-06	Literature [79]

Appendix B

Analytical and Simulation Results

Part of the analytical results and simulation results of the simulation analysis for both the reliability and availability, regarding every scenario mentioned in section 5.3, are presented in this section.

B1 – Analytical Results

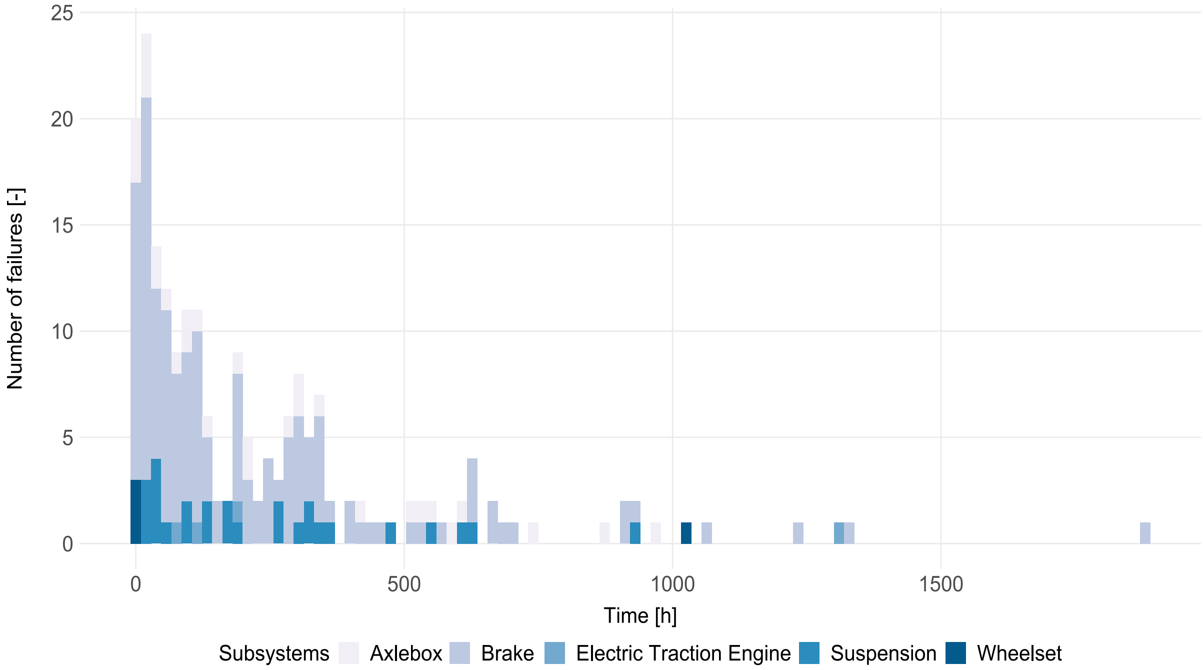
Table B.1 – Analytical reliability results for several time units

Time [h]	Total System	Wheelset	Axlebox	Bogie Frame	Brake	Suspension	Electric Traction Engine
0	1	1	1	1	1	1	1
25	0.8189	0.9825	0.9732	0.9989	0.8884	0.9674	0.9976
50	0.6678	0.9805	0.9427	0.9980	0.7804	0.9331	0.9941
75	0.5429	0.9783	0.9117	0.9972	0.6852	0.9000	0.9897
100	0.4402	0.9759	0.8806	0.9964	0.6014	0.8681	0.9846
200	0.1861	0.9636	0.7589	0.9935	0.3558	0.7515	0.9580
500	0.0117	0.8902	0.4540	0.9859	0.0722	0.4875	0.8354
1000	0.0001	0.5731	0.1650	0.9748	0.0048	0.2369	0.5740
2000	0.0000	0.0099	0.0145	0.9552	0.0000	0.0560	0.1729
3000	0.0000	0.0000	0.0008	0.9376	0.0000	0.0132	0.0313

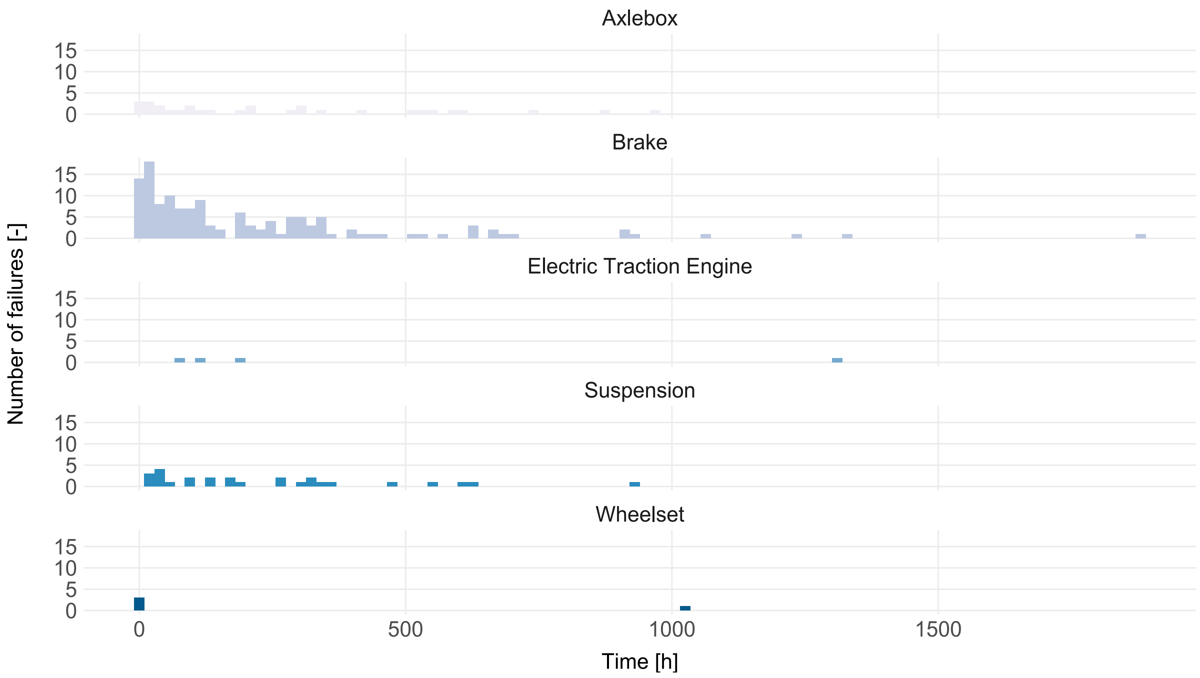
B2 – Reliability Simulation Results

The reliability simulation results for scenarios 2 to 5 are presented here. Note that for each scenario, the following results are presented: i) a histogram of the total system failure, where the number of failures for all simulations are demonstrated, ii) a decomposed histogram mentioning the number of failures in each subsystem and iii) the survival analysis behind the reliability curves of the total system and each subsystem.

Note: in the histogram of the total system, each bin is the sum of each subsystem failure.



a)



b)

Figure B.1 – Scenario 2 a) total histogram covering the number of failures of the system regarding each subsystem failure (note: each bin is the sum of each subsystem failure) and b) each subsystem histogram decomposed

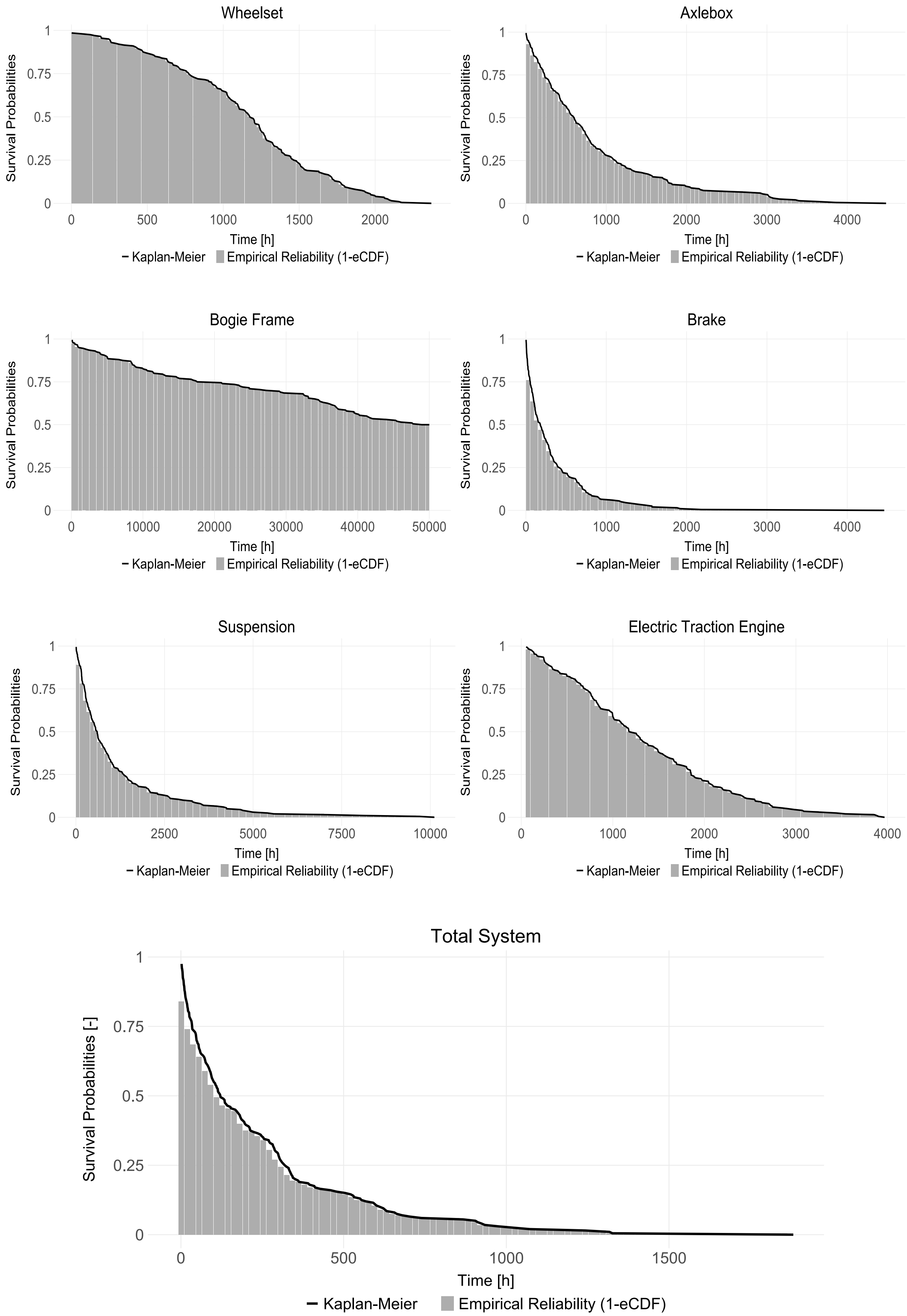


Figure B.2 – Scenario 2 survival Analysis of each subsystem and of the total system

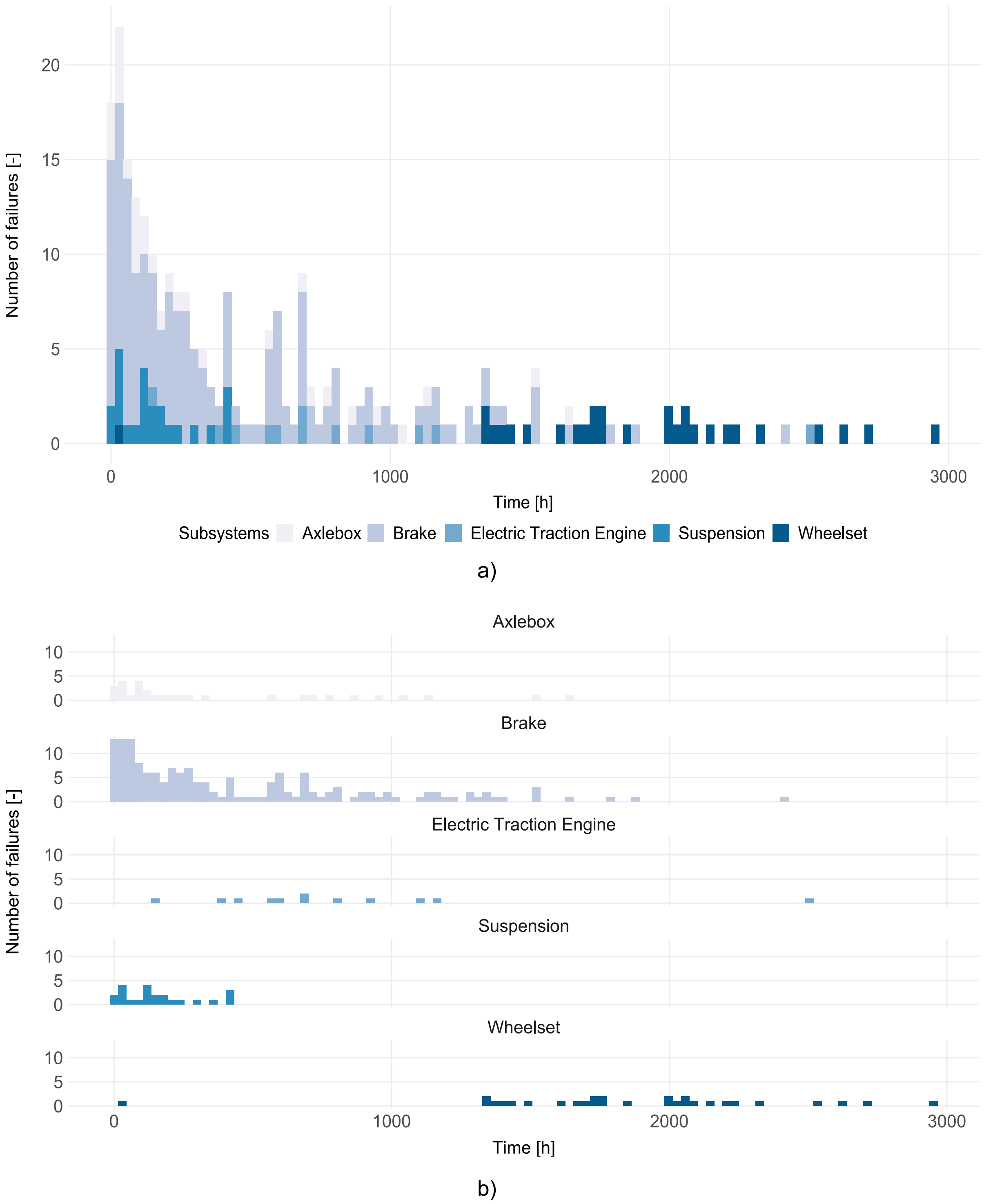


Figure B.3 – Scenario 3 a) total histogram covering the number of failures of the system regarding each subsystem failure and b) each subsystem histogram decomposed

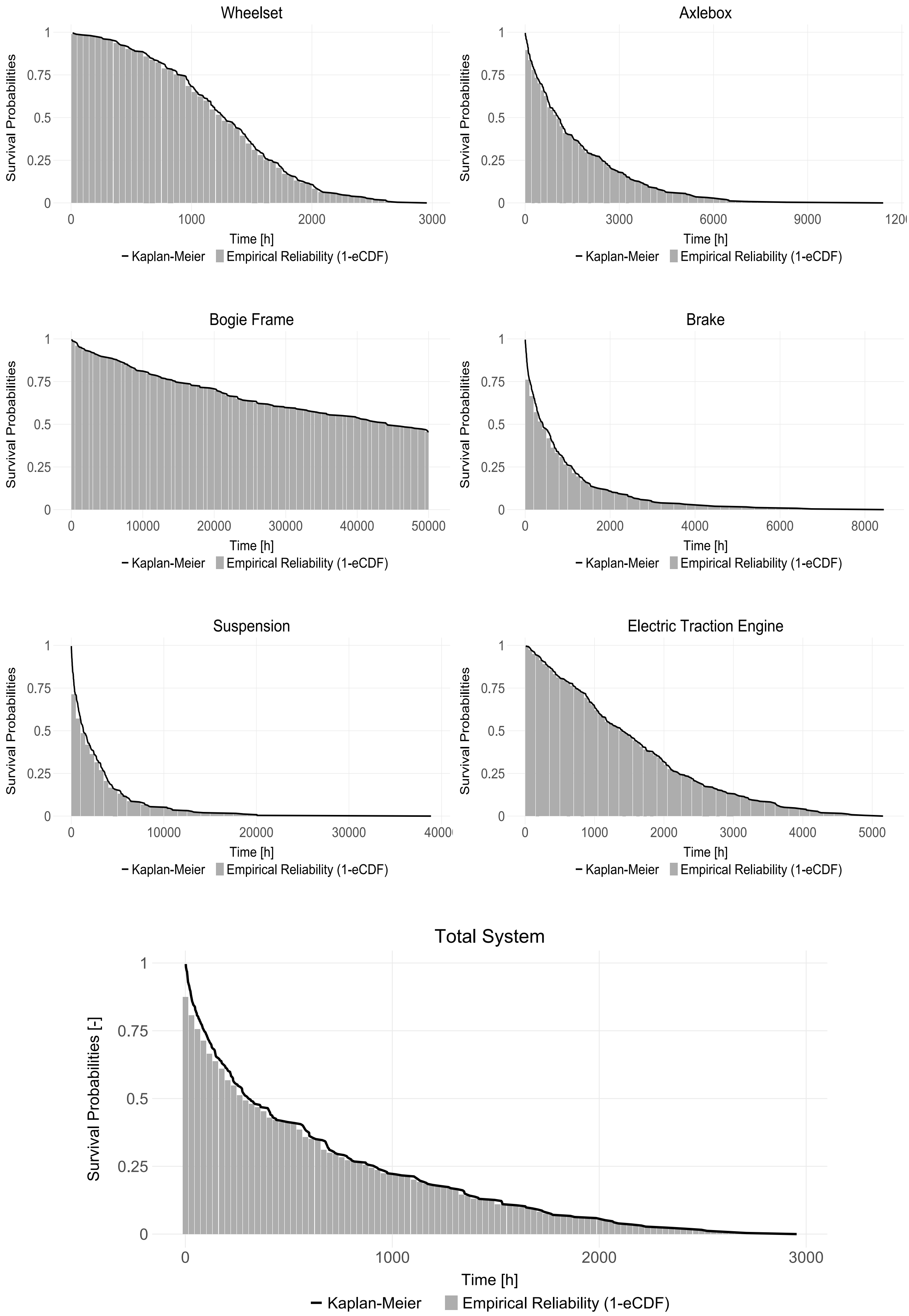
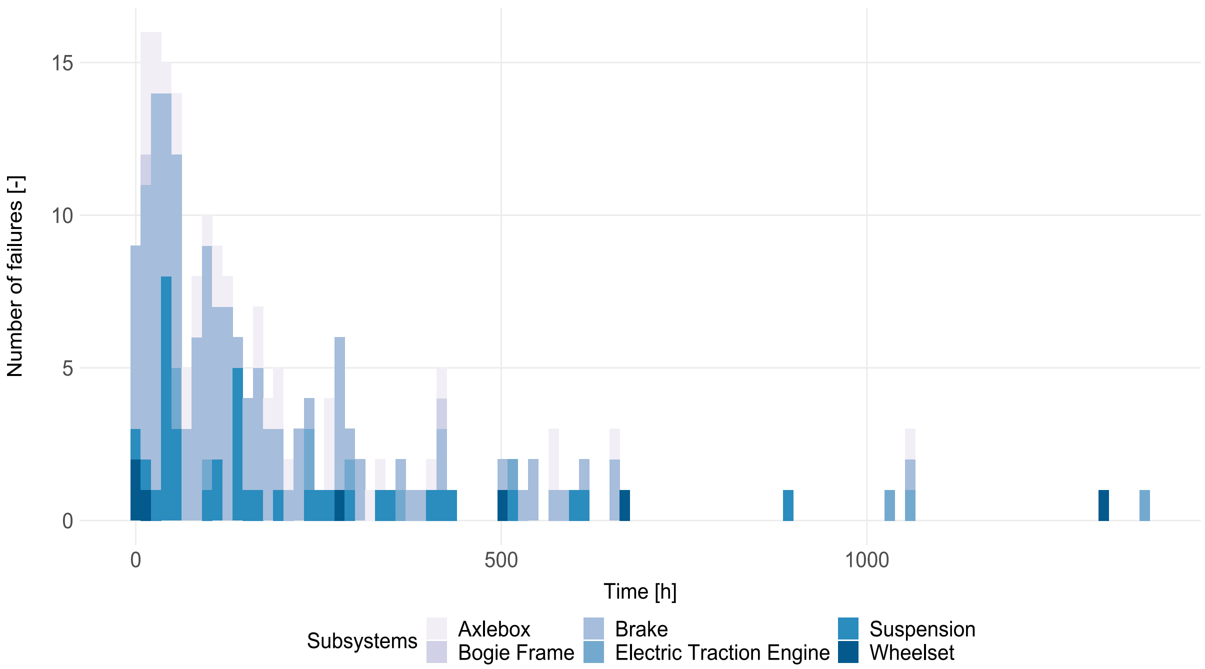
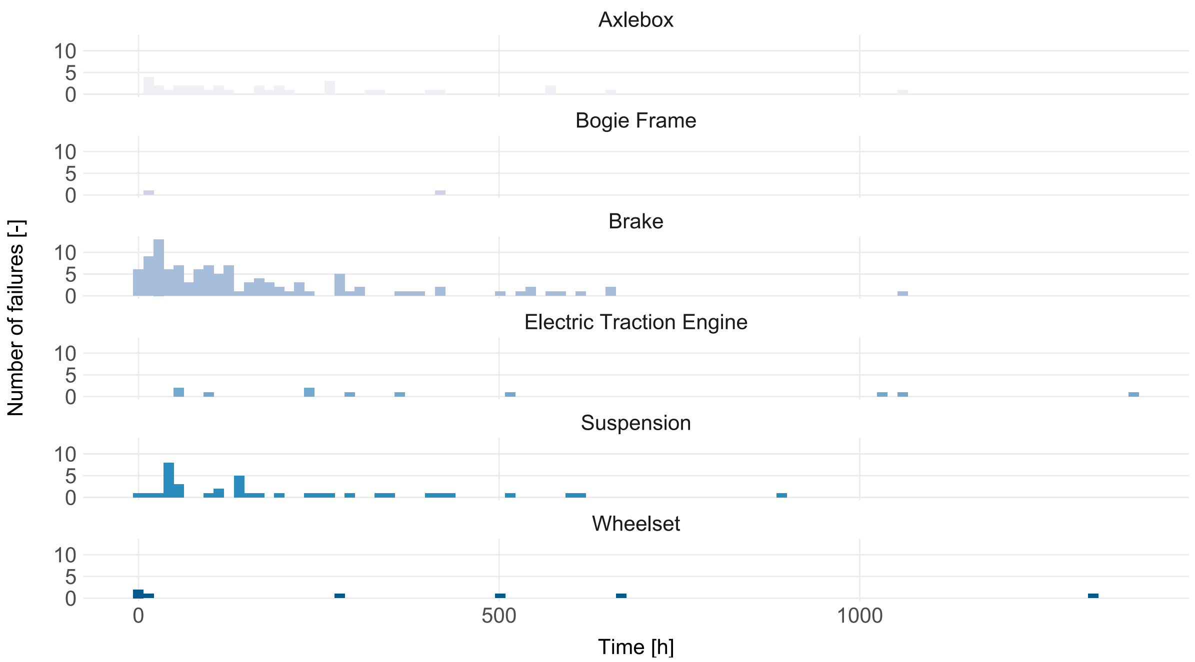


Figure B.4 – Scenario 3 survival Analysis of each subsystem and of the total system



a)



b)

Figure B.5 – Scenario 4 a) total histogram covering the number of failures of the system regarding each subsystem failure and b) each subsystem histogram decomposed

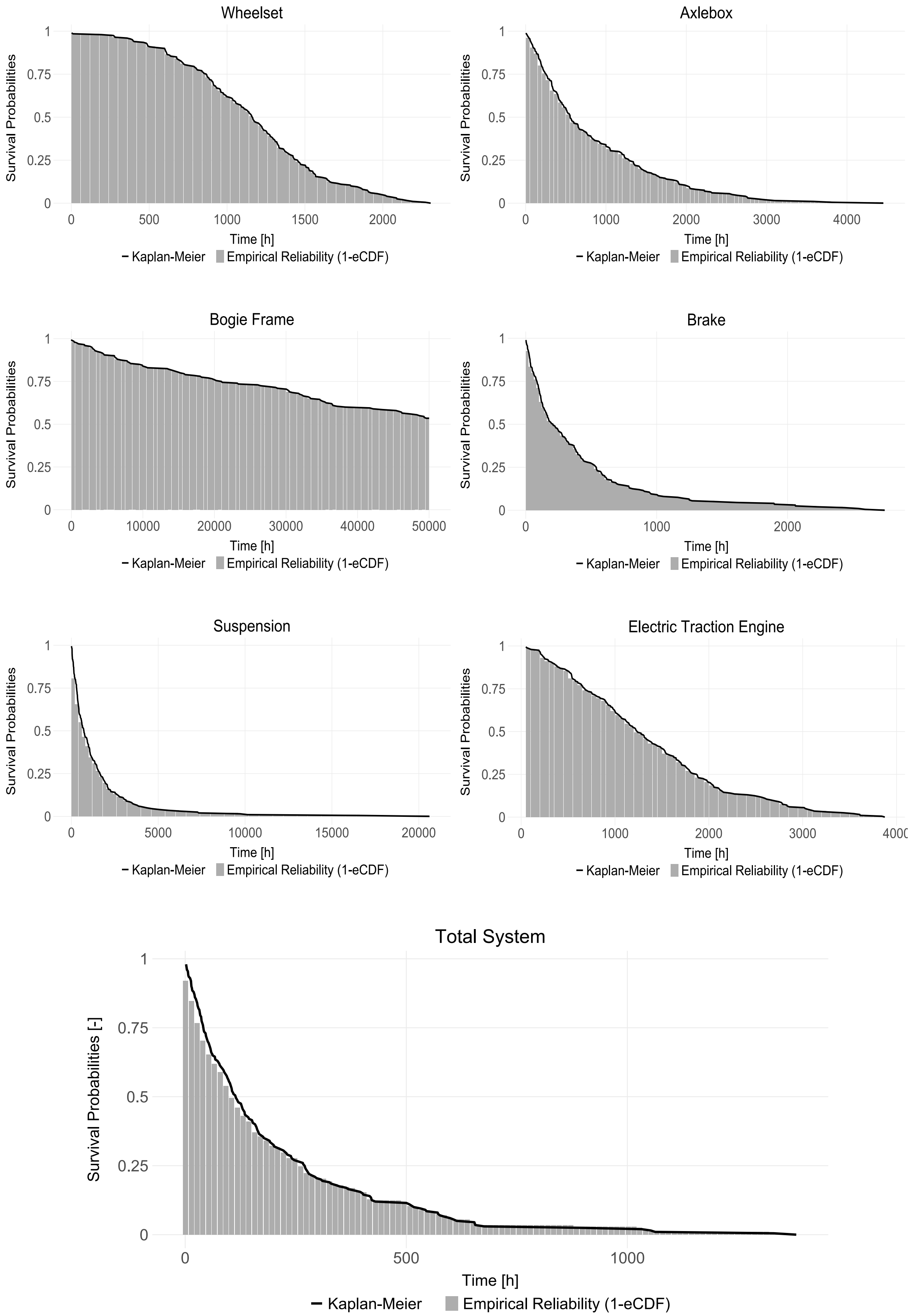


Figure B.6 – Scenario 4 survival Analysis of each subsystem and of the total system

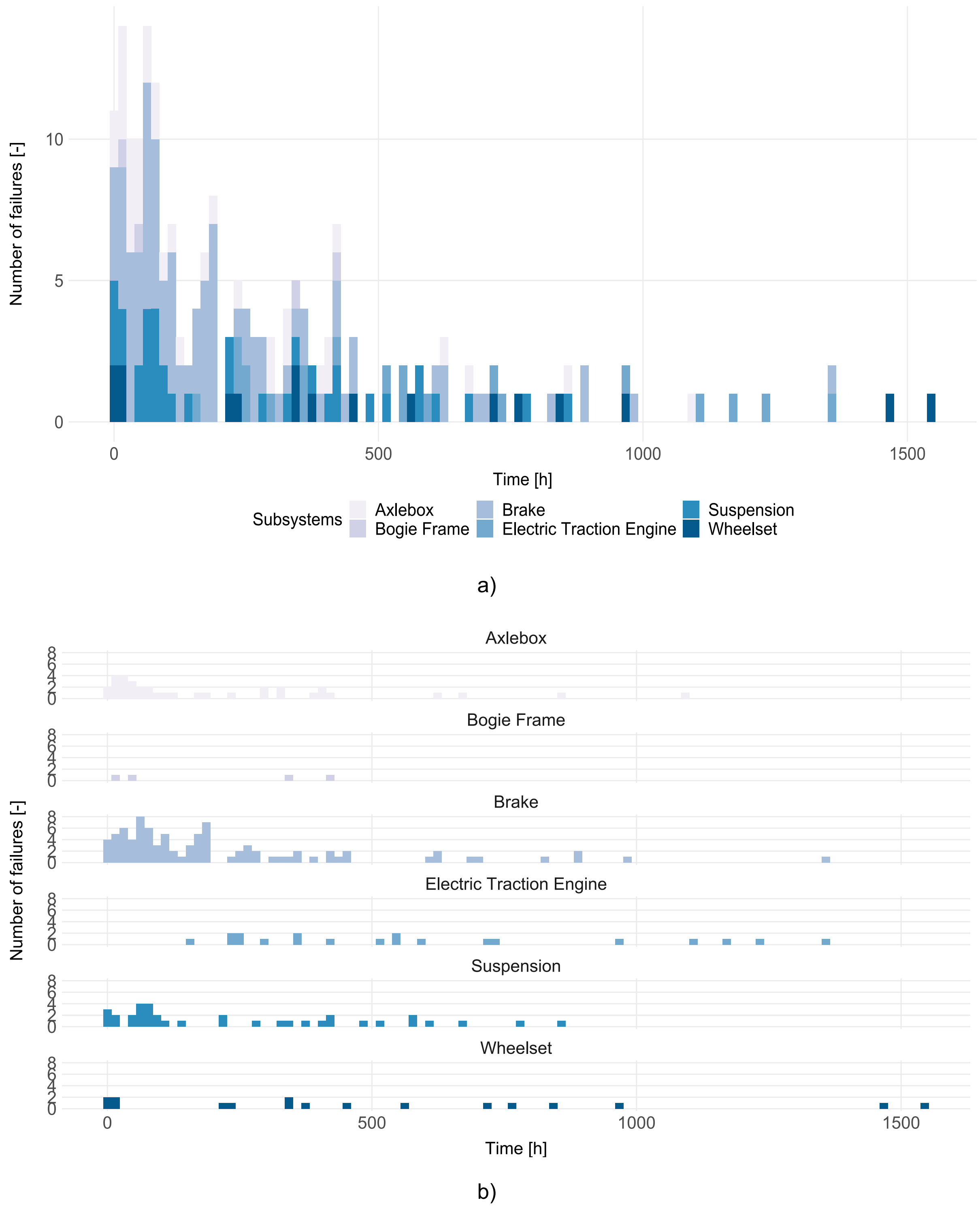


Figure B.7 – Scenario 5 a) total histogram covering the number of failures of the system regarding each subsystem failure and b) each subsystem histogram decomposed

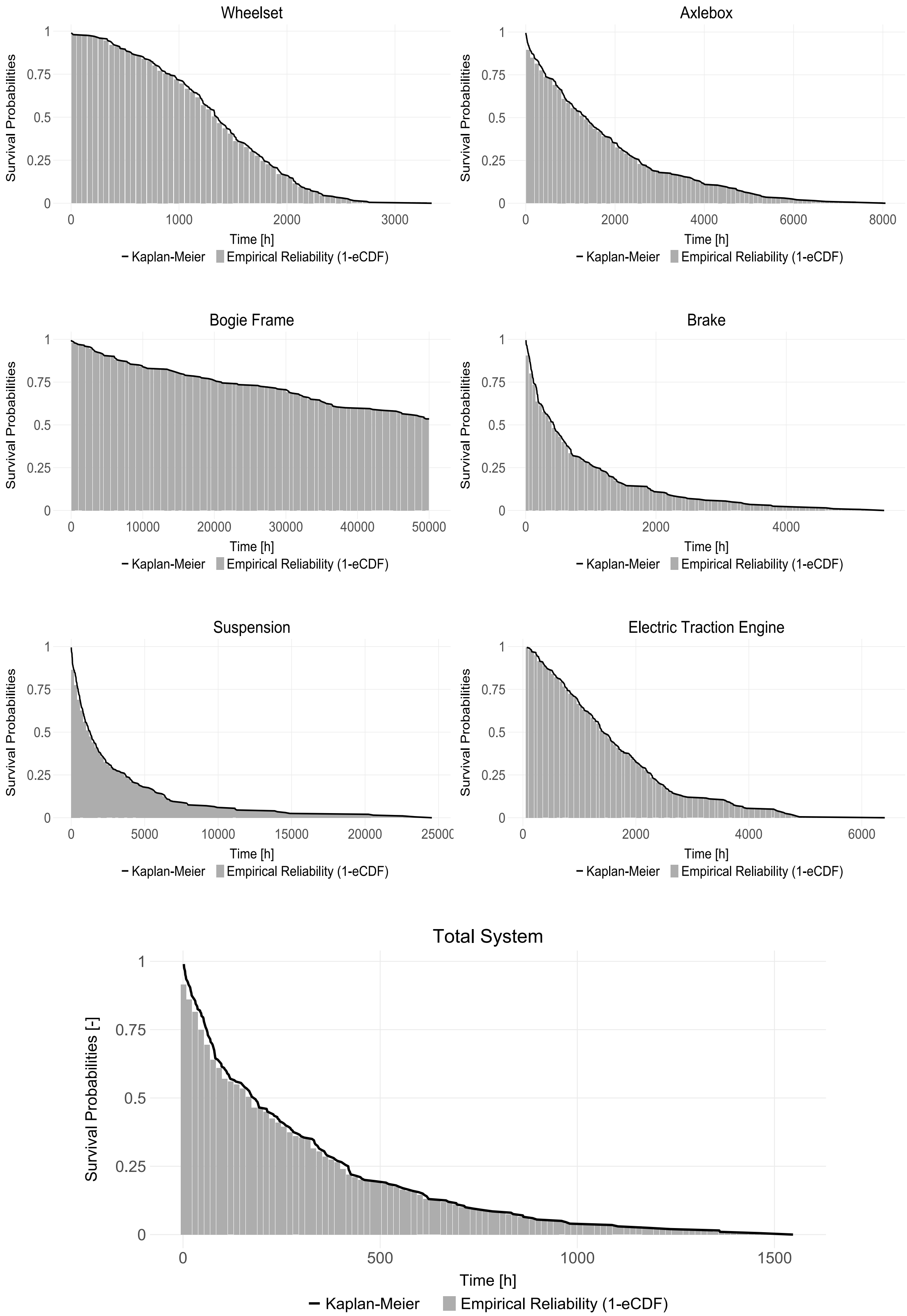


Figure B.8 – Scenario 5 survival Analysis of each subsystem and of the total system

B3 – Availability Simulation Results

Considering the results obtained for scenario 2, an additional scenario ($S2\_new$) with different PERT parameters was developed in order to validate the model implemented for all PERT scenarios. The parameters considered were the following:

$$a = 0.9 \times MTTR_i \qquad b = MTTR_i \qquad c = [1.2: 1.4] \times MTTR_i$$

The construction of the model is the same as in scenario 2, as well the assumptions for the model. Figure B.9 illustrates the results obtained in scenario 1, scenario 2_new and scenario 2. As one can verify, the validation of the model is achieved by relaxing the PERT distribution parameters, since $S2\_new$ mean availability results are between scenario 1 and scenario 2 mean availability results.

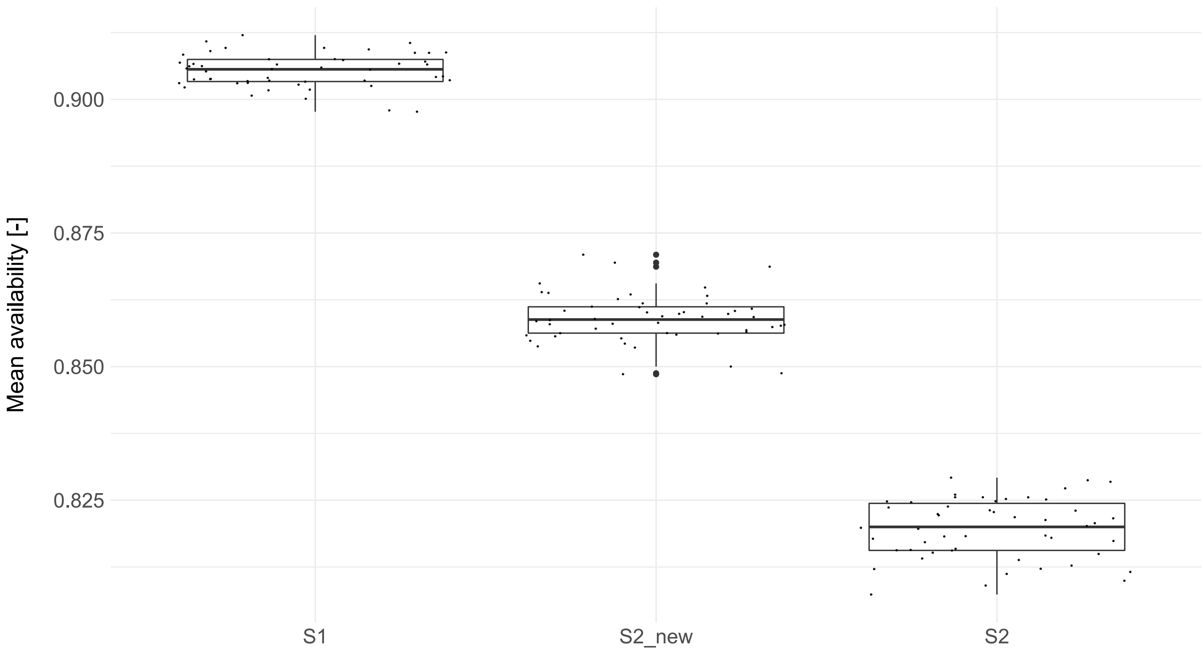


Figure B.9 – Comparison and validation of the mean availability results of scenario 2

The availability simulation results for scenarios 2 to 10 are presented here. Note that for each scenario, the following results are presented: i) the mean availability results of the bogie system for each simulation, ii) the mean availability in function of the simulation time for one simulation (which presents a mean availability identical to the average availability obtained from all simulations) and iii) the mean availability results for all simulations of all subsystems.

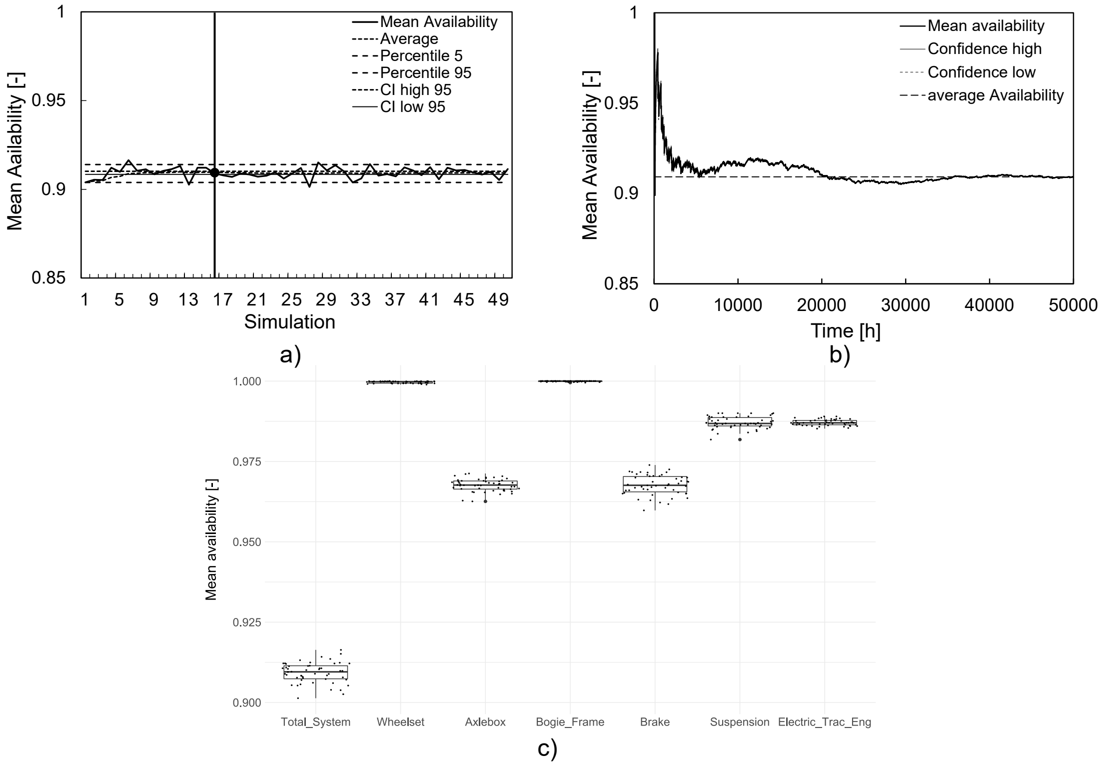


Figure B.10 – Scenario 1, model 2 (a) mean availability results of the bogie system for each simulation, (b) mean availability in function of time for one simulation ($n = 16$) and (c) the mean availability results for all simulations of all subsystems

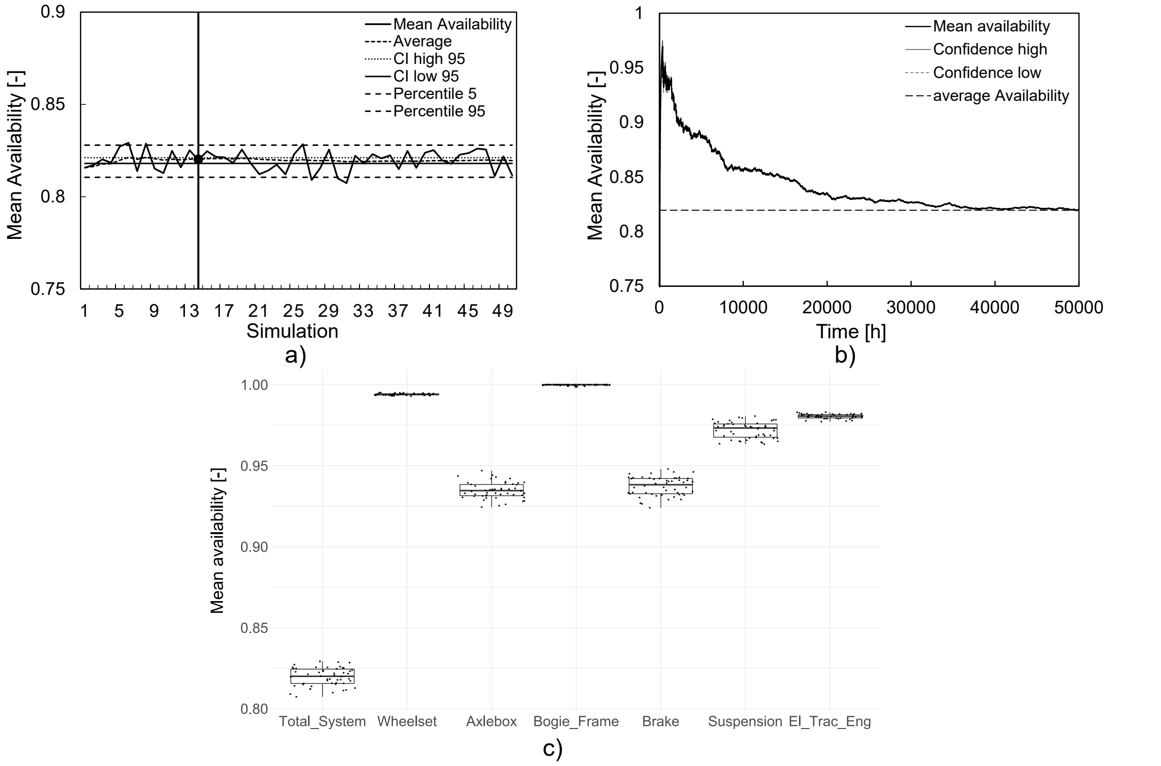


Figure B.11 – Scenario 2 (a) mean availability results of the bogie system for each simulation, (b) mean availability in function of time for one simulation ($n = 14$) and (c) the mean availability results for all simulations of all subsystems

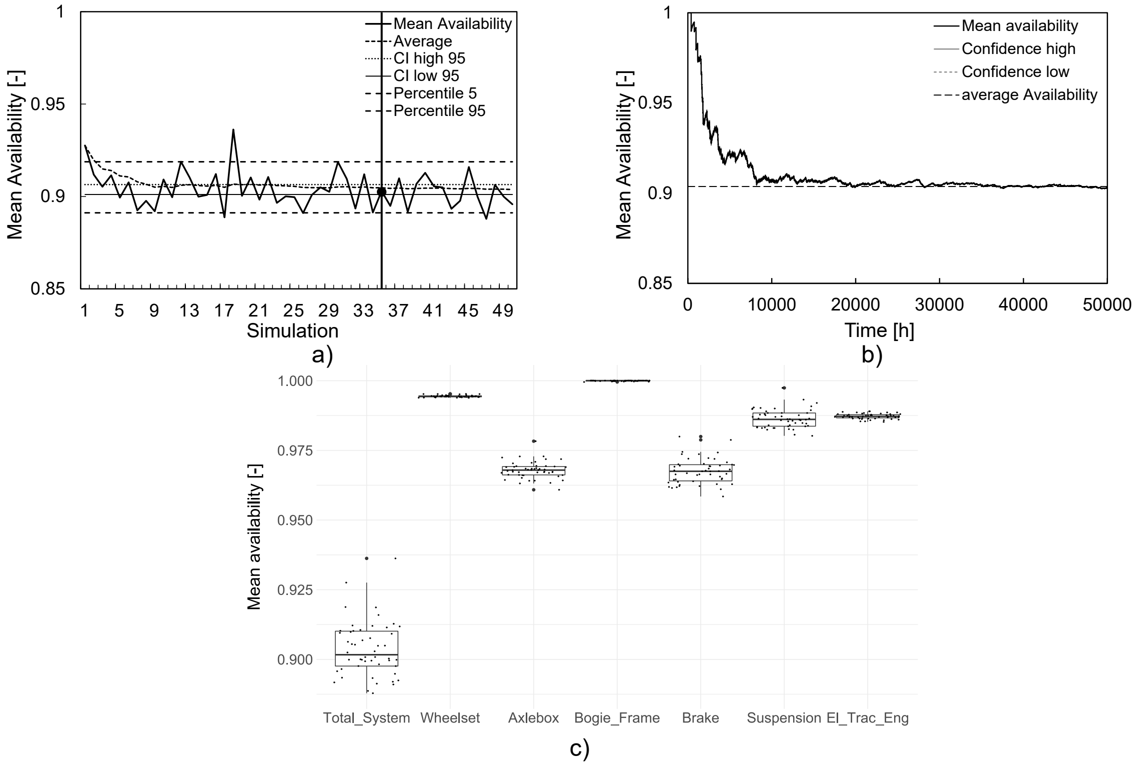


Figure B.12 – Scenario 3 (a) mean availability results of the bogie system for each simulation, (b) mean availability in function of time for one simulation ($n = 35$) and (c) the mean availability results for all simulations of all subsystems

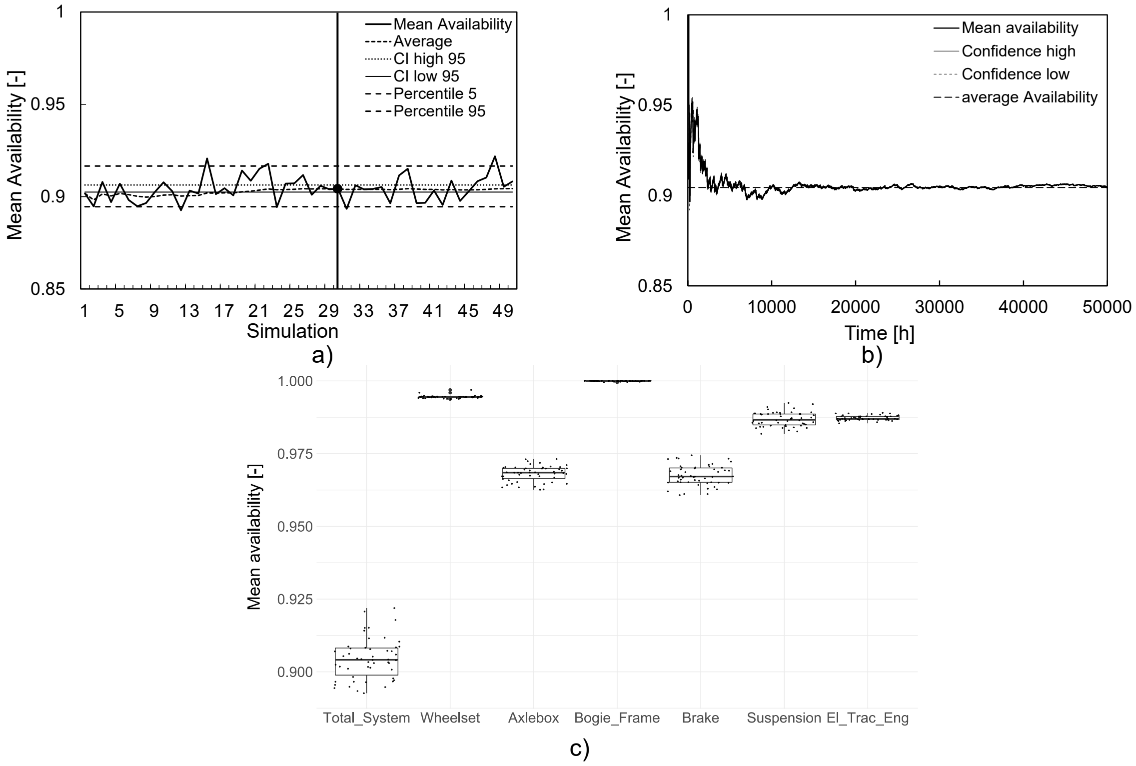


Figure B.13 – Scenario 4 (a) mean availability results of the bogie system for each simulation, (b) mean availability in function of time for one simulation ($n = 30$) and (c) the mean availability results for all simulations of all subsystems

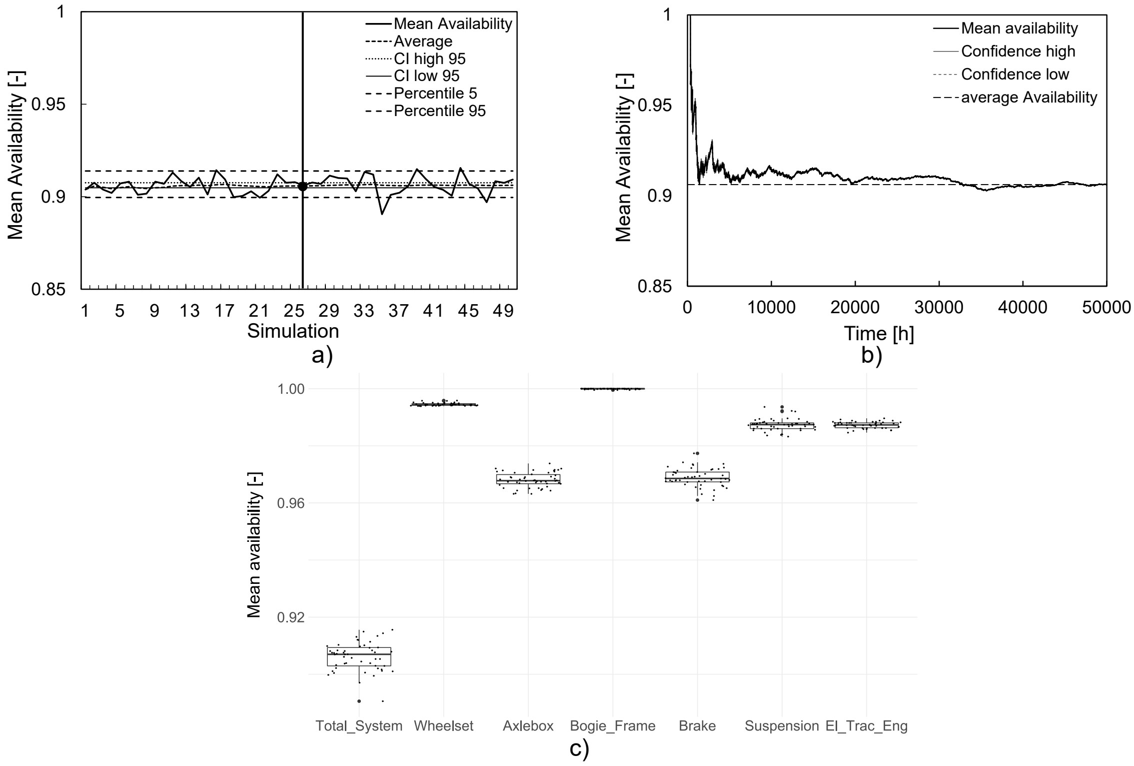


Figure B.14 – Scenario 5 (a) mean availability results of the bogie system for each simulation, (b) mean availability in function of time for one simulation ($n = 26$) and (c) the mean availability results for all simulations of all subsystems

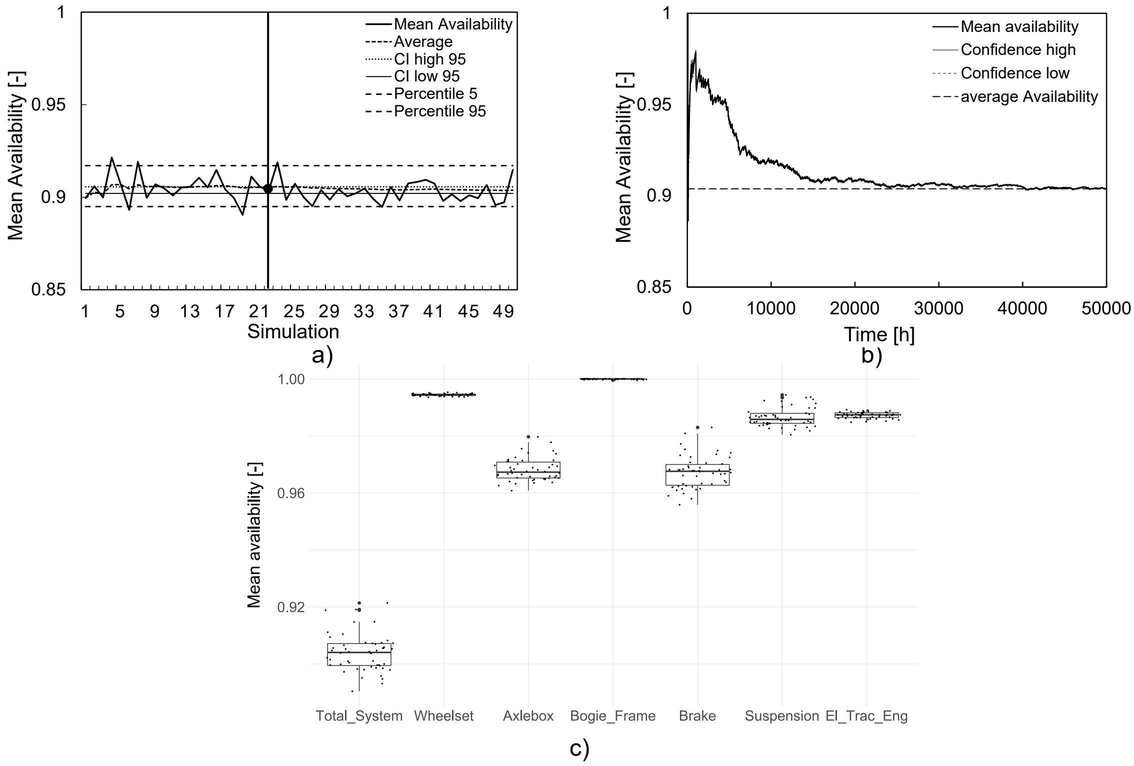


Figure B.15 – Scenario 6 (a) mean availability results of the bogie system for each simulation, (b) mean availability in function of time for one simulation ($n = 22$) and (c) the mean availability results for all simulations of all subsystems

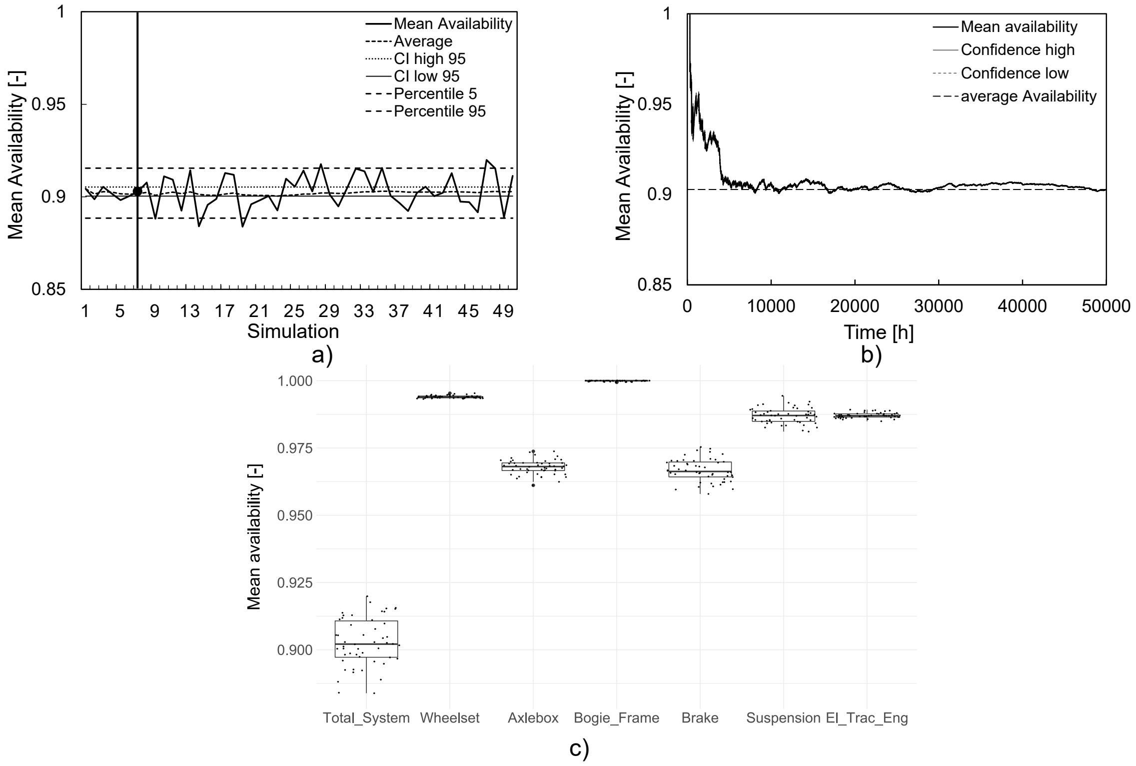


Figure B.16 – Scenario 7 (a) mean availability results of the bogie system for each simulation, (b) mean availability in function of time for one simulation ($n = 7$) and (c) the mean availability results for all simulations of all subsystems

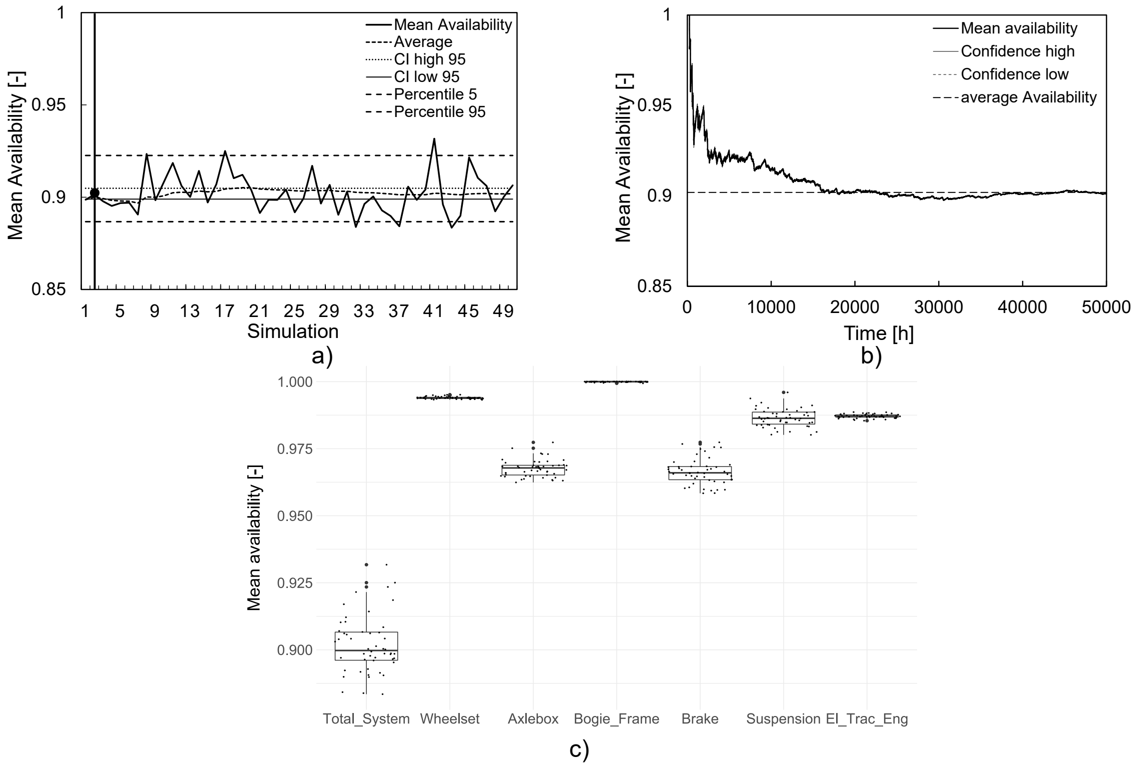


Figure B.17 – Scenario 8 (a) mean availability results of the bogie system for each simulation, (b) mean availability in function of time for one simulation ($n = 2$) and (c) the mean availability results for all simulations of all subsystems

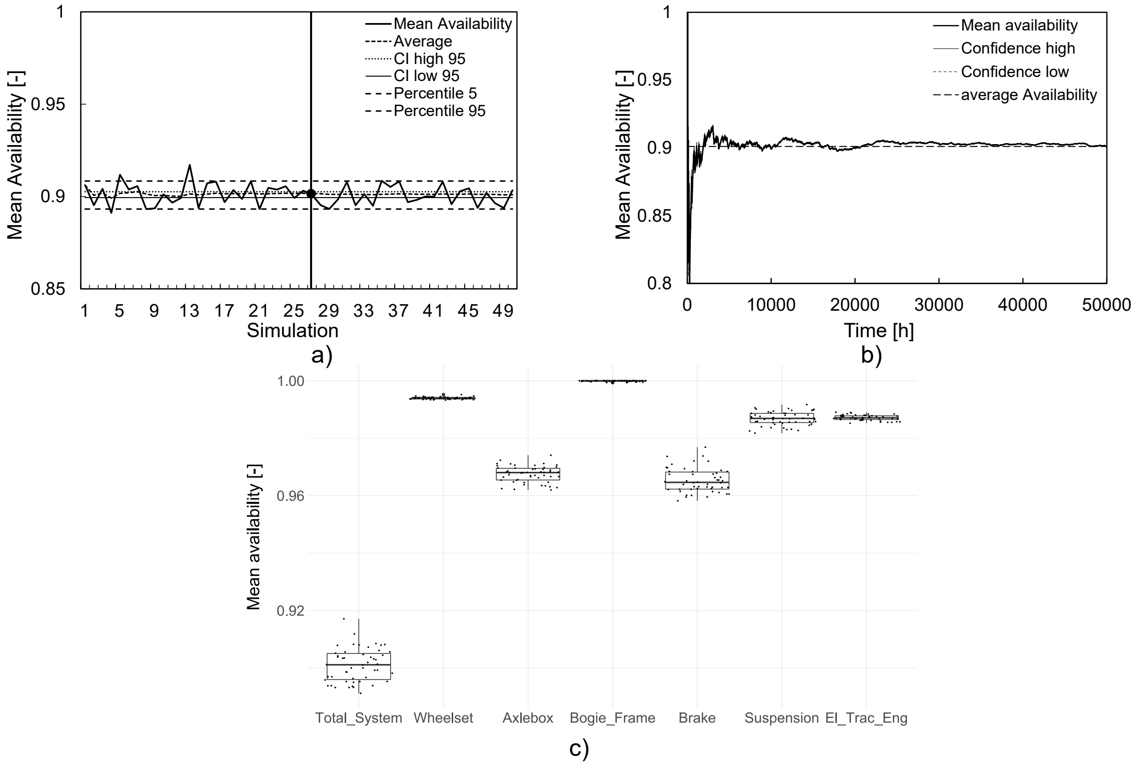


Figure B.18 – Scenario 9 (a) mean availability results of the bogie system for each simulation, (b) mean availability in function of time for one simulation ($n = 27$) and (c) the mean availability results for all simulations of all subsystems

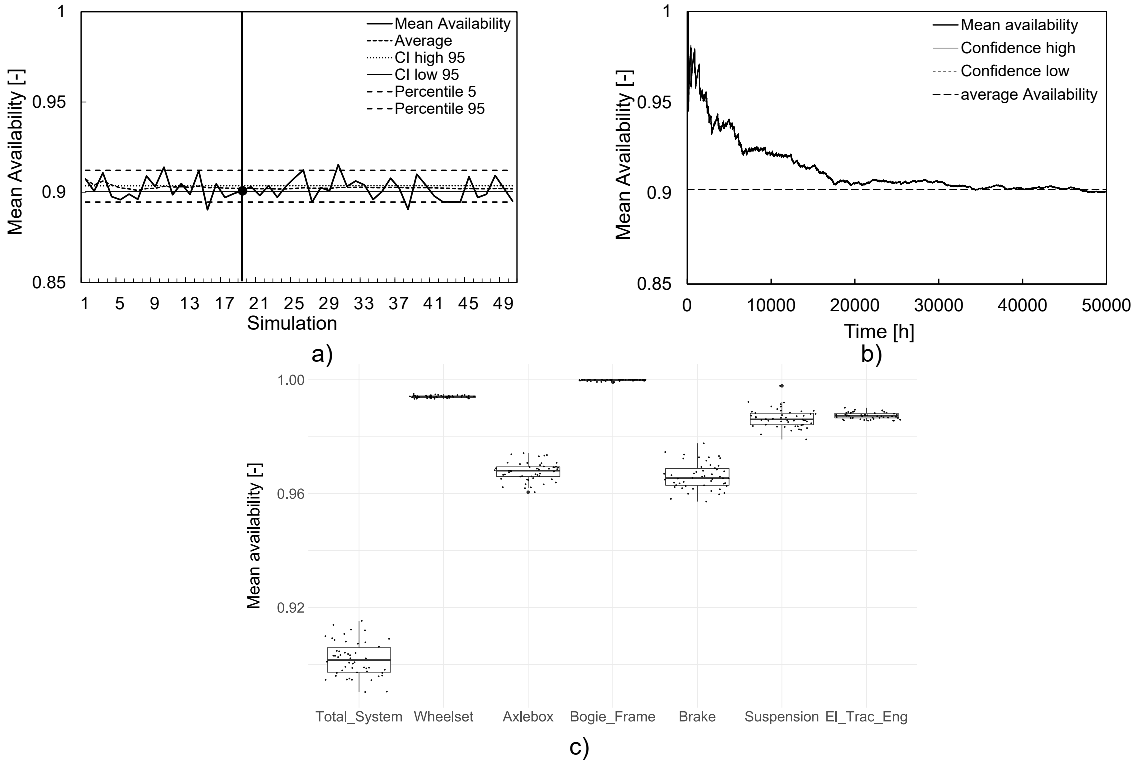


Figure B.19 – Scenario 10 (a) mean availability results of the bogie system for each simulation, (b) mean availability in function of time for one simulation ($n = 19$) and (c) the mean availability results for all simulations of all subsystems