Reliability and Availability Assessment of a cargo locomotive bogie

A contribution to a RAMS Analysis in the FGC case study

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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 paper, 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 obtaining a reference use case of the bogie, a reliability block diagram (RBD) of the reliability-wise relationships of the bogie is established and simulation models of both reliability and availability of the bogie 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 the models to be decisive solutions 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.

1. Introduction

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. This is achieved with the assessment and development of component prediction methods based on predictive tools. 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, crucial that in order to meet such goals, appropriate condition-based and prediction tools are developed, existing a clear interest regarding their research.

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

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 [1], 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 [2] 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. [3] 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 [4] 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 [5] 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 [6] propose a dynamic DES to study the reliability of railway crossing signalling devices based on the track rail circuit. Rhayma et al. [7] 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.

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. The goal of this paper 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.

2. RAMS Analysis

The RAMS (reliability, availability, maintainability, and safety) analysis process is an engineering technique, that comprises analytical methods and integrative concepts for a system to meet its functional requirements. 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 [8]. This is achieved through the definition, assessment and control of all hazards that influence the systems behaviour with the main goal of increasing productivity, reducing costs, and mitigating failure risks and undesirable events.

2.1 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. 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 [8,9]:

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

$$R(t) = 1 - P(T \leq t) = 1 - F(t) \qquad (2.2)$$

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:

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

Alternatively, the PDF can be defined with the use of the reliability function $R(t)$, where $f(t) = -\frac{dR(t)}{dt}$.
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:

$$MTTF = E(T) = \int_0^\infty t \cdot f(t)dt \qquad (2.4)$$

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, where failure rates are assumed to be quasi-static (constant). Assuming this, equation (2.4) can be simplified to:

$$MTTF = \frac{1}{\lambda} \qquad (2.5)$$

where λ is the constant failure rate of the system or component.

2.2 Availability

Availability (A) is commonly defined as the probability that a system or a component is executing its required function at a given 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 [10]:

$$A = \frac{uptime}{downtime + uptime} \qquad (2.6)$$

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:

$$A = \frac{MTTF}{MTTF + MTTR} \quad (2.7)$$

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. In order to predict availability, both failure and repair, deterministic or stochastic behaviours must be considered.

2.3 Maintainability and Safety

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 ($MTTR$).

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.

2.4 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.

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)"* [11], which provides a common process throughout the European Union (EU) for the specification and demonstration of the RAMS requirements. 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 [12], which are extremely relevant in design phases of railway systems. 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, the operating conditions, and the maintenance conditions. From a mathematical point of view, the analytical concepts, definitions and terminologies related to a railway RAMS analysis defined in the BS EN 50126 [11] standard go according to IEC 61703:2016 [12] international standard.

3. Discrete event simulation (DES)

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 [13]. 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.

3.1 General principles of DES modelling

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 [14]. 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 [3]. A typical DES 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 Δt. A DES algorithm conducts the progress of the stochastic model in each simulation of a Monte Carlo Simulation. 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. 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.

The stochastic failure and/or repair behaviour of components is typically represented by different probability distribution functions which are characterized by parameters. The most typical distributions to describe the reliability and availability of complex systems are the Exponential distribution, the Normal distribution, the Weibull distribution and the Lognormal distribution. For each distribution, the DES algorithm generates a random Time of failure (ToF), which goes in accordance with each distribution function.

3.2 Uncertain Maintenance Durations

To model the uncertainty in the repair durations, the PERT distribution is considered, which is based on [15] implementation of uncertain maintenance durations. 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 [16]

$$\mu = \frac{a + 4b + c}{6} \tag{3.1}$$

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 (ToF), 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 $B(x|a,b)$ and the complete Beta function $B(a,b)$ which are defined as:

$$B(x|\alpha,\beta) = \int_0^x t^{\alpha-1}(1-t)^{\beta-1}dt \tag{3.2}$$

$$B(\alpha,\beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)} \tag{3.3}$$

$$F_z(\alpha,\beta) = \mathrm{I}_z\,(\alpha,\beta) = \frac{B(z|\alpha,\beta)}{B(\alpha,\beta)} \tag{3.4}$$

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:

$$\alpha = 1 + 4\frac{b-a}{c-a} \tag{3.5}$$

$$\beta = 1 + 4\frac{c-b}{c-a} \tag{3.6}$$

$$z = \frac{(x-a)}{(c-a)} \tag{3.7}$$

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.

3.3 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 [17].

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 [18]:

$$\sum = \mathrm{E}[(\mathrm{X}-\vec{\mu})(X-\vec{\mu})^T] = \begin{pmatrix} \sigma_{1,1}\,\sigma_{1,2}\cdots\sigma_{1,d} \\ \sigma_{2,1}\,\sigma_{2,2}\cdots\sigma_{2,d} \\ \cdots\;\cdots\;\cdots\;\cdots \\ \sigma_{d,1}\sigma_{d,2}\cdots\sigma_{d,d} \end{pmatrix} \tag{3.8}$$

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

$$\sigma_{i,j} = \mathrm{E}[(x_i - \vec{\mu_i})(x_j - \vec{\mu_j})^T] \tag{3.9}$$

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 generation of multivariate normal random numbers is defined in [19]. After generating normally distributed random numbers X, the multivariate normal probabilities are obtained by applying X to the Standard Normal Distribution CDF $\Phi_Z(z)$. 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

The scope of this work is the study of the reliability and availability of a cargo locomotive bogie of a Spanish train operating company. The freight locomotive involved in the case study, the 254-class locomotive, is used for the transportation of cars and potash and is shown in Figure 4.1. 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.

Figure 8.1 – FGC Series 254 Class Locomotive

5. Simulation Model of FGC

5.1 Reliability Block Diagram (RBD)

The RBD for the present case study was built with the guidance of Figure 5.1 configuration of the bogie. For the analysis, the failure data and part of the repair data were obtained from previous studies [20,21], 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 [20]. 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 [22], a reference handbook of railway systems and vehicles composition and configuration. Note that 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.

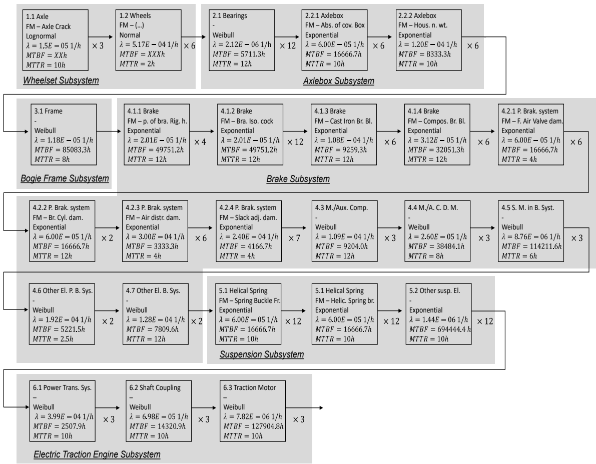


Figure 5.1 – RBD configuration of the 254 Class Locomotive Bogie

5.2 DES model

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. The implementation was done using an already under development program created by [23] and modelled in the commercial software package *Simulink* of *MATLAB*. 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.

5.2.1 Reliability and Availability 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. For the availability, 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 5.2 presents the flowchart algorithm of the reliability (a) and availability (b) DES model for N simulations. Note that TCT_i is the total cumulative time that component i is operating, $Clock_i$ each component individual clock, GFS the Global final signal and S_i each component signal.

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 [23] 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 and maintainability characteristics:
  - $MTBF_i$ and Failure rate λ_i;
  - $MTTR_i$;
- 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;
- 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 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;
- The simulation ends at a predetermined time T.

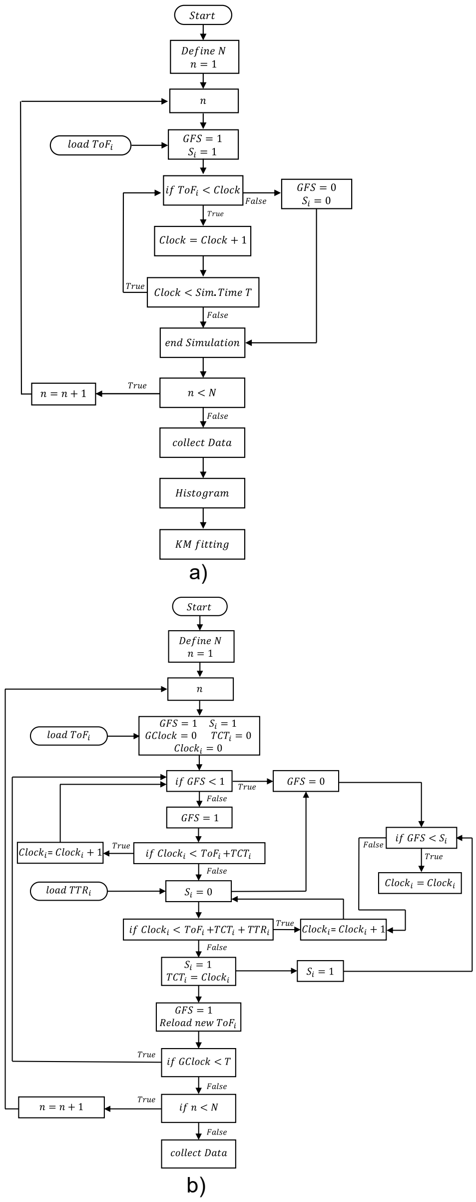


Figure 5.2 – Flowchart describing the algorithm of the reliability (a) and availability (b) DES model

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, while for the availability, ten scenarios were modelled . Table 5.1 summarizes each individual scenario, where emphasis is put on the generation of the ToF and the uncertain maintenance durations.

Table 5.1 – Summary of the different scenarios considered for the reliability and availability DES model of the cargo locomotive bogie

Reliability	
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 $\mathbf{0.5}$
Availability	
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 $\mathbf{0.5}$

For the scenarios where correlation of failure is modelled, the standard normal distribution is considered and the correlation factor $\rho_{i,j} = \sigma_{i,j}$. For the scenarios which consider uncertain maintenance durations, the repair durations are considered random variables, where the stochastic process is represented by a PERT distribution. The PERT parameters are the following:

$$a = 0.8 \times MTTR_i \quad b = MTTR_i \quad c = [1.5{:}\,2] \times MTTR_i$$

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 in order to admit different repair durations.

6. Simulation Results

6.1 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, Figure 6.1 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. To verify the reliability DES model, an analytical reliability model was developed. 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, verifying the DES implementation.

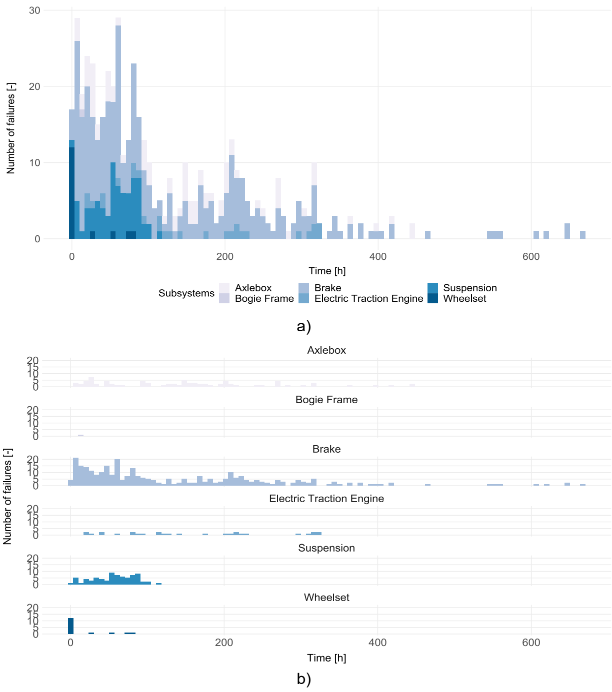


Figure 6.1 – Scenario 1 a) bogie total system histogram and b) each subsystems histogram

A summary of all scenarios is graphically exposed in Figure 6.2 where all the bogie total system reliability scenarios are represented.

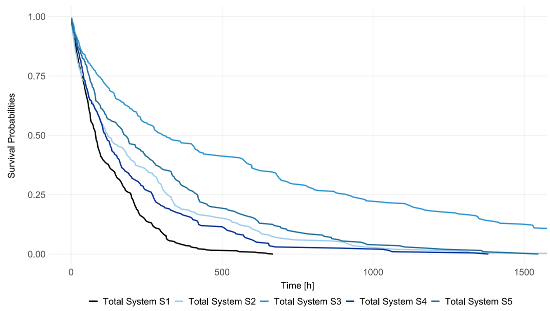
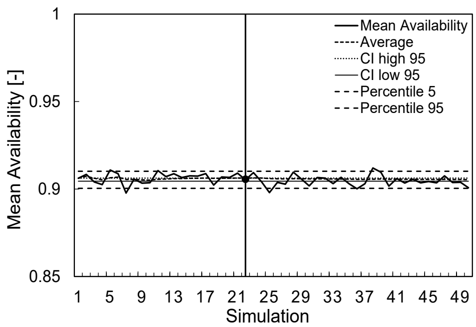


Figure 6.2 – Summary of the total bogie system reliability for scenarios S1 to S5

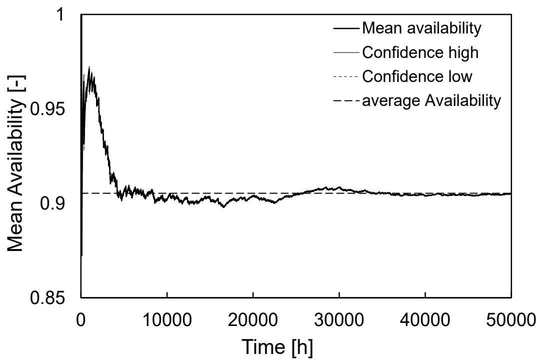
As expected, the bogie's reliability is higher in scenarios 2 to 5 than in the initial scenario 1 since a positive correlation of the failures is modelled in these scenarios. In addition, if one compares scenario 2 and scenario 3 with the bogie's reliability of scenario 4 and scenario 5, respectively, 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. Moreover, the higher the correlation factor $\rho_{i,j}$ between failures, the higher the bogie's reliability (S2 vs. S3 and S4 vs. S5).

6.2 Availability Simulation Results

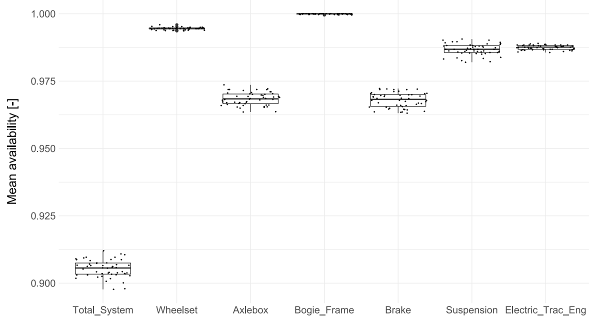
For scenario 1, Figure 6.3 shows the mean availability results for each simulation (a), the mean availability in function of the simulation time for one simulation, where the mean availability in one simulation is identical to the average availability obtained from all simulations (in this particular 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.



a)



b)



c)

Figure 6.3 – 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 $A_{S,1} = 90.53\%$. Based on the bogie configuration, an analytical model was developed to verify the availability DES implementation. 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.

A summary of the bogie's system mean availability results for each scenario is presented in Figure 6.4.

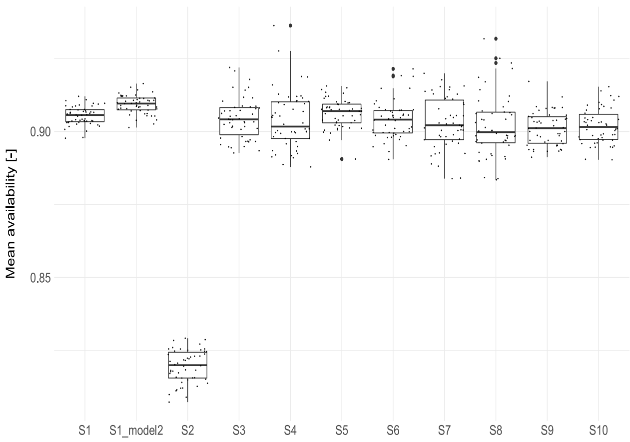


Figure 6.4 – Summary of the bogie's mean availability for each scenario

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 6.4, 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 $S2$.

6.3 Discussion

In this work 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.

7. Conclusion

This paper 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.

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.

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