# Assessing Reliability and Availability under Correlated Failures in Railway Locomotive Bogies

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## Abstract

Railway is the backbone of the transportation systems worldwide. To ensure reliability and availability of such systems, maintenance policies need to be optimized under a challenging and competitive environment. Condition-based and predictive maintenance strategies are key strategies in the European rail traffic system, where common advanced monitoring solutions of railway assets can serve as key performance indicators for the assessment and implementation of maintenance rules. Nevertheless, a good maintenance policy is intrinsically dependent on a clear assessment of the system, including aspects related to its complexity and financial dimension, in addition to the physical characteristics, the environmental and the operational conditions. Therefore, simulation models play a key role as they can mimic the behaviour of such systems, in particular the complex ones to solve analytically, incorporating the characteristics and their inherent stochastic behaviour, and their correlation structure. This study focuses on the locomotive bogie, as complex subsystem of the train onto which the wheels of the vehicle are fixed. The main components of the bogie are described, and their stochastic behaviour is associated with failure occurrence. It is proposed to study the impact on the system, using a Discrete Event Simulation (DES) model, in terms of reliability and availability, under different scenarios, and with different assumptions on the underlying failure modes, repairs, and on the failures' correlation structure. The findings suggest that the model is useful to represent the main characteristics of this train subsystem, while identifying the parameters and components that are more critical in terms of reliability and availability fluctuations, when compared with the variations imposed on the model, under different scenarios. Finally, the DES model allows to robustly assess where the focus should be put depending on the uncertainty embedded in the correlations of failures and/or in the maintenance durations.


Keywords: Reliability Assessment, Locomotive Availability, Railway Bogie Maintenance, Discrete Event Simulation, Monte Carlo Simulation.

## 1. Introduction and background

The bogie is an important part of a train, and it consists of a chassis that is attached to each of the train's vehicles, as shown in Figure 1. The bogie is designed to support the rail vehicle body and to distribute its weight through the wheels. Not only does it provide stability to the vehicle, by absorbing vibration and minimizing the impact of centrifugal forces when the vehicle runs, but it also houses several subsystems which are critical to the execution of the vehicle's function, such as the electric traction engine in the case of locomotives.

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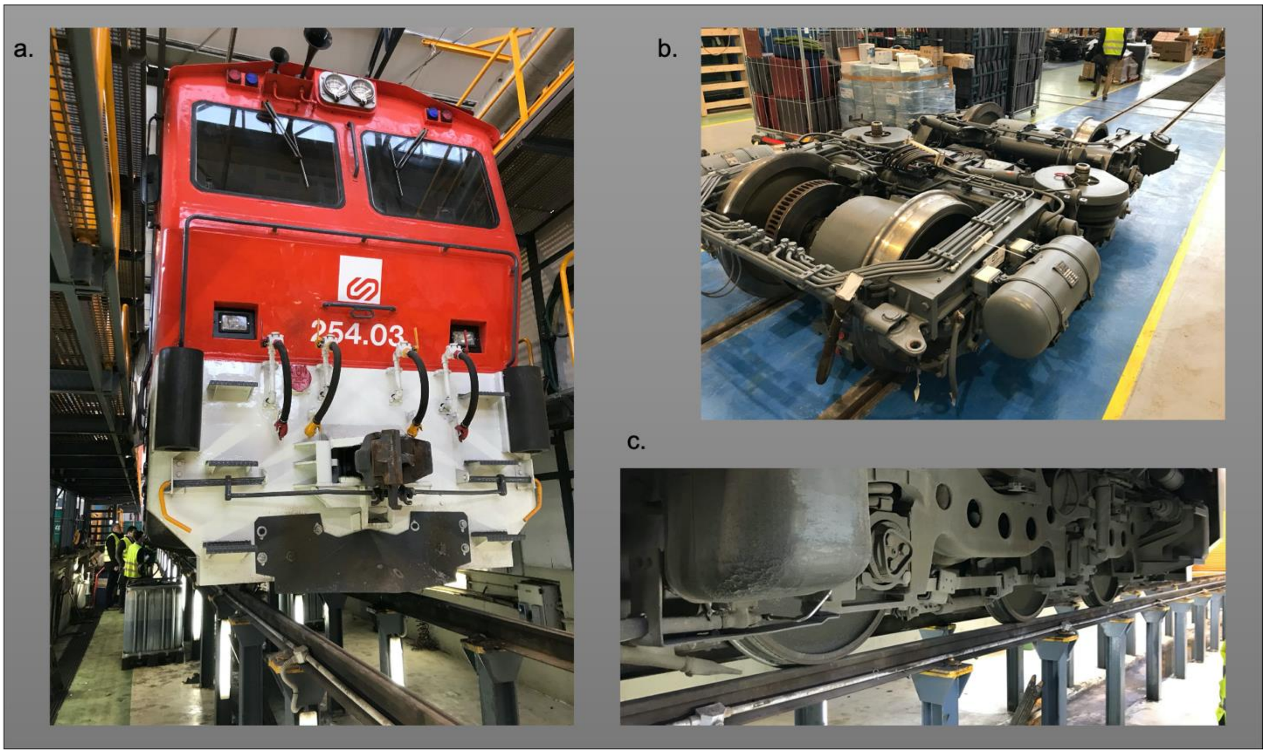


*Figure 1 – Railway bogie: a) Locomotive suspended in a platform; b) A restored bogie ready to be inserted back in the locomotive; c) Bogie attached underneath the locomotive*

Studying the reliability of the bogie is of pivotal importance to guarantee the reliability and operational safety of trains. In fact, there are some dedicated engineering guidelines that focus on analytical methods and integrative concepts for a system to meet its functional requirements. One such well-known analysis is the RAMS (Reliability, Availability, Maintainability, and Safety) analysis. It originated from the concepts of safety and reliability, which were introduced by the aerospace industry in 1930, becoming a crucial engineering discipline in the late 1950s due to the application of stochastic events in the system failure analysis [1]. 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, increasing productivity, reducing costs, and mitigating failure risks and undesirable events [2]. To achieve this, it studies the long-term operation of the system, with the consideration of its global function, hierarchical dependencies and interdependencies among other systems and subsystems. Definition, assessment and control of all hazards that influence the system's behaviour are steps constituting the RAMS analysis. Even though the failure rates of the components of the bogie are low, the severity of the economic and functional losses associated with the possible defects make them critical elements whose consideration in the RAMS analysis of rolling stocks is, therefore, of crucial importance. In railways, the international standard that specifies and demonstrates the application of RAMS is BS EN 50126-1 [3], and this paper refers to these guidelines for the reported analyses.

In a recent bibliometric review, Amin et al. [4] highlight that reliability analysis has gained increased attention from the research community, with a sharp increase in the number of publications in recent years. Conventionally, the probability model has been used to depict the uncertainties in reliability analysis [5]. In the literature, there are several contributions devoted to the numerical simulation of the reliability and availability of complex systems, and Monte Carlo simulation (MCS) and Markov models (MKM) are the two oldest and most popular tools used in these types of analyses [4]. Some of these works use 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, such applications for railway systems are still scarce. The majority of case studies with DES models for railways focus on (re)scheduling of train networks and maintenance activities according to the survey by Fang et al. [3], rather than models for the assessment of reliability and/or fault diagnosis.

As recent examples of applications of RAMS and MCS, Velásquez and Lara [6] use Monte Carlo simulations in RAM calculations for series capacitor banks of power lines and differentiate between scheduled and forced outage to provide expected value calculations of reliability and availability. In a railway application, Bemment et al. [7] use reliability block diagrams with a Monte Carlo simulation approach to model the availability of redundantly engineered track switches over expected asset lifetimes. Leite et al. [8] propose an FMECA analysis along with expert judgment techniques to estimate the bogie's main components failure rates as a first step required for the implementation of a RAMS program in a train operating company. This study is a continuation and validation of the results obtained in [8].

Most of the published works on probability models for reliability and availability assessment are developed under the typical assumption that the input random variables are independent from each other [5], ignoring the complex correlations among random variables and failure modes. Ignoring this dependence structure, however, could lead to severe flaws in the analysis results. Modelling the complex correlation structure is especially hard for multidimensional problems. In recent years there has been significant progress, although most applications do not consider real-life engineering problems [5].

Some authors use machine learning (ML) techniques that make use of massive amounts of data to train models for which the underlying stochastic model and relationships among variables are unknown or too complex to be formalized mathematically. For example, Márquez et al. [9] focus on the bogie axle bearings and propose four prediction algorithms for condition-based maintenance based on Artificial Neural Networks (ANN) aiming at enlarging the P-F (interval from potential failure to functional failure) of the bearings. Also relying on the availability of data, Sun et al. [5] use mixed Copula functions to describe the correlations among random variables and failure modes and evaluate the reliability of a main girder structure. Gathering good quality data is, however, not always an easy task among train operating companies. A lot of the information on the failure occurrence and details come in the form of free-text comments inserted by the technicians, content which is often overlooked by analysts due to the significant amount of resources required for a manual analysis [10].

In recent years, the use of smart technology inserted in the Industry 4.0 context has motivated the use of digital twins, which are virtual representations of a system that are useful to study and understand the parameters and variables that affect a process or outcome of interest. Therefore, it is a simulation tool that aids robust design and/or choice of parameters that directly impact the system's performance. Simulation is the imitation of a real-world process or system over time. It usually involves a series of assumptions regarding how the process or system of interest works and it is particularly useful to model systems that are too complex to be evaluated analytically. In a simulation, a computer evaluates a model numerically, and data is gathered to estimate the true characteristics of the model [11]. In general, it serves as a basis for experimental studies of systems, to describe and analyse conceptual system behaviour. In terms of reliability assessment, simulation is particularly useful since many key variables used to model the stochastic behaviour of a system, such as Time to Failure ($TTF$), Time between Failures ($TBF$), Time to Repair ($TTR$), downtime, among others, can be approximated via simulation techniques.

Simulation events are evaluated at a time basis, where three main approaches concerning how the time is modelled could be highlighted: i) time-slicing, ii) continuous and iii) discrete event [12]. The time-slicing and continuous simulation types work by dividing the time horizon into very small (and identifiably equal) parts, whereas discrete event simulation works by increasing the simulation clock only when an event occurs. DES is particularly useful to model systems at which the state variables change at discrete points in time (e.g. unscheduled downtime, update of wear indicator based on inspections, repair, etc.). It is also less computationally expensive and counts with greater availability of commercial packages in comparison to the other simulation approaches.

As one of the pioneers in the application of simulation models in reliability engineering, Chisman proposes a DES model to study large-scale system reliability in his initial simulation studies [13], where a framework for assessing the reliability of complex electro-mechanical systems is additionally proposed by the author. Significant development of DES applications has been put in structural reliability analysis, where a review of applications is gathered in the book by Faulin et. al [14]. In fact, most 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 combination of a DES with an MCS approach, where in addition to obtaining the structural lifetime generated by simulation, the DES also enables to acquire a detailed understanding of the lifetime progression of the analysed structure. Moreover, Gascard et al. [15] suggest that 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. More related to maintenance policies implementations, where the reliability and availability projections are crucial, Alrabghi and Tiwari [16] model complex maintenance systems using a DES algorithm, where condition-based, preventive, and corrective maintenance can be applied. Using Alrabghi and Tiwari work, Golbasi and Turan [17] 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 either maximize availability or minimize 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. [18] propose a dynamic DES to study the reliability of railway crossing signalling devices based on the track rail circuit. In a related application, Durmus et al. [19] use DES for fault diagnosis in a fixed-block railway signalling system, analysing the conceptual design of the modular system. Rhayma et al. [20] analyse the behaviour of the railway track geometry employing a numerical analysis which goes in accordance with a discrete event and MCS approach. In terms of railway bogie, it is often the case that data is scarce and/or unavailable. In addition, the correct assessment of the reliability of a system implies dealing with the complicated correlations among the various failure modes embedded in each of the components' stochastic behaviour. Most of the literature on rolling stock bogies study specific components of this system, e.g. Márquez et al. [9] focus on the axle bearings, Xiu et al. [21] make a review on main methods used for fatigue life assessment of bogie frame, especially from the design perspective, and Seo et al. [22] present a recent application of fatigue tests and finite element analysis (FEA) for bogie frame fatigue strength and residual stress evaluation. Nevertheless, to the best of the authors' knowledge, for railway bogie, 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.

To that end, the paper is organized as follows: Section 2 describes the case study introducing the locomotives, the subsystems, as well as the DES model and its main assumptions used for the assessment of reliability and availability. Section 3 discusses the implementation results in terms of the availability model and the reliability model. Finally, Section 4 presents the main conclusions and ideas for future research.

# 2. The bogie simulation model - a case study

The freight locomotive involved in the case study, the 254-class locomotive, is used for the transportation of cars and potash. The locomotive 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 of the locomotive box and the running gear, which in the case of interest is the bogie vehicle. There are two bogies per locomotive, three wheelsets per bogie and one electric traction engine per wheelset. Each traction engine is directly employed to an axle.

In line with this, the following case study aims to illustrate the simulation model developed to study the availability and reliability of different components of a bogie system, regarding the stochastic behaviour of the occurrence of failure and repair, and its impact on the system. To do so, the reliability block diagram (RBD) of the bogie system is described in subsection 2.1. and the algorithm of the proposed Discrete Event Simulation (DES) model is explained in subsection 2.2., while several potential simulation scenarios for the reliability and availability are assessed.

## 2.1. Input data (RBD)

The RBD for the present case study was built based on the typical configuration of a locomotive bogie. For the analysis, the failure data and part of the repair data were obtained from previous studies (electric traction module from [23], axlebox, bogie frame, brake systems and suspension elements from [24]), while the wheelset failure data and additional repair data was obtained from previous maintenance experiences using expert judgment techniques according to [8]. The reliability-wise relationships, which link each block, were also based on the FTA analysis performed in [24]. Moreover, the number of elements was based on the information made available by the train operating company as well as the KTH Railway Book [25], a reference handbook of railway systems and vehicles composition and configuration.

The model comprises six critical subsystems, namely: wheelset, axlebox, bogie frame, brake systems, suspension elements and electric traction module. For these subsystems, components and respective failure modes, the failure distribution, failure rate, Mean Time Between Failures (MTBF) and Mean Time To Failure (MTTR), which will feed the RBD of the proposed simulation model were defined. All this information was compiled into Table A.1 in the Appendix. From Table A.1, and considering all of the 122 elements linked in a series configuration (meaning that an item's or associated FM failure will bring the system down), the RBD presented in Figure 2 was obtained.

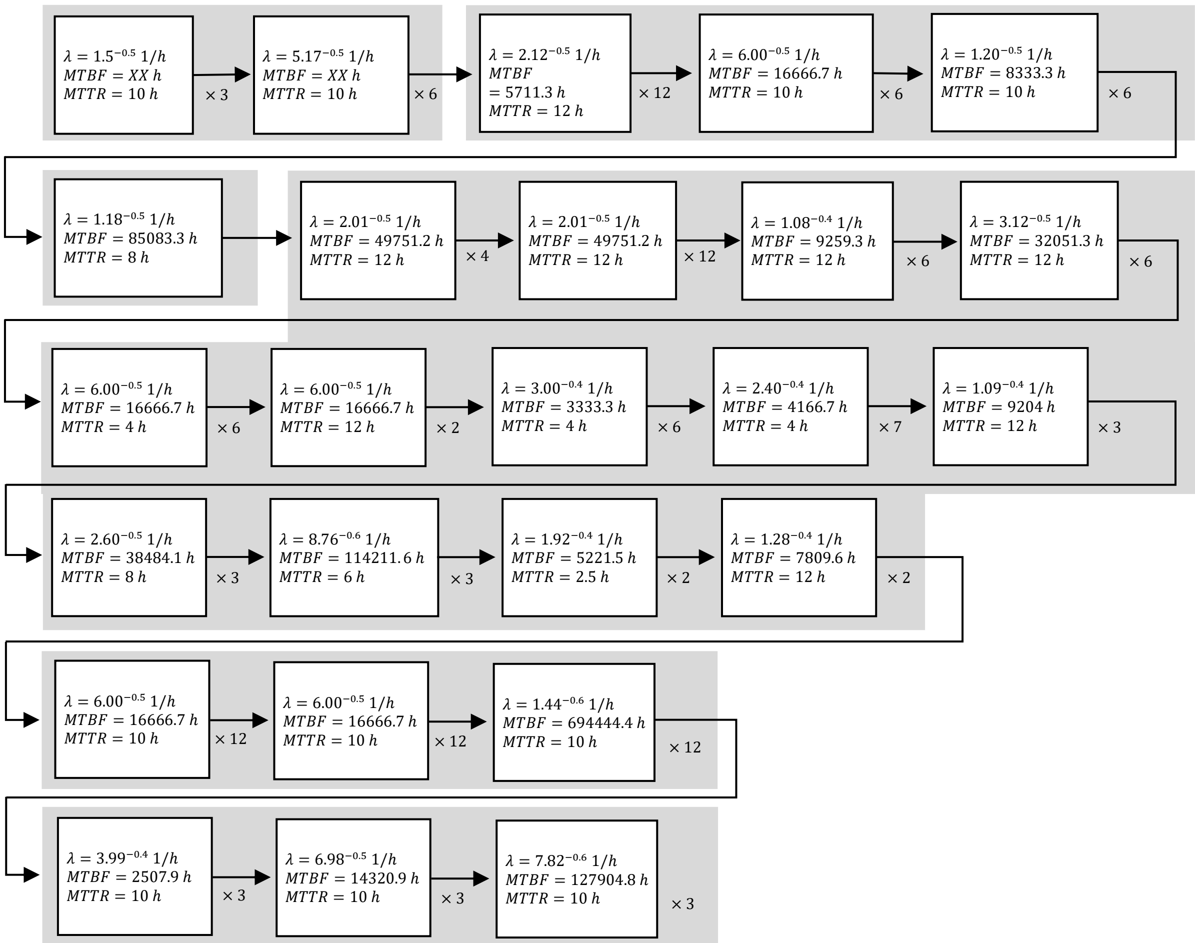


*Figure 2 – RBD configuration used in the simulation model.*

The RBD diagram, presented in Figure 2, is composed of several blocks, being each block characterized by: i) the item or Failure Mode 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. 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.

## 2.2. Discrete event simulation model

To produce a reliable operational behaviour, a DES model is typically defined with a step-by-step 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 sophisticated task, which typically includes the following activity blocks [26]:

- 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 needs to implement the operation of the case study of interest. A typical DES algorithm is described in Figure 3 flowchart.

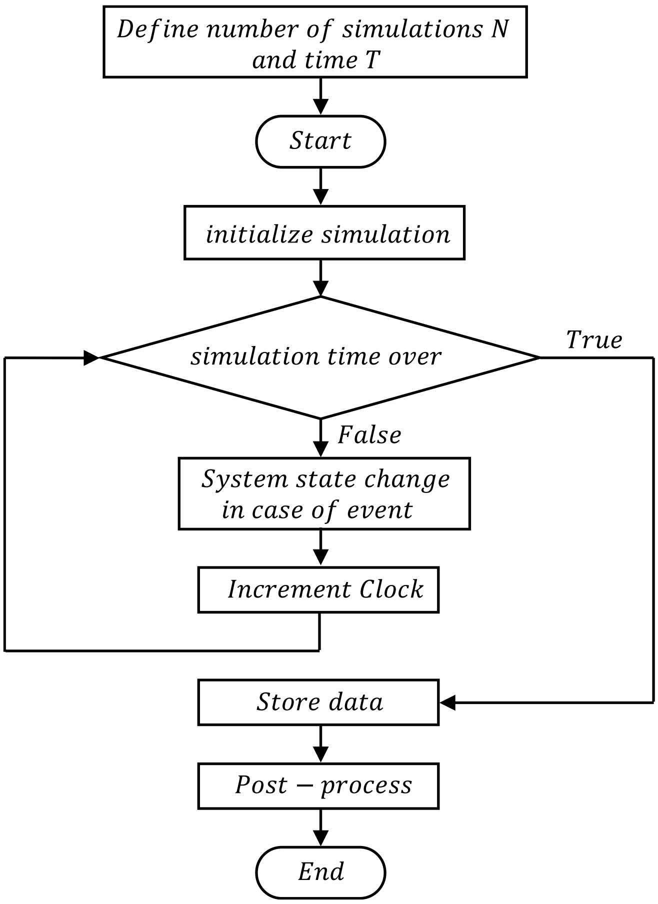


*Figure 3* – flowchart of a DES algorithm.

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). 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 $\Delta t$. 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.

A DES model is organized in a time interval, where the sequence of events is observed and analysed and each event is modelled as a discrete time step so that the resulting 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 are gathered.

In each simulation, a random failure or repair time from 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 by 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. This is a method called Monte Carlo Simulation (MCS), and the DES algorithm conducts the progress of the stochastic model in each simulation of the MCS. By running a model a considerable amount of times, in order to produce a large number of simulations, a very good approximation is obtained. The complete results after each simulation are posteriorly analysed to determine the behaviour of the system. The overall procedure to build an MCS algorithm within a DES goes in accordance with Figure 4.

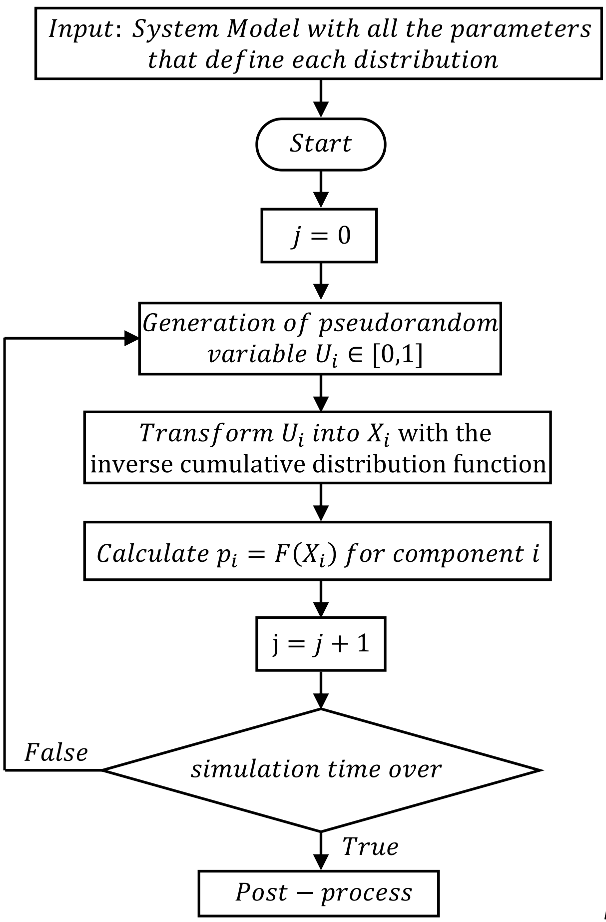


*Figure 4* – flowchart of MCS.The second step consists of generating uniformly the pseudo-random numbers $U_i[0,1]$ for each failure and/or repair distribution functions. A uniform random number is a variable that can take, with equal probabilities, one value between 0 and 1. When the algorithm that 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 Lehmer's Algorithm, which is a type of Linear Congruential Generator (LCG), a simple generator that uses seed variables to generate uniform random numbers [27]. The computational implementation of Lehmer's algorithm goes according to [28].

After generating $U_i[0,1]$, the conversion from a pseudo-random number to a random variate $X_i$ by way of appropriate mathematical transformations takes place. There are many approaches for converting random numbers into random variates, nevertheless, if one wants to guarantee uncorrelated random variates from distribution of interest, the inverse cumulative distribution function (cdf) $F^{-1}(X)$ should be used [27]. 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 function can be considered [15].

Finally, the random variates $X_i$ 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 behaviour of the system, a large sample size is recommended.

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 component's 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. 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 developed program created by [29] and [2] and modelled in the commercial software package *Simulink* of *MATLAB*, for the reliability and availability analysis of an experimental tokamak nuclear fusion reactor that was built 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.

To facilitate the understanding of the structure of the simulation models, Table 1 shows the list of variables and terms used, along with their description.

*Table 1 – List of variables and terms in each simulation model.*

| Variable | Description | Variable | Description |
|---|---|---|---|
| $N$ | Number of simulations | $Nf$ | Total number of failures and repairs in one simulation |
| $T$ | Termination time of simulation | $delay$ | Time for which the system is down to repair due to other components |
| $GFS$ | Global Final Signal | $\lambda_i$ | Failure Rate for component $i$ |
| $ToF$ | (Random) Time of failure | $p$ | (Random) draw from a |

| | | | |
|---|---|---|---|
| | | | standard uniform distribution |
| $GClock$ | Global clock | $\rho_{i,j}$ | Correlation factor between components $i$ and $j$ |
| $Clock_i$ | Clock for component $i$ | $\vec{\mu}$ | Mean vector of the Multivariate Normal Distribution (MVN) |
| $TCT_i$ | Total component time of each component $i$ | $\Sigma_k$ | Covariance matrix of the MVN for scenario $k$ |
| $S_i$ | Signal for component $i$ | $A$ | Availability |
| $MTBF_i$ | Mean time between failures for component $i$ | $R$ | Reliability |
| $MTTR_i$ | Mean time to repair for component $i$ | | |

### 2.2.1. 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 presents the flowchart algorithm of the reliability DES model for $N$ simulations.

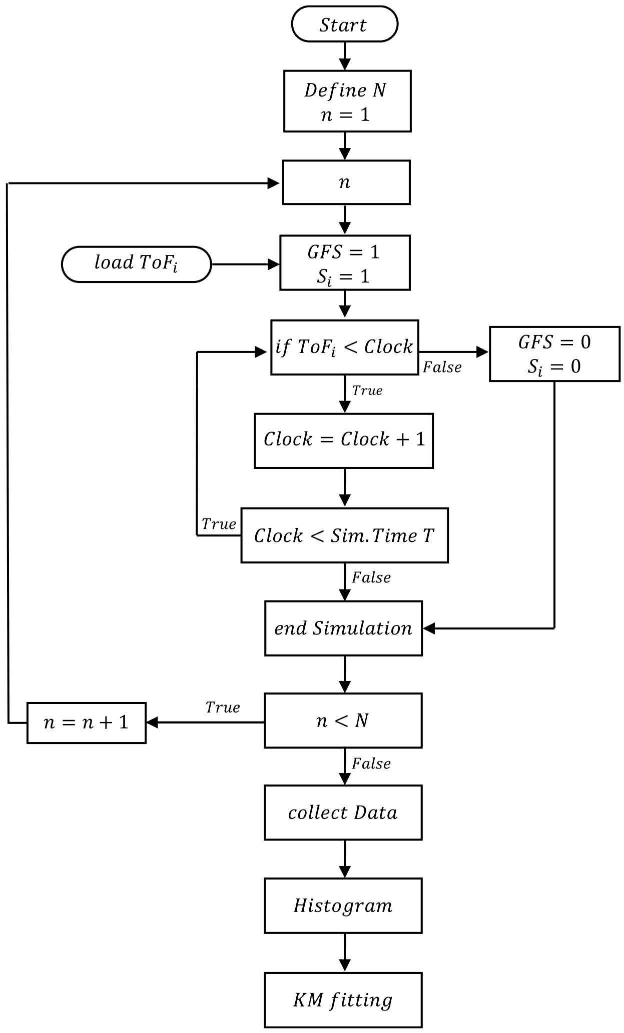

*Figure 5 – Flowchart describing the algorithm of the reliability DES model.*

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 ($S_i$). 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. 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 estimates 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 in *R* [30] software are used to estimate the reliability curves of the total system and each subsystem. A similar methodology has been applied successfully to railway wheelsets to estimate survival curves, see [31]-[32]. 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 a cargo locomotive bogie, there was the need to consider several assumptions. The assumptions for each block and the simulation model go according to [29] and are the following:

- Each component starts the simulation in a state “As Good as New” (AGAN);
- Each component has its 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 unique reliability characteristics:
  - $MTBF_i$ and Failure rate $\lambda_i$;
- Each component has its uniform $ToF$ generator, which is based on the failure distribution function associated with each 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 2 summarizes each scenario, where the emphasis is on the generation of the $ToF$, being this the only difference between each scenario.

*Table 2 – 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 0.2 |

| | | |
|---|---|---|
| Scenario 3 | - | all blocks (122) failures are correlated with a correlation factor $\rho_{i,j}$ of 0.5 |
| Scenario 4 | - | within each subsystem (6), all failures are correlated with a correlation factor $\rho_{i,j}$ of 0.2 |
| Scenario 5 | - | within each subsystem (6), all failures are correlated with a correlation factor $\rho_{i,j}$ of 0.5 |

As it could be verified, scenario 1 is the already described reliability DES model, where 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 $p_i \in [0,1],\ i \in \{1, 2, \ldots, 122\}$ are correlated with a correlation factor $\rho_{i,j}$ of $0.2$ and $0.5$ in scenarios 2 and 3, respectively. Note that when the standard normal distribution is considered the entries of the covariance matrix correspond to $\rho_{i,j}$. In each case, the covariance matrix is the following:

$$\sum\nolimits_2 = \begin{pmatrix} 1 & 0.2 & \cdots & 0.2 \\ 0.2 & 1 & \cdots & 0.2 \\ \cdots & \cdots & \cdots & \cdots \\ 0.2 & 0.2 & \cdots & 1 \end{pmatrix}_{[122\times122]} \quad [1] \qquad \sum\nolimits_3 = \begin{pmatrix} 1 & 0.5 & \cdots & 0.5 \\ 0.5 & 1 & \cdots & 0.5 \\ \cdots & \cdots & \cdots & \cdots \\ 0.5 & 0.5 & \cdots & 1 \end{pmatrix}_{[122\times122]} \quad [2]$$

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 within the *MATLAB* software. 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 $\vec{\mu} = [0\ 0 \ldots 0_n]_{[1xn]}$ where $n$ is the number of components or FMs considered.

### 2.2.2. Availability 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 designed to define all downtime events which impact the availability of the bogie system. Consequently, a single simulation objective is to compute all system's failures and their associated repairs to gather the total downtime considering the simulation time $T$. Figure 6 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 component's 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:

$$TCT_i = ToF_{1,i} + TTR_{1,i} + ToF_{2,i} + TTR_{2,i} + \cdots + ToF_{Nf,i} + TTR_{Nf,i} - delay = \left[\sum_{f=1}^{Nf}(ToF_{f,i} + TTR_{f,i})\right] - delay \quad [3]$$

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 three possible events can either bring no change to the signal or trigger the signal:

**(A)** there is no failure at all;
**(B)** there is a failure, but it does not come from component $i$;
**(C)** there is a failure and it is due to component $i$.

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 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.

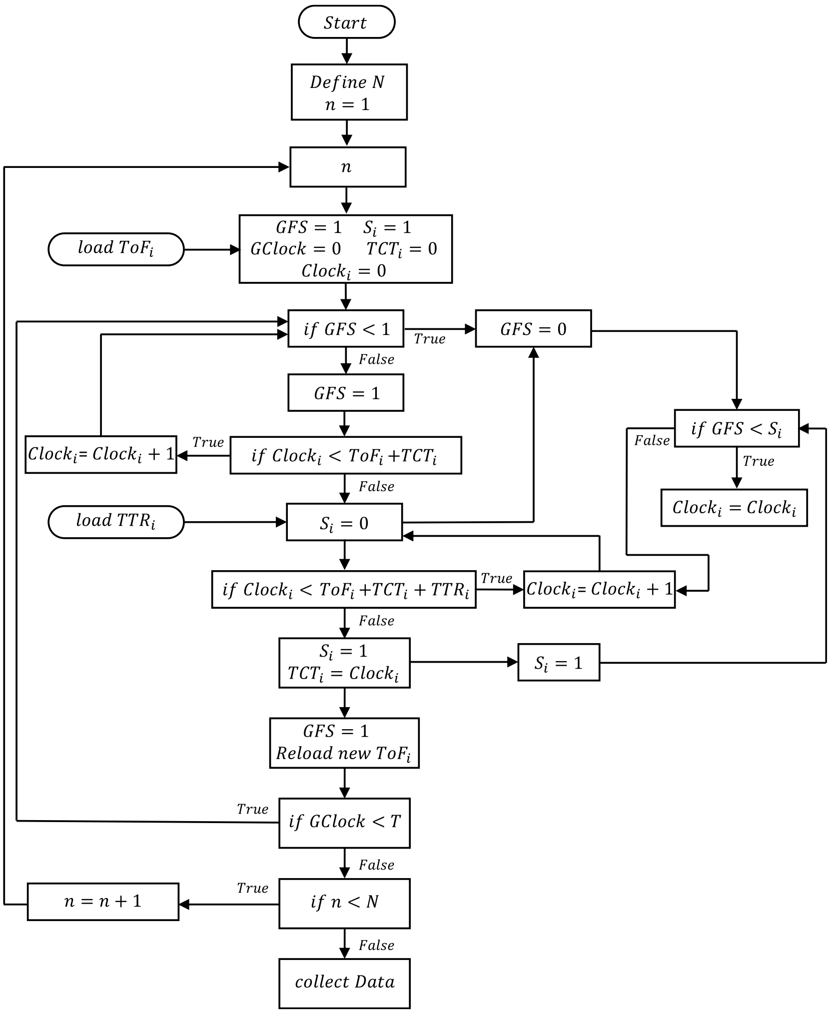


*Figure 6 – Flowchart describing the algorithm of the availability DES model for one component.*

In addition to the reliability DES model assumptions for each block, the following assumptions were also considered for the availability DES model [16]:

- 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 3 summarizes each individual scenario, where similarities can be verified which go according to the scenarios modelled for the reliability DES model.

*Table 3 – 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 0.2 |
| Scenario 4 | Sc.1 where all blocks (122) failures are correlated with a correlation factor $\rho_{i,j}$ of 0.5 |
| Scenario 5 | Sc.1 within each subsystem (6), all failures are correlated with a correlation factor $\rho_{i,j}$ of 0.2 |
| Scenario 6 | Sc.1 within each subsystem (6), all failures are correlated with a correlation factor $\rho_{i,j}$ of 0.5 |
| Scenario 7 | Sc.2 where all blocks (122) failures are correlated with a correlation factor $\rho_{i,j}$ of 0.2 |
| Scenario 8 | Sc.2 where all blocks (122) failures are correlated with a correlation factor $\rho_{i,j}$ of 0.5 |
| Scenario 9 | Sc.2 within each subsystem (6), all failures are correlated with a correlation factor $\rho_{i,j}$ of 0.2 |
| Scenario 10 | Sc.2 within each subsystem (6), all failures are correlated with a correlation factor $\rho_{i,j}$ of 0.5 |

As Table 3 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 3. 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:

$$a = 0.8 \times MTTR_i \quad [4] \qquad b = MTTR_i \quad [5] \qquad c = [1.5:2] \times MTTR_i \quad [6]$$

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 pseudo-random number between $[1.5:2]$ is generated to each block (122), to admit different repair durations. In scenarios 3 to 6, scenario 1 is used as a 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.

# 3. Simulation model results and remarks

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

## 3.1. Reliability DES results

Considering the reliability DES model algorithm, in each scenario a histogram of each subsystem and system failure is obtained, where 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 the company's maintenance and average operating times, while for the remaining scenarios (2 to 5), the same simulation time $T$ is considered, but $N = 250$, due to high computational efforts.

Considering scenario 1, Figure 7 shows the system's histogram (a), and every single subsystem's 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 (for all $N = 1100$ simulations). Consequently, some system failures, like the failures from the bogie frame, are not included in the total system since their failures occur very rarely.

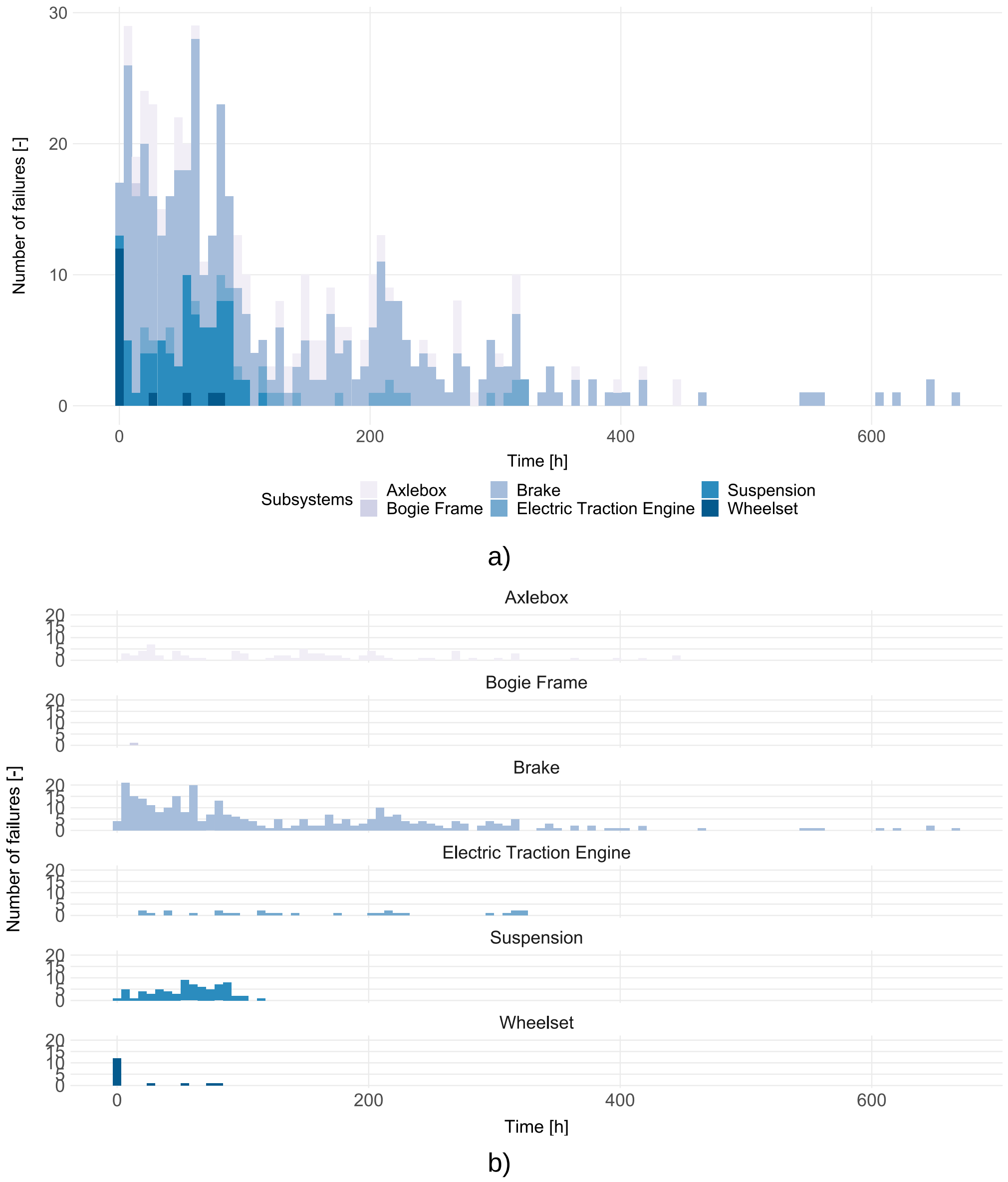


*Figure 7 – Scenario 1 a) bogie total system histogram and b) each subsystems histogram.*

From these histograms, survival analysis is performed to obtain the reliability curves of each subsystem and from the total bogie system. As mentioned in section 2.2.1., these curves were obtained by using the non-parametric Kaplan-Meier estimator ($KM$) on the failure data gathered from the simulation results. The KM product-limit estimator [33] is a nonparametric method for estimating survival curves and the probabilities of survival up to time $t_i$, given that a failure has not yet occurred, is given by the following equation:

$$\hat{S}(t) = \prod_{i:\, t_i \leq t} \left(1 - \frac{d_i}{r_i}\right), \text{ for } t \geq t_1;$$
$$\hat{S}(t) = 1, \qquad\qquad \text{for } t < t_1. \qquad [7]$$

In equation [7], $r_i$ represents the number of subsystems at risk and not censored at time $t_{i-1}$ and $d_i$ represents the number of subsystems out of $r_i$ that had a failure associated in the $i^{th}$ interval, $[t_{i-1,}t_i)$. The number of (right) censored in this interval is then easily computed as $l_i = r_i - r_{i-1} - d_i$. Hence, the denominator in equation [7] could also be interpreted as $r_i = r_{i-1} + l_i +$

$d_i$. Therefore, the Kaplan-Meier survival curves are step functions obtained from the practical survival probabilities derived from the Kaplan-Meier estimator. This estimator is a product of probabilities since it assumes the independence of events between time intervals.

If compared with the analytical results, it is possible to verify that all reliability curves behave similarly. For instance, when comparing the exact values from scenario 1 results withanalytical values, for a reliability of $R_s = 0.8$ and $R_s = 0.5$, the system needs to operate $T_s \cong 26h$ and $T_s \cong 82h$, respectively, which matchanalytical results. Consequently, 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. A summary of all scenarios is graphically exposed in Figure 8 where all the bogie total system reliability scenarios are represented.

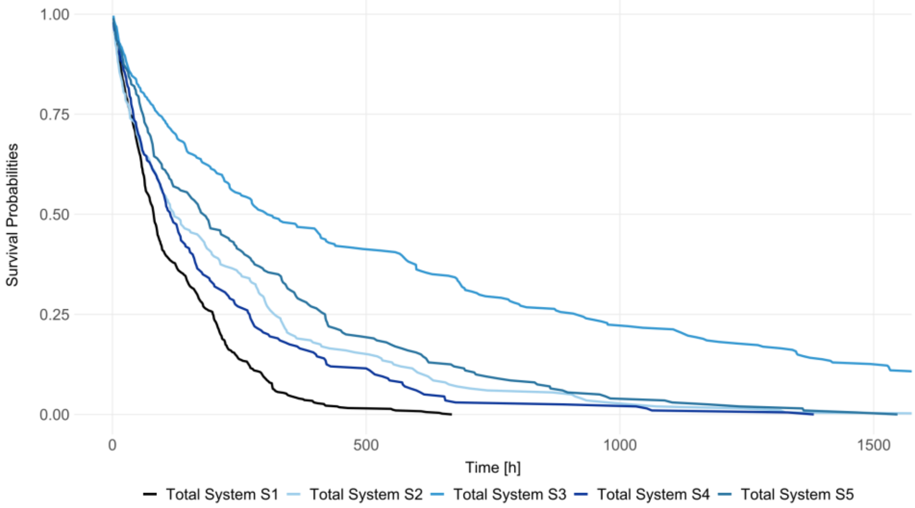


*Figure 8 – Summary of the total bogie system reliability for scenarios S1 to S5.*

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, a comparison between scenarios 2 and 3 with the bogie's reliability of scenarios 4 and 5, respectively, shows that 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. Moreover, the higher the correlation factor $\rho_{i,j}$ between failures, the higher the bogie's reliability (S2 vs. S3 and S4 vs. S5).

## 3.2. Availability simulation results

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

For instance, considering scenario 1, Figure 9 presents the mean availability results for each simulation (a), the mean availability as a 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). Still considering 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 some 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 higher total system availability.

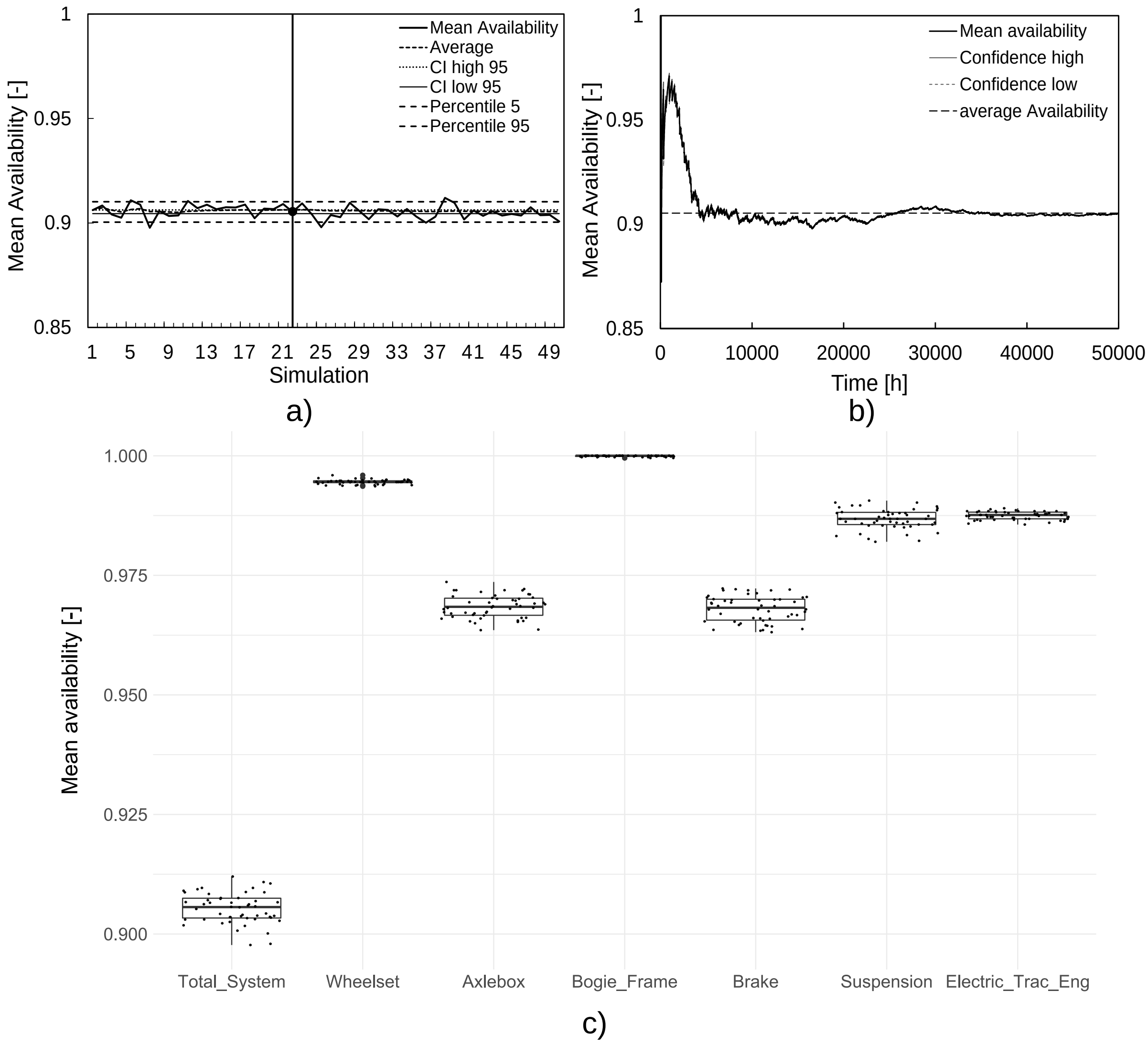


*Figure 9 – Scenario 1 (a) mean availability results of the bogie system for each simulation, (b) mean availability as a function of time for one simulation ($n = 22$) and (c) the mean availability results for all simulations of all subsystems.*

A summary of the bogie’s system mean availability results for each scenario is presented in Figure 10.

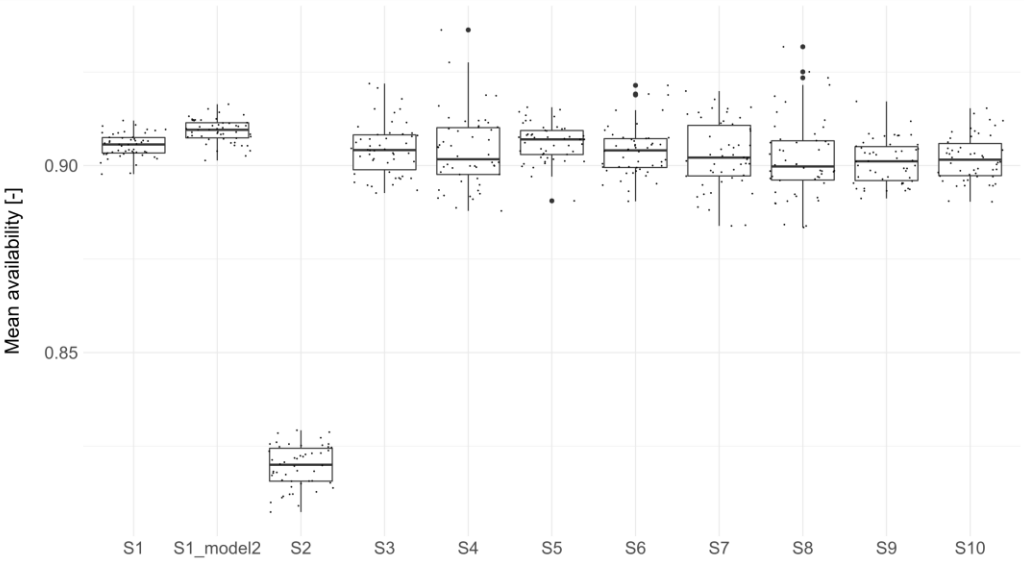


*Figure 10 – Summary of the bogie's mean availability for each scenario.*

Observe that an additional scenario ($S1\_model2$) was created, to model the acquisition of a new turning machine by the railway company. 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 10 it is possible to retrieve that the main difference between all scenarios is the variability of its results. Starting with $S1$ and $1\_model2$ ($A_{S,1_{model2}} = 90.93\%$), 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. 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 $S2$ extremely penalize the repair durations since the PERT parameter $c$ is considered to be farther apart from $b$ than $a$. By comparing the remaining scenarios ($S3 - S10$) with the initial scenario $S1$, the impact on the availability projections of correlated failures is only marginal. , especially if these availability projections are compared with the results obtained from the reliability simulations projections. Nevertheless, the main difference identified in scenarios $S3$ to $S10$ is the variability around the results. First, the scenarios with a correlation of failures in the component level (i.e., all blocks have correlated failures, $S3 - S4$ and $S7 - S8$) have higher variability than the scenarios with a 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 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 $S2$.

# 4. Conclusions

This study comprises a description of the railway bogie system, one of the most important subsystems of a train, its main components and their stochastic failure behaviour. After identifying the critical components and functional breakdown of the bogie, a Reliability Block Diagram (RBD) is constructed to identify the reliability-wise relationships of the bogie system. A DES model is proposed to measure the response, in terms of reliability and availability, of different potential scenarios with varying assumptions on the underlying failure modes, repairs, and on the system's correlation structure, where the emphasis is on the variability of the stochastic parameters. The model is verified by comparing analytical results with the simulation results from a baseline scenario.

The results obtained from the reliability and availability DES model show good suitability of the main assumptions. In terms of the reliability model, the most impactful subsystems in terms of the number of failures are the braking system, the axlebox system and the suspension system, respectively. Although the lowest $MTBF$ was associated with elements comprising the wheelset, the lower number of critical components, when compared to those of the other systems, offers compensation in terms of reliability, diminishing the impact of lower $MTBF$. A first notable result is that a correlation of all failures in a component level compared to the correlation of failures in a subsystem level, as well as a higher correlation factor $\rho_{i,j}$ between failures, brings greater reliability projections. For the availability model, the braking system and the axlebox are the most impactful systems, although they also present the highest variability. Most notably, and in opposition to the 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.

In general, the introduction of variability of one or more parameters increases the reality of the operation in the model, therefore, allowing for greater flexibility in the estimation of possible scenarios that can represent a wider range of different circumstances in operation. For example, since in analytical calculations the failures of some components do not delay other components' failures, the analytical model had lower availability than the simulated models. This sheds light on the numerous possibilities of modifying the proposed simulated framework for important analysis. As an example, a simulation assuming the acquisition of a new turning machine for wheelsets revealed the expected percentage of increase in availability due to reduced repair times. In general, these scenarios identify the reliability and availability variations to that same variation of parameters, which in turn leads to easy recognition of where the focus can be put according to the uncertainty embedded in the correlation of possible failures and/or in maintenance durations.

The proposed simulation model is confirmed to be a useful solution to predict the reliability and the availability of a cargo locomotive bogie system, which is an underexplored topic in the literature, although bogies are of crucial importance to railways. The framework developed could also be extrapolated for more complex systems, including other train's subsystems.

As future research, some interesting ideas arise. The first one is to explore the application of downtimes caused by preventive maintenance and inspection tasks in the availability DES model, which replicates a train operating company day-to-day operation. A second idea would be the implementation of imperfect maintenance tasks in the availability DES model, i.e. maintenance tasks that do not restore the components reliability to an $AGAN$ state. Finally, a design of experiments could be proposed to study the response to different correlation structures in the failure generation of components. These steps would certainly enhance the model’s ability to simulate scenarios that are closer to real-world railway operations.

## Acknowledgements

The authors would like to thank the support of the LOCATE Project and FGC train operating company, as well as all experts that supported the development of the present model.
This work has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No. 881805 (Locomotive bOgie Condition mAinTEnance (LOCATE) research project under the Shift2Rail Joint Undertaking). This work was also supported by the Foundation for Science and Technology (FCT), through IDMEC, under LAETA, project UIDB/50022/2020.
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Horizon 2020
European Union Funding
for Research & Innovation

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# 6. Appendix

*Table A.1 – Component's 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 | $\sigma_{log}$ 0.633; $\mu_{log}$ 10.91 | 10 |
| | Wheels | 6 | Wheel out of round, cracks/notches/flats, wheel build up material, profile under threshold. | Normal | 5.171E-04 | 1933.9 | $\sigma$ 693.52; $\mu$ 1933.86 | 2 |
| Axlebox | Axlebox | 6 | Absence of the cover box screw | Exponential | 6.00E-05 | 16666.7 | $\lambda$ 6.00E-05 | 10 |
| | | 6 | Housing not watertight | Exponential | 1.20E-04 | 8333.3 | $\lambda$ 1.20E-04 | 10 |
| | Bearings | 12 | Bearing failure | Weibull | 2.12E-06 | 5711.3 | $\beta$ 1.5193; $\eta$ 6336.1 | 12 |
| Bogie Frame | Frame | 1 | - | Weibull | 1.18E-05 | 85083.3 | $\beta$ 0.8422; $\eta$ 77751.2 | 8 |
| Brake System | Brake | 4 | Parts of Brake Rigging hanging | Exponential | 2.01E-05 | 49751.2 | $\lambda$ 2.01E-05 | 12 |
| | | 4 | Brake Rigging isolating cock | Exponential | 2.01E-05 | 49751.2 | $\lambda$ 2.01E-05 | 12 |
| | | 6 | Cast Iron Brake Block | Exponential | 1.08E-04 | 9259.3 | $\lambda$ 1.08E-04 | 12 |
| | | 6 | Composite Brake Block | Exponential | 3.12E-05 | 32051.3 | $\lambda$ 3.12E-05 | 12 |
| | Pneumatic Braking system | 6 | Front air valve damaged | Exponential | 6.00E-05 | 16666.7 | $\lambda$ 6.00E-05 | 4 |
| | | 2 | Brake cylinder damaged | Exponential | 6.00E-05 | 16666.7 | $\lambda$ 6.00E-05 | 12 |
| | | 6 | Air distributor damaged | Exponential | 3.00E-04 | 3333.3 | $\lambda$ 3.00E-04 | 4 |
| | | 6 | Slack adjuster damaged | Exponential | 2.40E-04 | 4166.7 | $\lambda$ 2.40E-04 | 4 |
| | Master/Auxiliary Compressor | 3 | - | Weibull | 1.09E-04 | 9204.0 | $\beta$ 1.1252; $\eta$ 9607.99 | 12 |
| | Master/Auxiliary Compressor Driving Motor | 3 | - | Weibull | 2.60E-05 | 38484.1 | $\beta$ 1.2142; $\eta$ 41034.1 | 8 |
| | Servo-motor in braking system | 3 | - | Weibull | 8.76E-06 | 114211.6 | $\beta$ 1.0221; $\eta$ 115243 | 6 |
| | Other Elements of the pneumatic braking system | 2 | - | Weibull | 1.92E-04 | 5221.5 | $\beta$ 1.7743; $\eta$ 5867.3 | 2.5 |
| | Other braking system elements (pins, sleeves, …) | 2 | - | Weibull | 1.28E-04 | 7809.6 | $\beta$ 2.4482; $\eta$ 8806.18 | 12 |
| Suspension Elements | Helical Spring | 12 | Spring Buckle Fracture | Exponential | 6.00E-05 | 16666.7 | $\lambda$ 6.00E-05 | 10 |
| | Helical Spring | 12 | Helical Spring broken | Exponential | 6.00E-05 | 16666.7 | $\lambda$ 6.00E-05 | 10 |
| | Other Suspension elements | 2 | Bottoming between Axle-box housing and bogie frame | Exponential | 1.44E-06 | 694444.4 | $\lambda$ 1.44E-06 | 10 |
| Electric Traction Module | Power transmission system | 3 | - | Weibull | 3.99E-04 | 2507.9 | $\beta$ 1.7098; $\eta$ 2811.91 | 10 |
| | Shaft Coupling | 3 | - | Weibull | 6.98E-05 | 14320.9 | $\beta$ 326.203; $\eta$ 14346.2 | 10 |
| | Traction Motor | 3 | - | Weibull | 7.82E-06 | 127904.8 | $\beta$ 0.87826; $\eta$ 119878 | 10 |
| Number of elements | | 122 | | | | | | |