This project has received funding from the Shift2Rail Joint Undertaking under the European Union's Horizon 2020 research and innovation programme under grant agreement no. 881805 (LOCATE)

Deliverable D 4.1
Available Models Assessment Report

Project acronym:	LOCATE
Full title	Locomotive bOgie Condition mAinTEnance
Starting date:	01/11/2019
Duration (in months):	24
Call (part) identifier:	S2R-OC-IP5-01-2019
Grant agreement no:	881805
Due date of deliverable:	Month 06
Actual submission date:	22-01-2021
Responsible/Author:	IST
Dissemination level:	PU
Status:	Final

Reviewed: yes

Document history		
Revision	*Date*	*Description*
0.1	10-03-2020	Draft version
0.2	21-06-2020	Partners Contributions
1.0	05-08-2020	First issue
1.1	21-01-2021	Revision after request from EC

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Contents

1. Executive summary

The online health monitoring of railway vehicles allows the optimisation of the maintenance strategies and, consequently, the reduction of the life cycle cost, with direct economic benefits for railway operators. Project LOCATE proposes the development of tools and methodologies to implement a condition-based maintenance policy for railway locomotives. The critical subsystems that will be addressed in this project are the brake system, wheelset, electric traction module, axle box, suspension system, and bogie frame. This work is supported by models and numerical simulations that identify the nominal and abnormal behaviour of the locomotive and its subsystems, in conditions that are representative of the operational context of the vehicle. These simulations also allow the definition of thresholds for warning limits and the prediction of component degradation of some of these critical subsystems. Some of these critical subsystems are not supported by modelling and simulation either because their sensor data is used directly for the maintenance strategies (brake systems and axle box) or because their development focus a very specific technology, such as the FGC diesel locomotive, which is basically discontinued (electric traction module). This report is a survey of the existing models and simulations applicable to project LOCATE, including results from associated projects, providing a baseline for new solutions to be developed. The preliminary requirements for the computer experiments are also briefly described in this document. Overall, there is a vast number of solutions for simulating and monitoring the degradation and failure of suspension elements. On the contrary, examples for the use of dynamic simulations to support the implementation of bogie structural monitoring are still scarce. LOCATE aims to contribute to fill this gap by proposing more advanced models to represent bogie frame flexibility and damage.

2. Abbreviations and acronyms

Acronym	Description
FGC	Ferrocarrils de la Generalitat de Catalunya
FMEA	Failure Mode and Effects Analysis
KPI	Key Performance Index
MSD	Mahalanobis Squared Distance
TD	Technology Demonstrator
WA	Work Action
WP	Work Package

3. Background

The present document constitutes the Deliverable D4.1 “Available Models Assessment Report” in the framework of Task 4.1 of WP4 – Reference Behaviour.

It does not contribute to any TD/WA.

4. Objective/Aim

Project LOCATE is aimed at the development of tools and methodologies to support the implementation of a condition-based maintenance strategy for the bogies of freight locomotives. This document was prepared to provide a survey of existing computational models and simulation tools for the study of the degradation of railway bogie components, including results from associated projects. This review will support the selection of the computational models to be developed and implemented during WP4 to study the degradation mechanisms associated to the failure modes identified in WP2. These models will be used to run dynamic simulations of the vehicle-track interaction in realistic conditions of operation, to predict the nominal and abnormal behaviour of the vehicle and its subsystems.

5. Selected components and failure modes

The identification of the use cases, i.e. the most relevant failure modes of critical components of the bogie using the results of a Failure Modes, Effects, and Criticality Analysis and data published on scientific literature is the focus of Deliverable D2.3. A range of sensors have been selected in the framework of WP3 to measure the behaviour of these use cases during operation. The selected components and associated failure modes are identified in Table 1. This table is an adaptation of the results presented in Table 23 of Deliverable D2.3, only featuring the failure modes that are reasonable candidates to be modelled in a virtual environment. The table lists the failure modes that show the potential to cause an impact on the dynamic behaviour of the locomotive that can be detected and measured by the sensor systems foreseen for implementation in this project.

Table 1 – Selected components, failure modes, and subsystem criticality ranking (adapted from LOCATE Deliverable D2.3)

Subsystem	Component	Failure Mode	Source	Ranking
1 Wheelset	Axle	1.1 Fatigue cracking	FMEA	2
	Wheels	1.2 Regular wear	FMEA	
	Wheels	1.3 Rolling Contact Fatigue	FMEA	
	Wheels	1.4 Out-of-roundness (incl. wheel flat)	FMEA	
	Wheels	1.5 Build-up of material	FMEA	
2 Axle box	Roller bearing	2.1 Rolling Contact Fatigue	Literature	4
	Roller bearing	2.2 Inadequate lubrication	Literature	
	Housing	2.3 Fatigue cracking	Literature	
3 Bogie frame	Frame	3.1 Fatigue cracking	Literature	6
4 Brake system	Brake shoe	4.1 Brake shoe wear	FMEA	1
	Pneumatic system	4.2 Brake cylinder damage	FMEA	
	Pneumatic system	4.3 Air distributor damage	FMEA	
	Master/aux. compressor	4.4 Compressor damage	Literature	
5 Suspension elements	Helicoidal spring	5.1 Spring buckle and other damages	FMEA	5
	Viscous damper	5.2 Leak and damage	Literature	
	Friction damper	5.3 Wear and contamination	Literature	
6 Electric traction module	Power transmission	-	Literature	3

The development of computational models to study each of the use cases presented in Table 1 is not feasible, due to the complexity of the different failure mechanisms, the number of parameters involved and the limited availability of computational models to study the failures. Therefore, the failure modes to be addressed using computer simulations must be further prioritised. For this reason, WP4 will focus primarily on the development and implementation of computational models that do not require an extensive failure and maintenance record database. The areas of technical expertise of the project partners are also considered in the selection of the use cases to be studied in WP4. In this sense, WP4 of project LOCATE includes the development of computational models to study:

- Structural health of the wheelset axle, a safety critical component that is subjected to cyclic loads that promote the growth of fatigue cracks. The wheelset ranks 2nd in the criticality ranking of the FMECA analysis;
- Structural health of the bogie frame, other safety critical component that withstands cyclic loads that may lead to the propagation of fatigue cracks on weld spots and areas of stress

concentration. The bogie frame ranks 6th in the criticality ranking of the FMECA analysis. However, the severity associated with a structural failure of the bogie frame is extreme;

- Degradation of suspension elements, such as helicoidal springs, viscous dampers and friction dampers that present a major impact on the quality of the running behaviour of the vehicle. The suspension system ranks 5th in the criticality ranking of the FMECA. Similar to the bogie frame, the failure of a suspension element presents a severe safety risk.

6. Survey of available models

The main goal of this report is the assessment of available solutions to support the development and implementation of computational models of the selected components and failure modes identified in the previous section. This review includes models and results published in the specialised scientific literature, as well as projects associated to Shift2Rail.

The specifications of the algorithms and models developed in WP4 will be reported in a future deliverable. However, the computational models must replicate the behaviour of the components considering different levels of degradation, providing the nominal and abnormal signal signatures recorded by sensors installed on the bogie components. These sensor signals must be post-processed, to provide the means for the quantitative characterisation of the component condition, supporting the definition of warning limits. It is also desirable that the models are able to predict the degradation of the component condition, offering an estimate of the remaining time/distance/load to failure. This requirement is relevant in the context of a condition-based maintenance strategy, effectively allowing the optimisation of maintenance plans. However, some failure modes may be assumed to initiate at a unexpected time instant being, in this case, the model expected to predict the evolution of the condition from the onset of failure.

Two different approaches can be distinguished concerning the development of computational models for the prediction of component degradation [1]:

- Use of machine learning algorithms that provide predictive models based on large history datasets of faults and inspections. Such models are commonly black boxes, i.e. purely mathematical abstractions that do use any information on the physical processes of component degradation and, consequently, should only be used as a last resort, i.e., when there is not enough knowledge on the physics of the problem;
- Use of deterministic, or stochastic, models that depend on expert knowledge and are representative of the mechanics of failure and degradation, requiring the definition of the geometrical, material, and mechanical properties that describe the system. The quality of these models is limited by the availability of data to describe the behaviour of the component or failure mechanism and expertise of the developers.

Not only because the use data driven models do not include the physics of the problem but also due to the lack of a comprehensive operational history database to support the use of artificial intelligence approaches, WP4 of LOCATE will prioritise the development and implementation of computational models based on expert knowledge of the system physics. However, the models developed will be used to simulate the vehicle-track interaction and the results will contribute to generate a database of the vehicle behaviour considering different levels of component degradation. The measured behaviour recorded in on-track tests in the context of WP3 will also be used to build, verify, and calibrate the database of the vehicle response. Therefore, the use of machine learning approaches may prove useful, in the future, to analyse this database, which is the result of using the knowledge of the problem physics.

6.1. Wheelset axle crack

The wheelset is the most fundamental component of a rail vehicle. It consists of two coned wheels rigidly connected to a common axle. In the case of a locomotive, the wheelset also includes some form of connection to the power transmission. In the case of the FGC 254 locomotive, tractive power is transmitted to the wheelset through a spur gear, visible in Figure 1. The wheelset is responsible for transmitting the loads, i.e. weight, inertia forces and traction/braking forces, from the vehicle to the track. These are the forces that support and guide the vehicle, as a result of the wheel-rail interaction. Therefore, the wheelset is a safety critical component of the vehicle. The failure of an axle or a wheel has the potential for catastrophic consequences.

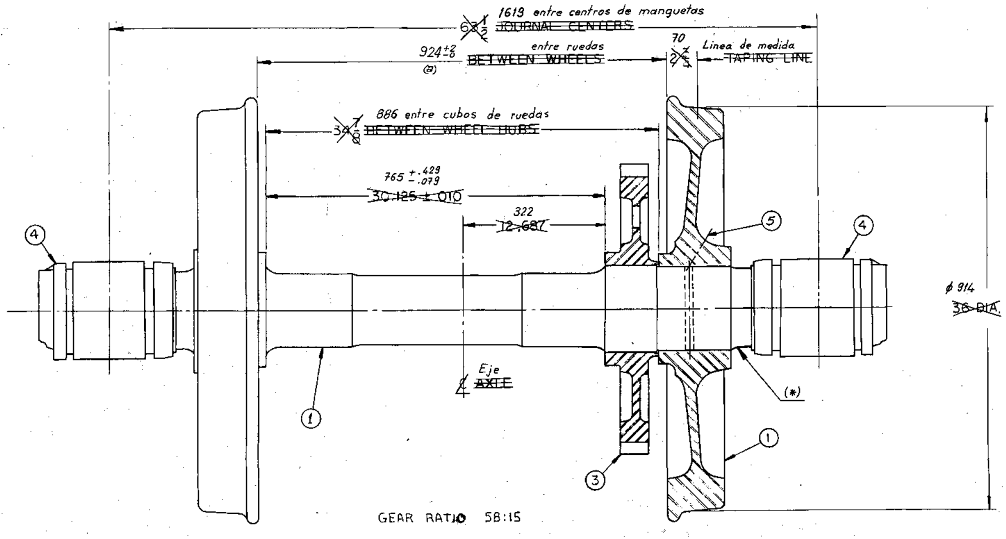

Figure 1 – Wheelset of locomotive FCG 254.

Crack initiation on an axle may result from manufacturing defects or damage during the operation, such as ballast projection and collision with foreign objects, combined with environmental effects, for instance corrosion pitting. The operations required to manufacture a railway axle are: forging, to roughly shape the axle in a cylindrical form; followed by a series of turning operations, shaping the axle into the required dimensional and geometrical tolerances and ensuring an adequate surface finish. Internal and external grooves, indentations, cutting marks and other damages inflicted during manufacturing are potential areas for crack initiation and propagation. Equally, during the operation the axle runs in an adverse environment, subjected to high dynamic loads, impacts, projection of ballast and potentially collisions with foreign objects, that further increase the probability for crack initiation.

Cracks may be characterised by length, depth, and percentage of axle section area, that combine to define the structural health of the axle. Railway axles are designed and manufactured aiming at virtually infinite lifetime. However, no mechanical component is fault-free and, as such, cracks are always present in railway axles. For this reason, the definition of the inspection intervals of axles is centred on a "damage tolerance" approach [2]. This approach involves the assessment of the performance of the inspection method, the minimum detectable crack size, the load spectra, the critical sections of the axle, the resistance of the material to crack growth and the estimate of the largest crack size that the axle can endure before failure. Therefore, the accuracy of this approach depends on the amount and quality of the data available. Computer simulations and the implementation of online condition monitoring have the potential to provide key support to extend the current inspection intervals. Computer simulations provide an estimate of the load spectra on the wheelset, that result from the vehicle-track interaction in the context of operation in specific lines and environmental conditions. The existing technologies for the condition monitoring of railway axles are still under development and are limited by the complexity of installation, data and power transmission, and the difficulty of the detection and characterisation of faults in such a noisy environment. Online condition monitoring is not expected to replace the existing types of inspection in the foreseeable future but has the potential to complement the current inspection strategies.

In the following subsections, two different approaches to the structural health monitoring of railway axles are presented and discussed.

6.1.1. Low-frequency vibration

Politecnico de Milano developed a methodology for monitoring the structural integrity of railway axles using acceleration signals from sensors installed on the axle boxes. This approach was implemented in project SUSTRAIL and published by Rolek et al. [3], being later extended in project INNOWAG and presented by Hassan and Bruni [4]. This methodology relies on the principle that the existence of a crack perturbs the axi-symmetric bending stiffness of the axle. Consequently, the bending vibration of the axle is affected at frequencies that are multiples of the frequency of wheelset rotation, designated as nxRev. The growth of an axle crack can be successfully detected by the analysis of the first three harmonic components of the bending vibration using the longitudinal component of the accelerations recorded by sensors installed on both axle boxes of the same axle.

Axle cracks propagate in the direction perpendicular to the axis of rotation, due to fatigue induced by a combination of axle bending and rotation. Under this load state, the crack periodically opens and closes, and this phenomenon is designated as the “crack breathing mechanism”, depicted in Figure 2. This process causes a variation of the resisting cross-section and associated area moments of inertia and, consequently, perturbs the axi-symmetric bending stiffness. The amplitude of the resulting bending vibrations is a function of the crack size, speed of rotation of the wheelset, position of the crack, and mechanical and geometrical characteristics of the axle.

The methodology is demonstrated using a mathematical description that incorporates a multibody model of a railway wagon, with one in four wheelsets having a cracked axle, shown in Figure 3. This faulty axle is modelled using Timoshenko beam finite elements, and the cross-section area and moments of inertia of the elements in the vicinity of the crack are a function of the wheelset angle of rotation, to represent the effect of the “breathing mechanism”. The wheel-rail contact forces, that provide the dynamic loads applied on the wheelset, are determined using a linear Kalker creep force theory and considering a constant value of wheel conicity. The effect of track irregularities and wheel out-of-roundness is also taken into account. The model developed allows the study of the interaction between the vehicle and the faulty wheelset up to a frequency of 200Hz.

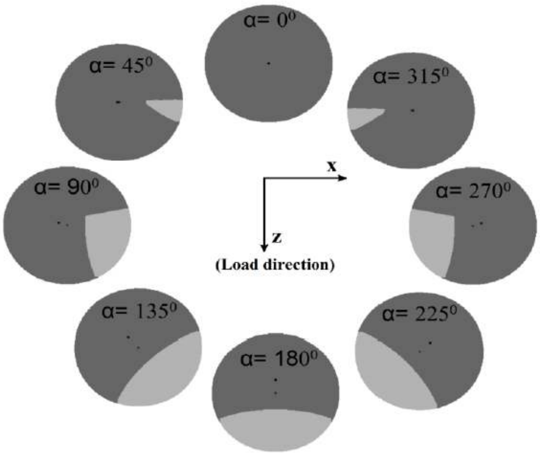

Figure 2 – Illustration of the “breathing mechanism”, present in a rotating cracked axle subjected to a bending moment. The light grey region represents the axle crack area [5].

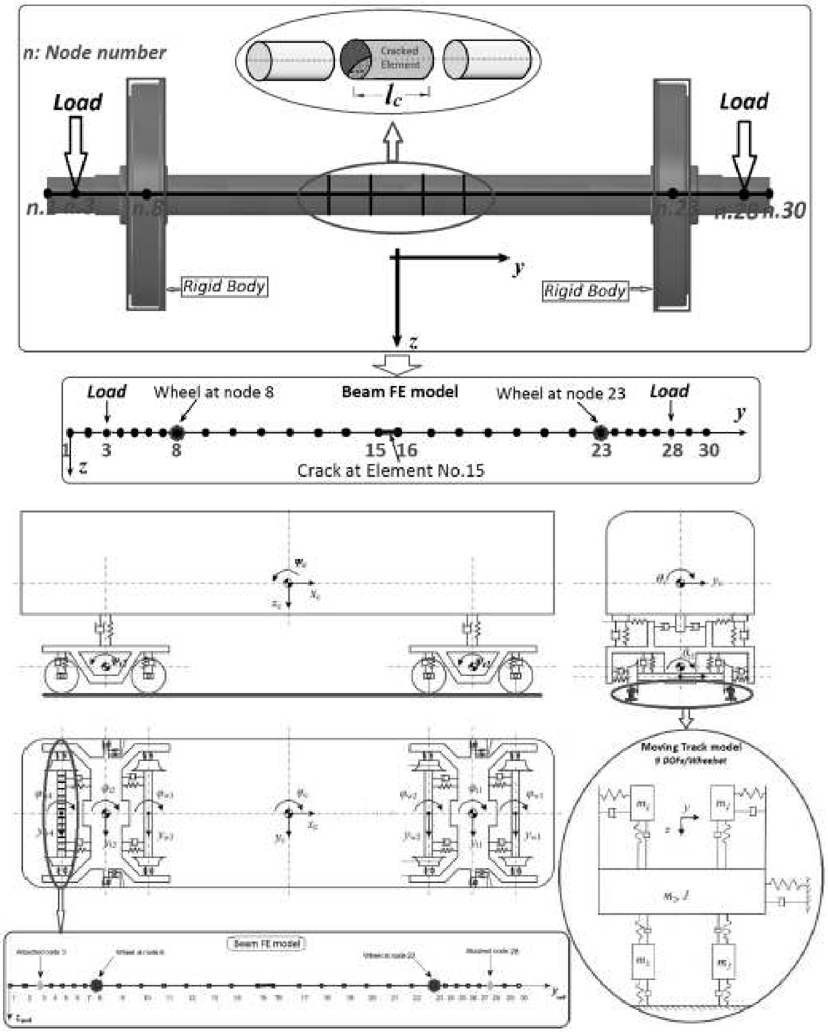

Figure 3 – Schematic representation of: (top) the Timoshenko finite element model of the cracked axle; and (bottom) the multibody model of the freight wagon [5].

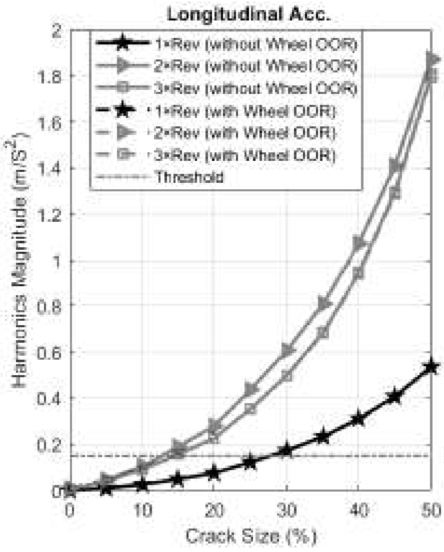

Figure 4 – First three harmonics of the longitudinal acceleration signal [5].

The acceleration signals at the axle box sensor positions are post-processed from the time domain into the frequency domain using the Discrete Fourier Transform. The increase in the amplitude of the horizontal magnitude of the first three harmonics can be associated with an increase in axle crack size, as shown in Figure 4.

The use of a methodology for condition monitoring of a railway axle requires the definition of a fault criterion that is able to generate timely warnings of imminent axle failure. The Mahalanobis Squared Distance (MSD) method is applied to a multi-variate data set formed by the amplitudes of the 2xRev and 3xRev harmonics of axle vibration, to support the definition of a limit MSD. Figure 5 illustrates the sharp increase of the MSD value on the onset of reaching a crack size of 4% of cross-sectional area, well before a critical reduction of the resisting cross-section area that would result in the catastrophic failure of the axle.

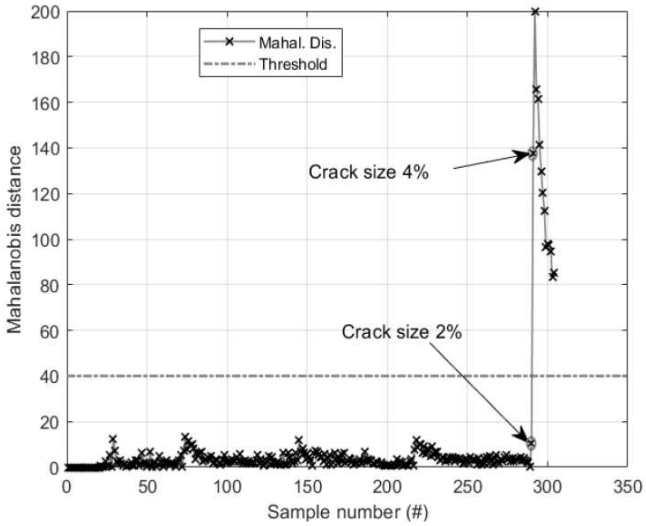

Figure 5 – Mahalanobis distance of 2xRev and 3xRev amplitudes of numerical simulation results from multibody-finite element model [5].

6.1.2. Acoustic emission

Acoustic emission (AE) is the high-frequency elastic wave energy generated when materials deform when subjected to dynamic mechanical loads. This is the case of railway axles under normal operation, that are exposed to static forces due to the vehicle weight and dynamic forces associated with the wheel-rail interaction. However, the AE released during normal operation differs from that emitted during fracture of the material. This fact provides the opportunity for monitoring the axle condition using piezoelectric sensors. The high sensitivity of AE sensors allows the early detection of crack initiation and propagation, which is a key factor for effective condition monitoring, increasing safety levels and providing the opportunity for maintenance optimisation [2].

Although AE is already commercially available to assess the condition of the wheel surface and axle bearings, its application to railway axles is still in a stage of research and development. Jiang et al. [6,7] apply a translation invariant wavelet to denoise the AE signal used to monitor the condition of cracked railway axles in a test-rig environment. However, the use of AE data to evaluate the structural condition of railway axles during the operation is still prevented by physical constraints. The problem of acoustic attenuation prevents the evaluation of axle cracks that are not in the immediate vicinity of the sensors, limiting the monitored areas to the regions that are close to the axle boxes. Power and data transmission also continue to be a current limitation. Ultimately, in the context of Work Package 4, AE poses difficulties of implementation, associated with the requirement for computational models that must be accurate in the high frequency range.

British project MONAXLE, led by Perpetuum in partnership with TWI and the University of Southampton, developed and successfully demonstrated a concept for the continuous monitoring of the structural integrity of axles using a self-powered wireless system. This concept relies on the complementary use of high frequency vibrations and AE to assess axle crack growth. Signal processing techniques have been used to identify the fault signal immersed in a noisy environment.

6.2. Axle box

The developments achieved in the project MAXBE, as well as the industrial solution existing in the market, can be directly explored for the monitoring of the axleboxes, not requiring the development of specific digital twins, in this project. The implementation of on-board monitoring systems for freight locomotive bogies is quite expensive and, most probably, not feasible. The off-board (on-track) monitoring systems are well established providing the mains requirements for collecting the data (temperature and vibrations), as demonstrated in project MAXBE, required to support maintenance decisions. The results of project MAXBE can be directly applied to the advance of the monitoring process of axleboxes of any type of rolling stock, as there is no particular feature that differentiates the axleboxes, or bearings, of freight or passenger vehicles. For these reasons, the development of models and computational tools to address the axleboxes in project LOCATE, will be based on the results of the former project MAXBE framework. This implementation is aligned with the objectives of LOCATE project to use the results of previous research project in Railways.

6.3. Bogie frame cracking

The bogie frame is the structure that supports the vehicle body, traction and braking equipment, and limits the movement of the axle boxes through the action of the rigid and flexible suspension elements. Similar to the axle, the bogie frame is a safety critical component of the vehicle that is regularly subjected to different types of inspections following a calendar defined using the "damage tolerance" approach. The bogie frame is frequently a large intricate structure with fixtures, holes and weld points that are difficult and time-consuming to inspect. For this reason, there is a potential for great benefits of replacing, or at least complementing, visual, magnetic, and ultrasonic inspections by an online monitoring procedure.
The development of computational models and simulations to support a methodology to monitor the condition of the bogie frame requires the use of adequate formulations to study the mechanical loads developed on the wheel-rail interface and transmitted into the bogie frame. These loads exert fatigue in the stress concentration areas and may lead to fracture if not detected in time. In the following subsections, emphasis will be given to the methods used to study fatigue in bogie frames, as well as the techniques used for monitoring the condition of mechanical structures.

6.3.1. Fatigue assessment of railway bogie structures

The wheel-rail contact is a source of dynamic forces that are transmitted from the wheelsets into the suspension elements and further into the bogie. Consequently, the design of the bogie frame must consider the effect of the cyclic loads that may potentially expose the structure to fatigue. Numerical simulations are key to the development and optimisation of bogie frame designs, minimising the risk of catastrophic failure of the component.

Claus and Schiehlen determined the areas of stress concentration on the bogie frame of a high-speed train using a flexible multibody approach that applies the floating reference frame formulation [8]. Figure 6 depicts the strategy used to analyse the flexible motion of the bogie frame. The track irregularities are used to excite the vehicle and bogie frame presents resonant oscillations in the low and middle frequencies

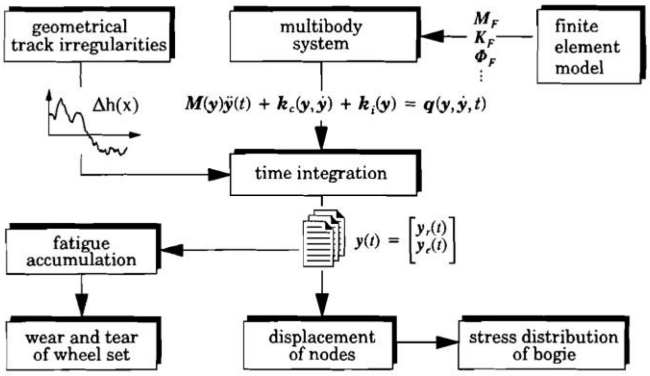

Figure 6 – Schematic representation of the stress and fatigue analysis of the bogie frame using a flexible multibody formulation [8].

Dietz et al. predicted the fatigue life of a bogie frame using multibody simulations to determine the service loads [9]. The bogie frame is represented by a flexible body that incorporates the first three eigenmodes of the structure, determined using the finite element method. The multibody simulations are performed and the forces and moments on the bogie frame are post-processed in two steps: first, the finite element method is used to determine the stresses on the locations of critical stress concentration; second, and last, the time history of the stresses is transmitted into a post-processor to determine the fatigue life of the structure.

Fu et al. investigated the cause for fatigue cracks in the bogie frames of a series of Beijing metro vehicles [10]. Using a finite element model of the bogie frame and acceleration and stress data from on-track tests, an analysis in the time and frequency domains revealed that the natural vibration modes of the frame are excited by rail joints and excessive wheel out-of-roundness. These adverse conditions of operation result in high stresses in welding spots of the bogie frame.

6.3.2. Damage detection via structural vibrations

The principle of the vibration-based methods for the structural health monitoring is that the damage and degradation of a structure result in a local modification of its physical properties, i.e. stiffness, mass or damping. Consequently, these physical modifications induce changes in the modal characteristics of the structure, i.e. natural frequencies, mode shapes and their derivatives, and damping ratios. Therefore, there is the potential for assessing the condition of the structure by adequately monitoring its vibration characteristics.

The vibration based-techniques can be classified into natural frequency-based methods [11–13], mode shape-based methods [14–16], and mode shape curvature/strain-based methods [17], depending on the type of modal characteristics used to analyse the structure. The various types of methods present different advantages and disadvantages, associated with the number of measure points required for a given structure, sensitivity of the modal parameters to structural damage, and sensitivity to noise and environmental conditions. The methods for damage detection and identification can also be classified into response-based and model-based methods. Response-based methods commonly require the access to experimental data from physical tests, while model-based techniques depend on the existence of a computational model of the structure. Fatigue cracks are frequently represented by a change of stiffness in the vicinity of the crack. Nonetheless, more advanced alternatives exist, that include the effects of normal and tangential contact between crack surfaces.

Since the early 1990s, several authors reviewed the state-of the art of the vibration-based techniques for structural health monitoring [18–20]. Overall, common applications of these methods can be found in the fields of civil and aerospace engineering, where the structures are difficult to access and inspect. However, the number of scientific publications focused on the application of such methods in the railway bogie frame structure is scarce.

6.4. Brake system

All the failure modes of the brake system are associated to direct measured quantities, either by sensors (temperature or pressure of the brake piping system) or via visual, camera or sensor inspections of the components (brake shoes). Such data can be used directly on the maintenance framework developed in WP5 and, therefore, no specific models or computational analysis tools directed at the development of digital twins are required.

6.5. Degradation of suspension elements

All railway vehicles have some form of suspension to protect the payload, i.e. passengers and goods, and the vehicle structure by filtering the vibrations caused by the interaction between the wheelsets and the track. The suspension also offers flexibility between the wheelsets and the rest of the vehicle, to assist in curve negotiation and decrease the risk of derailment. Common suspension elements present in railway vehicle are different types of springs, guides, bump stops and dampers. Online condition monitoring of suspension elements presents the potential to reduce maintenance costs, through a decrease of routine inspection time and maintenance costs, while increasing the safety and reliability of the operation.

Li et al. reviewed the approaches developed to monitor the condition of suspension systems and wheel-rail contact in railway vehicles [21]. These techniques can be classified into model-based methods and signal-based methods. Model-based methods use mathematical models to establish the relationship between the external excitation and the vehicle behaviour. These models are fed with input data of the excitation, such as speed, track geometry, and track irregularities, and the output is a prediction of the vehicle response. This output is compared with the measured output sensor data, such as accelerations. The residual differences between the reference output behaviour and the measured output behaviour are compared and used to estimate the vehicle condition. Hayashi et al. propose the use of an Interacting Multiple-model algorithm to detect the failure of a lateral yaw damper from on-board accelerometers [22]. Li et al. developed a method that involves the use of a Rao-Blackwellized Particle filter to estimate the wheel conicity and the yaw damper parameters using different sensor configurations [23]. Wei et al. apply a Kalman filter to generate the residual that is used to detect the failure of vertical dampers, vertical springs and also the failure of the sensor system [24,25]. Jesussek and Ellermann demonstrate how a Hybrid Extended Kalman Filter can be used to detect failures of non-linear suspension elements [26]. Jesussek and Ellermann also propose the use of multiple model Kalman filters to minimise the detection error, improving the capacity for better identification of the causes for the changes in vehicle behaviour [27]. Liu et al. propose the combined use of Extended Kalman filter with the Recursive Least Square algorithm to detect the failure of primary suspension elements. More recently, Lebel et al. proposed a Bayesian calibration approach using a Gaussian process surrogate model of the likelihood function for the monitoring of parameters of the suspension of a high-speed train [28].

Signal-based methods allow the detection of faults through the direct analysis of the output signals. The signal-based methods require the construction of fault database, comprising the expected nominal behaviour and the abnormal signal signatures related to the condition of the components. This fault feature database can be created using multibody simulations, on-track test runs or even both. A fault classifier uses classification algorithms to associate the changes of the output signals with the probable failures. Mei and Ding developed a model-less approach to detect and monitor the failure of dampers of a two-axle bogie, using the cross-correlation of the acceleration signals of sensors installed on the bogie frame [29,30]. Martinod et al. suggest the application of the least-squares complex exponential method to identify the modal parameters of the multibody model of a suburban train [31]. Gasparetto et al. present a method to detect increased wheel conicity and degradation of yaw dampers, using the random decrement technique to analyse the lateral accelerations of the bogie frame. The authors also compare the reliability of two different fault classification algorithms [32]. Li et al. identify different spring faults specific to three-piece freight bogies, and discuss their impact and detectability using multibody simulations. The results are analysed using the cross-correlation of the accelerations on two points of the bogie frame and different fault indicators are compared [33].

The development and testing of methodologies to monitor the condition of the suspension elements requires the access to the signals measured by an appropriate network of sensors installed on the vehicle. This sensor data may be obtained from direct measurement during on-track testing, but most commonly it is the result of computer simulations. These computer experiments are either supported by simple mathematical models of the vehicle and the wheel-rail interaction, or more complete multibody models combined with a realistic description of the railway track and complex wheel-rail contact models. These computational models allow the modification of the linear and non-linear properties of the suspension elements, such as spring axial and shear stiffness, damping and friction coefficients, and preloads. The different states of degradation of suspension components can be represented. Bruni et al. reviewed the state of the art on the available approaches for modelling railway suspension components [34]. Ambrósio et al. proposed a novel approach to modelling complex mechanical systems, using imperfect kinematic joints [35]. This formulation has the potential to provide a realistic representation of the geometrical and mechanical non-linearities, that is useful to examine the degradation and failure of vehicle suspension elements.

The use of numerical simulations to support the definition of a health monitoring methodology for primary suspension elements can be illustrated by the demonstration from project INNOWAG [5]. A multibody model of a freight wagon equipped with Y25 bogies was developed and used to run dynamics simulations to obtain the nominal behaviour of the vehicle. The abnormal behaviour was also obtained, simulating various scenarios associated to the different levels of component degradation. For instance, the failure of a spring is represented by a variation in percentage of the spring stiffness: null stiffness in the case of a broken spring, and up to, 200% representing a locked suspension. The same logic applies to the failure of a friction damper, through the modification of the friction coefficient. The fault detection algorithm is based on the correlation of the acceleration signals measured by virtual sensors installed on the bogie frame. The principle of this method is that the failure of a vertical suspension component perturbs the symmetry of the rigid body modes of vibration of the bogie frame. This means that under normal operation, the bounce, pitch, and roll motions of the bogie are decoupled, and their correlation is low. However, when a suspension element is degraded, the symmetry between the bogie modes of vibration no longer exists, increasing the correlation between the bounce, pitch, and roll accelerations. The fault indicators are defined using the standard deviations and absolute values of the cross-correlations at different time delays and using different levels of signal filtration. The reliability of the methodology and the selected fault indicators is discussed and the potential of the method for condition monitoring of the suspension elements is highlighted.

6.6. Electric traction module

The major issue associated to this critical component concerns the power transmission, which would require the development of electro-mechanical models of the complete traction module which could associate sensor data (measures of the electric current and of the available mechanical power) to the physical failure mechanisms of the different components of the electric traction module. However, the diesel locomotive available in this project is a legacy model that is discontinued and with obsolete technology, thus making its electric traction module digital twins unusable for other freight locomotive bogies. However, all relevant data is obtained by sensors and stored either for direct use in the maintenance decisions, particularly for the thresholds values used in WP5 of this project (on which LUTs can be created for normal behaviour during time, and deviations from historical records can be used as thresholds), or to support the development of future models and computational tools. The methodologies developed and applied in this project for the development of digital twins of the critical subsystems (based on the use of Design of Experiments methodologies) are foreseen as being directly applicable to the future development of digital twins for electric traction modules to complement the maintenance decisions.

7. Definition of simulation scenarios

Project LOCATE aims to develop a framework to implement a condition-based maintenance strategy on the series 254 locomotives owned by FGC. These locomotives regularly operate the potash traffic from the mines in Súria to the Port of Barcelona, using FGC dedicated metre gauge lines. On average, the locomotives perform a total of 3 laden runs, totalling 6 trips every day. The wagons used in this service are the FGC series 62.000 hoppers, that run on a pair of three-piece bogies.

The operational context is crucial to the definition of the mechanical loads and the degradation experienced by the bogie components. Therefore, the dynamic simulations performed in WP4 must be representative of the load spectrum applied on the locomotives during the operation. This involves a track model that includes track layout and track irregularity data measured by an inspection vehicle on the line operated by FGC. The first dynamic simulations will focus on capturing the nominal behaviour of the locomotive under the two fundamental load regimes: laden from Súria to the Port of Barcelona; and empty in the opposite direction. The subsequent dynamic simulations will focus on bogie component degradation and the resulting signatures recorded by the virtual sensors positioned on the bogie. The simulations will allow investigating the impact of bogie frame cracking, wheelset cracking, and the degradation of primary suspension elements. The latter include:

- Failure of inner and outer coil springs, represented by a variation of the spring stiffness constant;
- Failure of the viscous dampers connected to the centre wheelset, represented by a variation of the linear damping coefficient;
- Failure of the friction dampers that provide damping when there is rigid contact between the axle boxes and the horn guides of the bogie frame, represented by a variation of the coefficient of friction of the friction surfaces.

The scenarios associated with component degradation are to be defined using a Design of Experiments methodology. This approach minimises the number of simulations required to build a fault database that accurately represents the nominal and abnormal vehicle behaviour and support the identification of threshold limits to trigger future maintenance actions. This option is particularly relevant considering the large computational effort required to run detailed models of the vehicle in realistic conditions of operation.

8. Conclusions

In this report, different solutions were presented to study the degradation of bogie components using numerical simulations. Railway axle cracks can be detected by taking advantage of the periodicity of the fault signatures, which is related with the velocity of rotation of the axle. Several methods exist that allow the study of fatigue phenomena in railway bogies. Likewise, various techniques exist that are already in use to monitor the condition of mechanical structures such as bridges and planes. However, to the knowledge of the authors, there is no published solution to monitor the bogie structure regarding fatigue. There is the potential for project LOCATE to fill this open point. A great number of solutions exist to assess the damage and degradation of suspension elements, both in the context of the modelling of the defective components, as well as the signal processing techniques for fault detection and identification.

Project LOCATE expects to contribute with more advanced models to represent body flexibility and damage, such as fatigue cracks in the railway axle and bogie frame. This will be achieved using a flexible multibody formulation that employs modal reduction techniques to allow the efficient simulation of complex mechanical systems. Additionally, the degradation of suspension elements will be analysed using multibody simulations, taking advantage of imperfect kinematic joints to allow a realistic representation of friction, local compliances, and clearances.

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