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Monitoring and Thresholds Rules Specification

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Farouk Balouchi	HUD	Principal author, standards and literature review. Contribution sections: 1, 2, 3 4, 5, 6, 7 and 8.
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Table of Contents

1. Executive Summary

The LOCATE project aims to develop a generic framework for condition-based and predictive maintenance (CBM) of locomotives bogies. To achieve this aim the research has followed the high-level framework for condition monitoring and diagnostics of machines and prognostics from international standards and literature. This has involved: the selection of use cases and identification of failure modes, effects, and criticality (WP2), and the identification of parameters to be measured and relevant measurements techniques (WP3). The remaining work packages aim to establish the reference behaviour (WP4) for the selected use cases, the thresholds and rules to apply to the measured and reference behaviour to diagnose a fault and determine the required maintenance actions (WP5), and finally the integration and testing of the developed CBM scheme (WP6).

To support the development of a decision-making framework for condition monitoring, diagnosis and prognosis for the scheduling of bogie maintenance it is important to understand the main operational constraints in maintenance depots which are relevant to the LOCATE project. This was carried out by reviewing the FMECA, developed during WP2, and through further discussions with the use-case owner FGC, with the outputs compiled in a separate RAMS table.

The potential for the application of diagnostic and prognostics has been found to be of significant benefit to railway rolling stock maintenance; however there remains considerable gaps to translate machine CM&DP standards to rolling stock. This deliverable has identified strategies that other industries, have successfully applied machine CM&DP to their asset management processes effectively. Key standards and frameworks have been found to be very useful in this regard with significant value being afforded in bridging the gap between machine CM&DP to CBM for rolling stock in the development methods in establishing monitoring thresholds and decision support rules.

Initially the failure rates defined in the FMECA (WP2) and/or manufacturing data with recommended periodicities (if available) should be utilised to provide the most accurate representation of functional life expectancy for the components (accounting for any variation between components/operation). An example of Weibull probability densities and hazard functions for typical failure patterns was suggested by D5.2 and adopted by Task 5.3. These should be combined with the condition data to provide an estimate of the remaining useful life (RUL) linked to maintenance and the estimated P-F intervals. These can be combined with the operational constraints, from D5.1, to support the linear piecewise approximation models (proposed in Task 5.4 for tactical planning of maintenance). An example of the proportional hazard model linking conditional data from sensors was provided in section 6.3 of this deliverable outlining its limitations and providing other more recent model suggestions. The P-F intervals should be continually reviewed during the demonstrator in collaboration with FGC and provide a feedback to the accuracy of the LOCATE system updating designated calibration parameters.

The information obtained through discussion with FGC and the Advisory Board is included in the separate RAMS / FMSA table, will provide useful information for subsequent tasks in WP5 to better understand the failure modes and development of the diagnostic and prognostic functionalities.

2. Abbreviations and acronyms

Abbreviation / Acronyms	Description
PdM	Predictive maintenance
CBM	Condition based maintenance
TCMS	Train control and monitoring system integrated in the locomotive
RUL	Remaining useful life (period of time after which the risk of defect become intolerable)
CM	Condition monitoring
CM&DP	Condition monitoring & Diagnostics and Prognostics
PHM	Proportional Hazard Model
MIMOSA	Machinery Information Management Open System Alliance
OSA-CBM	Open System Architeture for Condition Based Maintenace
ROI	Return on Investment
RoE	Return on Experience
FMECA	Failure Mode Effect and Criticality Analysis
INNOWAG	INNOvative monitoring and predictive maintenance solutions on lightweight WAGon
MSG3	Maintenance Steering Group 3 (Aviation)
RCM	Reliability Centred Maintenance
MTTF	Mean Time to Failure
MTBF	Mean Time Before Failure
FMEA	Failure Mode Effects Analysis
LCC	Life Cycle Costs
FTA	Failure Tree Analysis
OEM	Original Equipment Manufacturer
IAMS	Integrated Asset Management System
FMSA	Failure Mode Symptoms Analysis
RPN	Risk Priority Number
ETTF	Estimated Time to Failure
SM	Scheduled Maintenance
PM	Preventative Maintenance
CM	Corrective Maintenance
PIM	Proportional Intensity Model
P-F	Potential-Failure (P) Functional-Failure (F)
SMARTE	Smart Maintenance and the Rail Traveller Experience
IP	Innovation Programme
CC	Cross Cutting
ECM	Entity in Charge of Maintenance

3. Background

The present document constitutes the Deliverable D5.2 “Monitoring and Thresholds Rules Specification”. The specification of monitoring threshold and rules have been developed in the framework of Task 5.2 “Monitoring and Thresholds Rules Definition” of WP5 “Operational Behaviour”.

To establish an effective CBM and predictive maintenance program, a set of thresholds and rules are required to provide an indication of when maintenance is required based on the health status of the system/component determined from the measured (WP3) and reference (WP4) behaviour. This might include the generation of alert limits which indicate that an unexpected event has occurred (e.g., exceedance in a vibration signal or temperature reading), comparison of measured and reference behaviour to indicate a change in component performance or degradation (e.g., P-F curve) and definition of rules to estimate the time to failure (or remaining useful life, RUL) to trigger a particular maintenance activity.

To support the definition of initial thresholds and rules, existing standards and techniques for condition monitoring and prognostics have been reviewed. Techniques, such as failure mode symptoms analysis, were shown to provide useful information for identifying the symptoms which potentially lead to a particular failure, the current means of detection and thresholds which trigger a maintenance action. This technique has been applied to each of the selected use cases to link the main failure mode identified in WP2 with the proposed measured and reference data.

4. Objective/Aim

The objective of condition-based predictive maintenance (PM) is to replace typical condition based maintenance (CBM), in which repairs are undertaken before the locomotive can be used again in operation, by predictive maintenance in which (a) unnecessary inspections are avoided by replacing them by continuous monitoring of the assets (more than 70% of the mechanical inspections do not give rise to repairs and the corresponding stops of the assets) and (b) future failures are predicted before they occur in operation so that repair work can be scheduled in accordance with operational requirements and maintenance processing capabilities.

To achieve this the following aims must be delivered for each possible failure mode of a sub-system or component to be maintained:

- Information obtained by processing the raw data from the sensors installed on the locomotive
- The state of these parameters is simulated by means of the LOCATE simulation system (digital twin), providing a reference corresponding to a good working condition.
- The evolution of these parameters (as a function of time or operating conditions) until the risk of failure in operation becomes intolerable. The time needed in operation depends on the repairs to be done. This time is to be given by the operator, FGC. A function, based on the maximum time in operation of the parameters, can then be defined for each defect.
- Fleet managers must also have information on the availability of manpower and repair facilities to be able to schedule stops in accordance with the transport plan

This deliverable aims to define a set of specifications for the development of initial thresholds and rules to support future maintenance decisions within the condition-based maintenance (CBM) optimisation framework described in D5.3.

5. State-of-the-art and Relevant Standards

The total railway system comprises a host of standards, defined by European Union (EU) standards working groups and committees, some of which are relevant to Condition Based Maintenance (CBM) and the LOCATE project as shown in Figure 1.

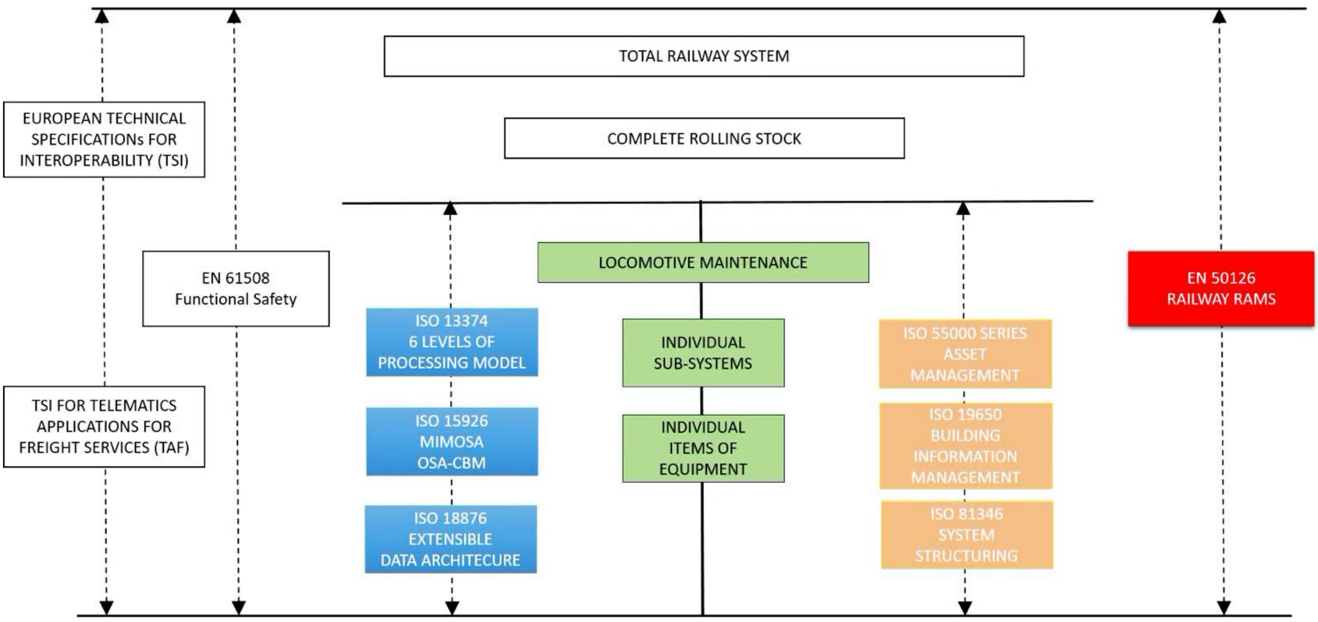

Figure 1 Selected European Union Railway Standards for CBM

The overarching group of standards developed to support internationally coordinated efforts in railway systems can be seen in such examples as the European Technical Specification for Interoperability (TSI), shown on the left of the figure, from the EU Agency for Railway [1]. These can cover a range of specifications from Energy, Infrastructure and Safety to the specifics of Telematics Applications for Freight Services (TAF) directly applicable to the LOCATE deliverables.

A particularly important standard for railways is EN 50126 [2], shown in red on the right of the figure. This focuses on the critical aspects of total railway systems concerning Reliability, Availability Maintainability and Safety (RAMS) and their interaction. It has been developed to define a systems approach to lifecycle management of railways from concept to decommissioning and deposal. EN 50126-1 is quoted in the “Loc. and Pass” TSI application guideline as a methodology for the demonstration of safety requirements, IEC is not quoted.

The LOCATE project is primarily concerned with improving the maintainability of railway systems with indirect benefits to RAMS; this is illustrated by the orange, green and blue boxes in the figure. LOCATE will set out to achieve this by the demonstration of technologies, techniques, and the development of a framework for CBM using established methods through the evaluation of novel approaches that are beginning to see adoption in other heavy asset industries. The Asset Management (AM) series of standards, ISO 55000 [3], shown in orange provide context from a logistics management standpoint; other highly adopted standards, such as Buildings Information Management (BIM) [4] and ISO 81346 [5] provide guidance in systems structure management. This aspect of maintainability of the railway systems will be discussed further in other deliverables within Work Package 5 (WP5) and briefly touched upon in later sections for completeness.

Within the specialisation of Prognostic Health Management (PHM), which encompasses CBM, there are a number of key standards that have gained widespread adoption in industries such as aviation [6], automotive [7] and others [8][9]; these standards are illustrated by the blue boxes in the figure, which will be the main focus of this deliverable as discussed in more detail in the following sections.

5.1. Condition Monitory and Diagnostics of Machinery and Systems (ISO 13374)

An extensively adopted standard in PHM used in the CBM is Condition Monitory and Diagnostics of Machinery and Systems, internationally recognised as ISO 13374 [10]. Its constituent parts are illustrated in Figure 2.

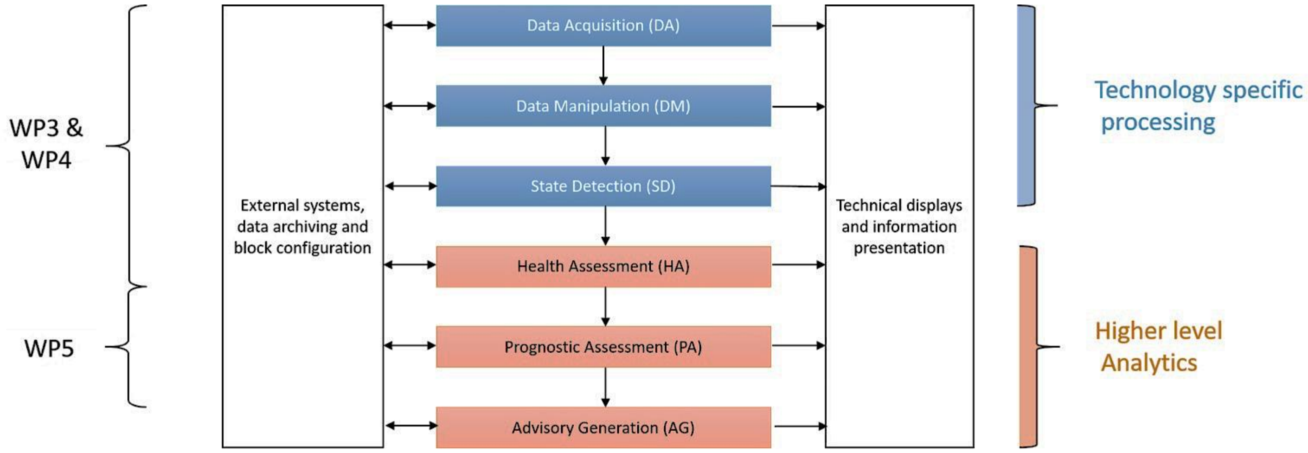

Figure 2 Condition Monitory and Diagnostics of Machinery and Systems (ISO 13374) [10]

The first three functional blocks are technology-specific and can be related to monitoring inputs such as vibration, temperature, or any other physical quantity from a sensory device. These processing blocks are described as follows [10]:

Data Acquisition (DA): converts an output from the transducer to a digital parameter representing a physical quantity and related information (such as the time, calibration, data quality, and data collector utilised, sensor configuration).

Data Manipulation (DM): performs signal analysis, computes meaningful descriptors, and derives virtual sensor readings from the raw measurements.

State Detection (SD): facilitates the creation and maintenance of normal baseline 'profiles', searches for abnormalities whenever new data is acquired, and determines in which abnormality zone, if any, the data belongs (e.g., alert or alarm).

The next set of functional blocks combine higher-level analytics using human concepts with monitoring technologies in order to assess the current health state of the machine, predict future failures and provide recommended action steps to operations and maintenance personnel:

Health Assessment (HA): diagnoses of any faults and rates in the current health of the equipment or process, considering all state information.

Prognostics Assessment (PA): determine future health states and failure modes based on the current health assessment and projected usage loads on the equipment and/or process, as well as Remaining Useful Life (RUL).

Advisory Generation (AG): provides actionable information regarding maintenance or operational changes required to optimize the life of the process and/or equipment.

A direct mapping of the LOCATE work packages (WP) to the ISO 13374 processing model can be seen to the left of the figure. WP3 (Measured Behaviour) and WP4 (Reference Behaviour) can be associated with technology-specific functional blocks, whilst WP5 (Operational Behaviour) can be seen to be represented by the higher analytical processing blocks.

The six levels of processing, summarised above, are adopted in LOCATE to enable the incorporation of standardised approaches in asset and logistics management building upon the ISO 13374 functional specification.

5.2. Machinery Information Management Open System Alliance (MIMOSA)

Recent developments building upon ISO 13374 are efforts from the Machinery Information Management Open System Alliance (MIMOSA) [11]; combing asset heath and usage, reliability and maintenance management within an open anticipatory logistics hierarchy, illustrated in Figure 3.

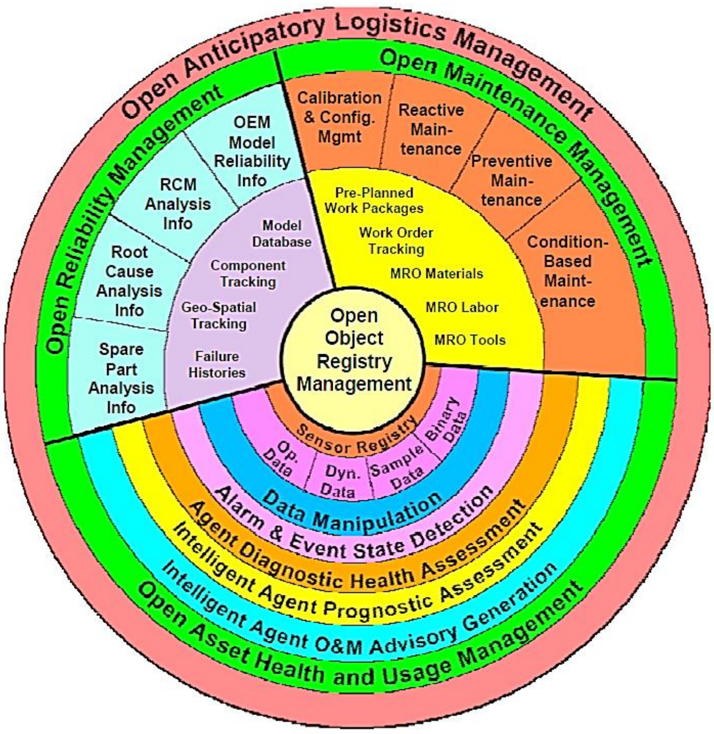

Figure 3 Machinery Information Management Opens System Alliance (MIMOSA) [12]

MIMOSA provides solutions for enterprise-level interoperability in asset lifecycle management. The alliance encourages the adoption of the open, supplier-neutral digitalisation platforms; specifically of interest to LOCATE, it has developed the Open System Architecture for Condition Based Maintenace

(OSA-CBM) [12] targeting real-time monitoring applications and Open System Architecture for Enterprise Application Integration (OSA-EAI) [12] for asynchronous enterprise-level communications for decision support technologies, illustrated in the figure below. ISO15926 [13] and ISO18876 [14], presented in Figure 1, are used in MIMOSA to develop best practices in open data systems using no-knowledge data transfer/encapsulation and providing extensible data integration methodologies, respectively.

The real-time (or at time of monitoring) asset health and usage segment built on the ISO 13374 system architecture can be seen in the lower segment of the figure detailing the six levels of processing discussed in the previous section. The enterprise-level architecture dedicated to the higher-level analytics and geared towards the central or distributed database-driven information management activities informing advisory generation and decision support are represented by the reliability and maintenance segments, seen in the outer green circumference of the figure.

5.3. System Behaviour

During the initial development phase of the LOCATE project several work packages, seen to the left of Figure 2, were conceived to define the behaviour of the system to support predictive maintenance from condition monitoring. It was envisaged that the system could be assessed for maintainability using measured, reference and operational behaviour. Each block in the system behaviour is responsible for the provision of information describing its function: measured behaviour (WP3) is concerned with physical quantities received from the fitment of sensors to the selected components or subsystem; reference behaviour (WP4) is derived from analytical models representing the system through dynamic modelling and simulation, and the operational behaviour (WP5) represents the movement and the logistics of assets.

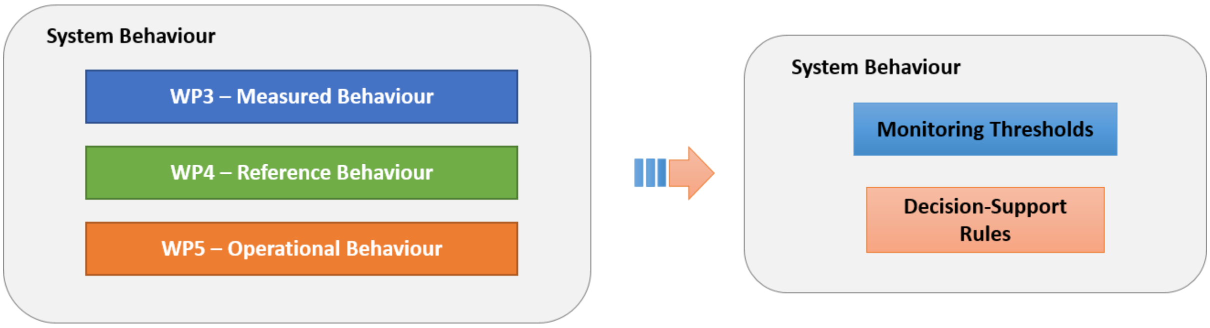

Figure 4 Behavioural Function Transpose

An approach to combine the system behavioural function into a group of thresholds and a set of logical rules for decision making is required for a CBM functional specification for predictive maintenance. To enable this the three functions for system behaviour are translated to monitoring thresholds from which, decision-support rules, seen to the right of the figure, are derived.

To establish system monitoring thresholds and decision support rules standardised techniques in machine diagnostics and prognostics are adopted as described in the following sections.

5.4. Technical Specification

In the wider context of the LOCATE project, the methodologies for the selection of behavioural functions discussed in the previous section are examined to highlight the processes for the development of monitoring thresholds and decision-support rules. The transposed system behavioural function block developed in the previous section can be seen at the centre of Figure 5 below.

Deliverable D5.2 is concerned with the development of thresholds for condition monitoring and rules for maintenance decisions. These two functions of the CBM framework are defined in Section 4. For the discussion in this section, it is necessary to examine processes sequentially prior to the system behaviour block and briefly revisit some of the earlier processes for context.

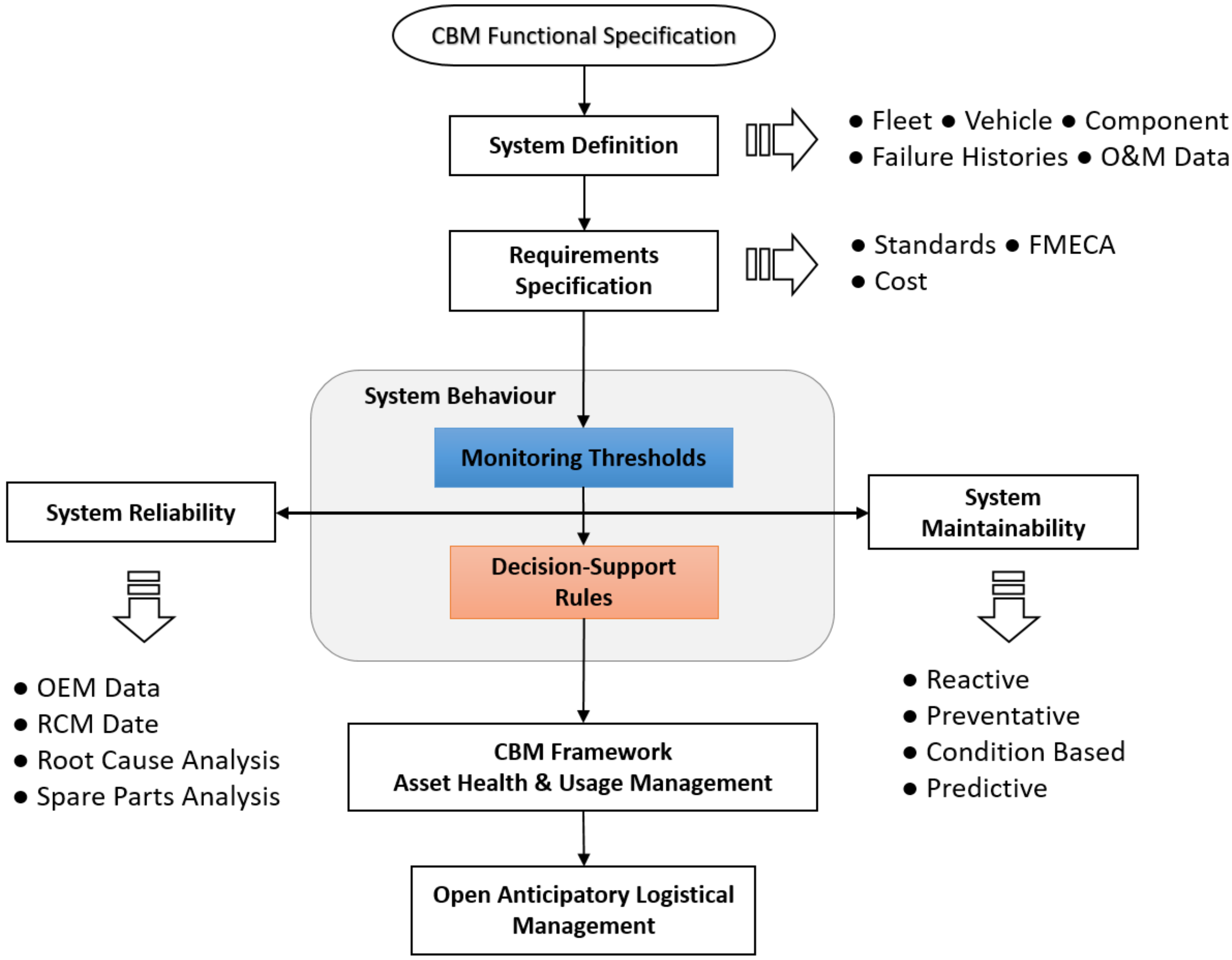

Figure 5 CBM Functional Specification

The main elements for creating a functional specification for CBM are described below. This includes the definition of relevant information and techniques to develop useable thresholds for condition monitoring and diagnostics and a set of rules for efficient and timely maintenance through the use of prognostic techniques.

System Definition

The system definition process describes the equipment audit focussed on identification of equipment and processes to be monitored. Tagging all equipment and codifying items to enable digital records to be kept for future interrogations using descriptive techniques, selection and placement of sensors for condition monitoring and the extraction of features from the sensors to diagnose the health status of components and provide a prediction on future health. This process includes return on investment

(RoI) analysis based on life cycle costs and a return on experience (RoE) analysis via a questionnaire process to consider fully all the causes, effects, and consequences of failure modes with the maintenance practitioners at FGC. The process identifies the functional requirement of a component and the point at which potential failures become detectable providing estimates of the intervals between them and the period from the potential failure to the functional failure known as the nett P-F interval [15][16].

Requirements Specification

Following the initial Failure Mode Effect and Criticality Analysis (FMECA) [17] that LOCATE made use of from the outputs of the INNOWAG Project [18] and its costs benefits analysis conducted incorporating life cycle costs that observed the correct standardised approaches governing the use of equipment and services from railway group standards. The requirements specification process is a reliability and criticality audit performed for the system considering the functional requirements of the CBM concept. This is an extensive discussion beyond the scope of the monitoring threshold and decision support rules that are the focus of this report; however, it is highly recommended that LOCATE and the current use-case at FGC take advantage of the work undertaken in the S2R cross-cutting activity project, SMaRTE, where the best practices from the aviation industry were investigated in relation to railway rolling stock maintenance; a particular benefit to developing the initial requirements specification is perhaps a detailed review of MSG3 provided in deliverable D2.1 [19]. In this deliverable, it was concluded that many similarities exist between rolling stock and aircraft maintenance. The detailed review highlighted the aviation maintenance concepts that could be beneficial in developing cost-effective maintenance policies for rolling stock using the most appropriate elements of MSG3. It is not expected that the approach could be applied directly since it was developed for the aviation industry; however, the foundation of MSG3 is based on Reliability Centred Maintenance (RCM) which has been shown to be of use in many other industries that have multifaceted complex assets requirements as is the case for rolling stock [20].

System Reliability

In the context of reliability management, dependability has many attributes; it is usually described in terms of reliability, maintainability, and supportability (including maintenance, operations, and support to both) [21]. One set of principles for maintainability, reliability, and supportability states that these three elements can be balanced and traded-off to achieve availability, which is commonly associated with recoverability and maintenance on a component level.

An important concept to introduce within dependability is the definition of systematic or residual weaknesses that then become failures. Systematic weaknesses are normally related to design deficiencies, component selection, manufacturing processes or similar procedures. Residual weaknesses are uncontrolled random variations of the item or its components [22]. For the FGC use-case, the latter is of importance; residual weaknesses in design or from improper use that generate faults becoming failure modes are the focus for LOCATE.

Within dependability management the foremost concern from a business point of view is the cost of ownership of the asset. The principals offered in the application guide BS EN 60300-3-3:2017 for dependability management concerning life cycle costing provides essential contextual background for the effective implementation of CBM policies. The guide identifies the trade-offs in one alternative system solution to another where future cost of ownership comprising maintenance, operations, enhancement, and disposal actions are significant and require a balance between the cost of acquisition and the residual unrealised risk of ownership. Such a balance is achieved by technical and monetary assessments that consider varying outcomes of availability, reliability, maintainability, and supportability [23].

Reliability assessment for systems depend on data from market of similar items, field data and test data from suppliers of components and modules; this type of data is generally used on early equipment design decision at the system architecture level as well as the operational and economic level concerning cost of warranties and maintenance. Furthermore, the assessment methods can form the safety assurance of a system the use of techniques such as failure tree analysis FTA. The international standard on reliability assessment method BS EN 62308 [24] describes in detail the methods employed by industry to assure reliability. The standard describes the application of three main approaches in reliability assessment: similarity analysis (e.g., in-service reliability data from similar equipment), durability analysis (e.g., stresses imposed by operational use, maintenance, storage shipping etc.) and handbook of prediction for reliability (e.g., probability that the equipment reliability targets and goals can be met). The standard provides methods to quote reliability in a number of ways including accumulated percentage of failures, call rate, probability of survival, failure intensity, instantaneous failure rate, mean time to failure (MTTF) and mean time before failure (MTBF). There are numerous reasons for performing a reliability assessment; the standard provides a comprehensive list, some of which are: risk analysis, safety assessment, failure mode effects analysis (FMEA), life cycle costs (LCC), failure tree analysis (FTA) and more. General purpose of a reliability assessment should be the basis of any fundamental change to a maintenance policy and would be of particular use in, for example, adopting CBM from a preventative maintenance programme.

In the context of dependability, a system can be described as a set of interrelated elements that can be defined in terms of the functional requirements, its conditions of operation and the defined boundaries within which it operates. The initial step of the reliability analysis undertaken for LOCATE was an FMECA. After this step data from original equipment manufacturers (OEM) should be included to form the reliability analysis for the component deemed significant for maintenance. The table in Annex A gives the current state of the discussions in terms of the failures modes listed alongside the causes, symptoms, descriptors, and parameters that will enable the descriptive diagnosis and prognosis for decision support. The estimated P-F intervals linked to maintenance at FGC is identified as a key measure to link failure modes to the inspection intervals. Reliability can be assured and estimated from consideration of monitoring thresholds where the manufacturer provides information about the service life of a component. This can include information about precursors to failure that can assist to determine some of the conditions that indicate the presence of a potential failure; these indicators should be considered in the design of a monitoring system and incorporated into the thresholds that the component is measured against whilst in operation to providing guidance for maintenance to ensure safety, operational and economic effectiveness.

System Maintainability

A maintenance plan is a structured and documented set of tasks activities, procedures, resources, and the time scales required to carry out the maintenance [25]. Maintainability is the ease and speed with which an item can be brought back to an operational state having failed in some way. Maintenance is the actual delivery of operational support applied to undertake the restoration or preventative maintenance activity which is characterised by the items design, construction, installation, and commissioning, together constituting maintainability of an item [26].

Depending at which point the item is at in its lifecycle and what demands are on its functional operation, varying degrees of maintainability will be required. In the FGC case, the locomotives are nearing the end of their service life therefore it is not the ideal time to carry out a dependability assessment or review and install a new maintenance programme; however, this exercise can be beneficial even at this stage as it will allow some novel techniques in predictive maintenance to be applied to existing rolling stock without a full a development of the new maintenance concepts and policy. FGC intend to replace the ageing rolling stock therefore this exercise will allow them to investigate more proactive and cost-effective maintenance strategies before the new rolling stocks are brought into operation. Perhaps when the new locomotives are brought into operation elements of the CBM programme deployed in LOCATE will be adapted to suit the new vehicles.

From the moment it is brought into service and to the point a decision is made to dispose of it, the utilisation of an item is the most enduring part of its life cycle and can be considered the centrepiece of its service life. During this stage, effort is focused on the continued availability of an item to provide a defined service and on the maintenance and support of the systems to assure a service capability. The type of maintenance tasks necessary to achieve the required availability are ideally identified before a maintainability programme is defined and implemented. It might be that an item or component within a system is not maintainable and should be assigned run-to-failure actions; some items may be unmaintainable after failure for example when the item's resistance to failure is exceeded or if an item's repair is not cost-effective and replacement is more conducive. Comparatively, maintenance is the number of tasks taken to return an item to a serviceable condition whereas maintainability is a measure of the ease of completing those tasks and their effectiveness. Support is the external resources required to complete the tasks and supportability is the ease of provision of the resources and their effectiveness [26].

The following discussion will expand upon the application Reliability Centred Maintenance (RCM) within the context of CBM. The IEC 60300 group of dependability standards introduced above will remain the focus; the RCM application guide [27] from this set of documents will be used to expand upon the use of RCM in railway. Basic steps of setting up an RCM programme are to initiate the planning, which could be the steps as described above, followed by a functional failure analysis, maintenance task selection, implementation and continuous improvement of the programme through a dedicated review cycle. The tasks are based on safety in respect of personnel and the environment, and on operational and economic concerns; however, it should be noted that the criteria considered will depend on the application. For example, in the case of the FGC use-case safety of personnel and the environment both in operation and during maintenance tasks have a higher significance compared to the operational and economic concerns, whereas in a defence application, the operational concerns will have more significance over safety, environmental and economic concerns.

RCM identifies the optimal maintenance tasks from a preventative and corrective maintenance approach. Preventative maintenance is undertaken prior to failure; this can be condition-based, which can be achieved by monitoring the condition until failure is imminent or by functional checks to detect failure of hidden functions. Preventative maintenance can also be predetermined based on operating hours or distance based consisting of a scheduled programme of refurbishment or replacement.

Corrective maintenance restores the function of an item after failure has occurred or the performance of an item falls below a given threshold. A predetermined trade-off between safety and environmental concerns as compared to operational and economic criteria is used to decide whether the failure is acceptable provided the consequences of failure are tolerable compared to the cost of preventative maintenance and the subsequent loss due to failure. In corrective maintenance, this is an example of a planned run-to-failure occurrence. It is also not unusual to permit an item to remain in service until a more convenient time when redundancy preserves function.

A maintenance programme consists of the initial programme developed in collaboration between the supplier and the operator and a dynamic part advised by operational experience from service conditions. An RCM programme is likely to be implemented before service, based on manufactures recommendations or during a later part in the service-life of a vehicle. Maintainability within the specification of CBM system is creating the flexibility to select an appropriate maintenance strategy within the constraints of the system; specifically, its safety and environmental constraints and its operational and economic requirements.

Measures of maintainability and assessment of effectiveness of a maintenance programme should be considered when implementing a CBM programme. The recommended measures of assessment are specified in the standards and can include three broad categories of maintainability assessment being frequency of maintenance actions, duration of maintenance actions and human effort required. The standard specifies testability in fault coverage, false alarm rates, test length and observability **Erro! A origem da referência não foi encontrada.**.

<u>**CBM Architecture for Asset Health and Usage Management**</u>

Effective control and governance of asset health and usage through structured management policies is essential to realise value through managing risk and opportunity to achieve the desired balance of cost, risk, and performance [3]. The legislative and regulatory requirements for rolling stock maintenance are mandated for safety and environmental concerns and complemented through the supplier and operator collaboratively ensuring operational and economic concerns are upheld through effective maintainability and maintenance programmes assuring the assets fulfil the desired lifecycle requirements through supportability provisions [27]. The MIMOSA standard discussed in Section 5.2 provides a fully harmonised asset management platform able to make use of off-the-shelf (OTS) condition monitoring technology, providing an open system architecture for CBM that can be implemented with a high level of assurance through tested interfaces. Combined with the ISO5500 set of standards, it can be a powerfull asset management system.

<u>**Open Anticipatory Logistical Management**</u>

Although out of the scope of the current deliverable, it is worth discussing how CBM can support non-engineering factors such as logistic concerns, inventory and supply chain management, maintenance planning and logistics of supportability and dependability. The asset management standards in the ISO 55000 series outlines the methodologies to develop Integrated Asset Management Systems (IAMS) that allow anticipatory logistical management to be established in an organisation. The IT infrastructure and investment is considerable, however the benefits for data-driven processes is a very attractive proposition in the long term.

<u>**System Behaviour**</u>

Defining the, normal and abnormal, system behaviour from the monitoring techniques underpins the CBM functional specification. Parameters are identified from the fault and failure characteristics selected for the components being monitored. Appropriate measurement techniques are assigned to locations on the components that are designated significant for maintenance and specifically for condition monitoring to acquire the signals for the parameters that are to represent the faults according to the symptoms and descriptors for the fault. Operating conditions are a factor in defining the representative system characteristics where reference behaviour will be measured. Setting the initial alert and alarm criteria will determine the threshold to which the monitoring system reacts to provide warning and the context for the recommended maintenance actions. For this deliverable, the system behaviour will be the focus of the discussion and covered extensively in the following sections.

6. Condition Monitoring Diagnostics and Prognostics

The key rolling stock maintenance strategies include:

- Prescriptive maintenance - dynamic condition, agile and responsive, low cost (PdM ROI), highly disruptive
- Preventative maintenance - time or distance based, safety implications, loss of time, low-cost reliable, high Maintenance costs, loss of availability
- Predictive Maintenance (PdM) - condition-based, timely intervention, lower overall cost but potentially initial higher cost
- Corrective Maintenance - run to failure, safety implications, loss of time, costly implications, unreliable

To move to a more predictive maintenance strategy requires the inclusion of diagnostic and prognostic techniques in addition to condition monitoring. This requires the definition of a set of monitoring thresholds and decisions support rules and some techniques for this are provided in the subsequent sections.

6.1. Diagnostic Techniques

A condition monitoring and diagnostic cycle consists of several activities in a study to establish the monitoring technologies and strategies that can identify the underlying faults during the failure of components and subsystems. It forms a vital component of asset management providing methods to evaluate the function and condition of rolling stock based on performance, condition, or inherent reliability of off-the-shelf (OTS) products [28]. Typically, the diagnostics and activities are divided into tasks in a design phase and tasks in the usage phase of an application. The tasks undertaken in the design phase define the processes in the systems being monitored providing a breakdown of the components that list the failure modes with symptoms and descriptors for the faults from the sensors measuring the parameters on selected locations. The remaining tasks that describe the usage are generally around processing the measured signals, deriving signature profiles, diagnosing the faults, and developing prognostics to predict the RUL of the components and subsystems. More advanced considerations regarding decision support for maintenance actions are covered in the prognostic techniques discussed in the proceeding section.

In condition monitoring applications a preliminary diagnostics study is normally conducted to establish the requirements of the application. This can be a generic list of activities described in the condition monitoring and diagnostic standards referring to the four initial tasks in the process described within an FMECA. These include familiar processes, seen in previous LOCATE deliverables, such as an initial assessment of the system availability, maintainability and criticality with respect to the whole system, a description of the major components in the system and their functionality, an analysis of the component failure modes and their causes and a numeric criticality analysis taking in to account the significance of the component in terms of safety, availability, maintenance costs and the overall occurrence of the failure of the component.

The remaining steps in the process are described in Section 4.3 of ISO13379 [29] and outline the process of generating a Failure Mode Symptoms Analysis (FMSA) which builds upon the previous FMECA making use of its numeric Risk Priority Number (RPN). The steps in an FMSA review are used to decide which of the failure modes can be diagnosed from the selected parameters, symptoms and descriptors assigned to the failure mode; an analysis under which operating conditions the different faults can be observed and the reference conditions are defined. The symptoms are expressed to assess the condition of the component used for diagnostics, the descriptors are listed to evaluate the different symptoms and the necessary measurements are identified from which the descriptors are derived.

6.1.1. Diagnostic Approaches

Diagnostic approaches can be categorised into data-driven or knowledge-based methods. Data-driven approaches can be simple trending techniques or more sophisticated statistical methods using machine learning or artificial intelligence. Conversely, knowledge-based approaches rely on explicit representation of faults behaviour and symptoms are identified from fault models or analytical models from first principles.

The chosen approach for a particular application can depend on several factors, some of which are listed below [29]:

- Specific system being diagnosed
- Monitoring techniques
- Complexity of the system being modelled
- Requirement for the model to be explainable (unlike black box models used in machine learning)
- Requirement to retrain the model if the initial conditions change
- Availability of existing data with known faults in normal operation (measured behaviour)

The following section discusses the key considerations, adapted from existing condition monitoring and diagnostic techniques, when proposing a standardised approach for establishing monitoring thresholds and decision support rules within the LOCATE project.

6.1.2. Monitoring Thresholds

The processing blocks defined in ISO 13374, described in Section 5.1 and highlighted in Figure 6 below, illustrate some of the considerations for developing thresholds for condition monitoring. These are shown as black boxes to the left of the figure and illustrate how the processing blocks use inputs and return outputs. The elements used in diagnostics are typically generated from the condition monitoring data as part of the acquisition process. The measurements taken for CM are used in the diagnostics for faults identification.

Descriptors, which are used more often than raw measurements, can offer more selectivity when diagnosing a fault. Measurements and parameters used for diagnostics are routinely characterised by performance indicators such as efficiency, power consumption, operating temperature or for the FGC use-cases ride performance, bogie stability, breaking performance, and engine performance that describe the condition of the component being measured. Feature extraction from a data manipulation process is used to develop descriptors from the symptoms and parameters assigned to failure modes. The selectivity of the descriptors to the faults is critical as this enables the confidence in the diagnosis to be more predictable.

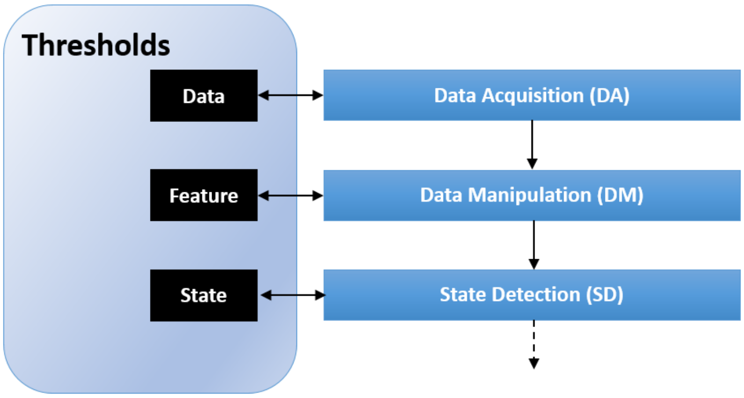

Figure 6 Condition Monitoring Thresholds

Symptoms can be expressed using characteristics such as the time constant of the evolution of a descriptor, a magnitude change in a parameter, a feature of the descriptor (e.g., third harmonic of the vibration), the location of the transducer or the circumstance around the operating conditions.

The development of the baseline profiles for the monitoring system is an important consideration in defining a threshold from a descriptor or parameters. These profiles are normally taken when the equipment is operating under acceptable conditions. All subsequent measurements are compared to these baseline values to detect an abnormal condition. The operating state is generally taken under conditions where parameters can be held at a constant to enable the descriptors to be defined by a reduced number of symptoms or parameters. Using baseline measurements, trips, alerts, and alarms can be used to describe abnormality zones which can provide warning of degradation in a parameter or symptom. Where alarms, alerts and trips (shutdowns) provide context for the advised maintenance actions in the form of decision support rules discussed in the next section.

6.2. Prognostic Techniques

Within the scope of the LOCATE project, it is desirable that some prognostic techniques may be developed that can deliver a set of rules to support timely maintenance decisions. Prognosis can be defined as the time to failure and risk for one or more incipient failure modes and analysis of the symptoms of faults to predict future conditions and residual life within design parameters [30].

The project requirements specification and prerequisites outlined in the previous section for the diagnostic techniques should form the basis for the prognostics that can support the development of rules for maintenance decisions. The LOCATE project has chosen to employ knowledge-based approach using first principle models combined with a multi-pronged data-driven approach that will initially obtain baseline profiles from a preliminary monitoring campaign for calibration and a long-term semi-permanent condition monitoring acquisition system on the locomotives building degradation data repositories which could then enable more data-driven approaches to be used when historical data archives are compiled. Subsequently, this could allow feedback to enhance the knowledge-based models from first principles enabling prognostics models to be built for the estimation of RUL to support the management of asset health and usage.

6.2.1. Decision-Support Rules

Prognosis depends on structured data that is built on an understanding of the physics underlying the fault modes, previous duty and cumulative duty parameters, previous maintenance history, inspection records and operational data. Condition monitoring performance parameters will assist extrapolation or more sophisticated projection models and forecasts for asset health and usage.

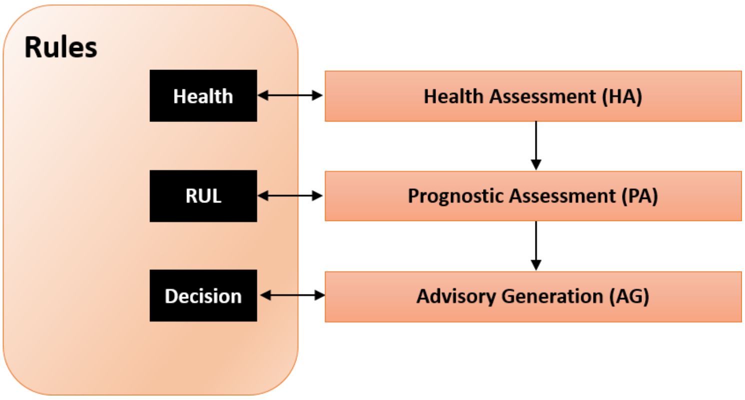

Figure 7 Decision-Support Rules

The perspectives of diagnostics and prognostics processes are based on the principle that diagnostics is descriptive focusing on existing data and prognostics is concerned with future events. The prognostics process must consider factors such as existing single or multiple failure modes and deterioration rates, the initiation of future failure modes, the role of existing failure modes in the initiation of future failure modes, the influence between existing and future failure modes and their deterioration rates. In addition, it must also consider the sensitivity to the detection of existing and future failure modes by the monitoring techniques employed for condition monitoring and the effect of maintenance actions and operating conditions [30].

Prognostics and diagnostics across the failure progression timeline will attempt to establish the proper working order of a system using diagnostics and prognostics at the component level where the detection of an early incipient fault will trigger an estimation of the remaining useful life of the component leading to a system, component, or sub-component failure. Descriptive diagnostics will determine the effectiveness of the wider system that without prognostics may have led to secondary damage or catastrophic failure.

Component failure can be considered to have occurred when the parameter or descriptor value reaches or exceeds a set of pre-defined points or limits, as illustrated in Figure 8. The value can be determined using historical data from failure histories or it can be obtained from diagnostic and prognostic techniques.

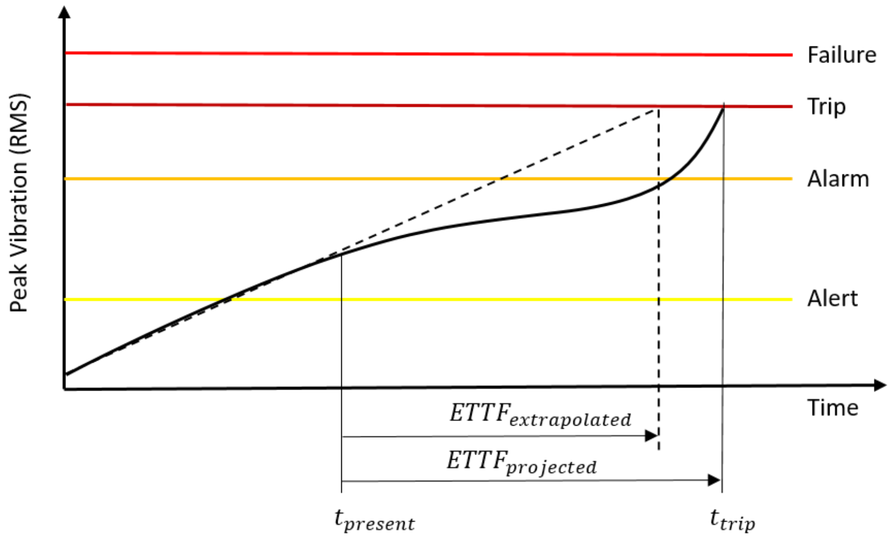

Figure 8 Threshold limit values

The trip point, shown in Figure 8, is a value less than the failure point that the machine is shut down to prevent catastrophic failure resulting in damage to the wider system, often having safety implications. This value is normally defined using standards, manufacturer's guidelines, and expert knowledge from maintenance practitioners.

Alert and alarm limits are normally set at prescribed values less than the trip value and are dependent on the maintenance lead times. However, in a predictive maintenance system, these values are generally set using confidence levels from the prognostics using the diagnostic models (measured and reference baseline behaviours), future duties of the component, subsystem and systems, spare parts procurement lead-time, scope of the work to resolve the faults and trending / projections to establish the Estimated Time To Failure (ETTF). Projection requires the estimation of future data followed by curve fitting, whereas trend projection or extrapolation fits to existing data before $t_{present}$ (time-zero).

6.3. Predictive Maintenance (PdM)

Preventative maintenance (PM) periodicities are conventionally established on well-known survival models for key rolling stock components. Manufacturers typically guarantee some performances thresholds in terms of reliability that can be represented by the Weibull distribution, that can be described as the Probability Density Function (PDF), according to the equation below:

$$f(t) = \left(\frac{\beta}{\alpha^{\beta}}\right) t^{\beta-1} \cdot e^{-\left(\frac{t}{\alpha}\right)^{\beta}}$$

This distribution is widely used for scheduled maintenance (SM) as it can exhibit a variety of shapes closely related to failure patterns associated with mechanical systems, amongst others. The shape parameter defined by β, and α is the scale parameter for the distribution, also known as the characteristic life. The characteristic life can be used to describe the reliability of a component up to when an incipience is detected and corresponds to the 63rd percentile or a standard deviation away from the mean for the cumulative failure distribution. In other words, it is expected that 63% of Weibull failures occur by time $t = \alpha$. The curves for variety of shapes are shown in Figure 9(a) below; for illustrative purposes the scaling factor is held at unity.

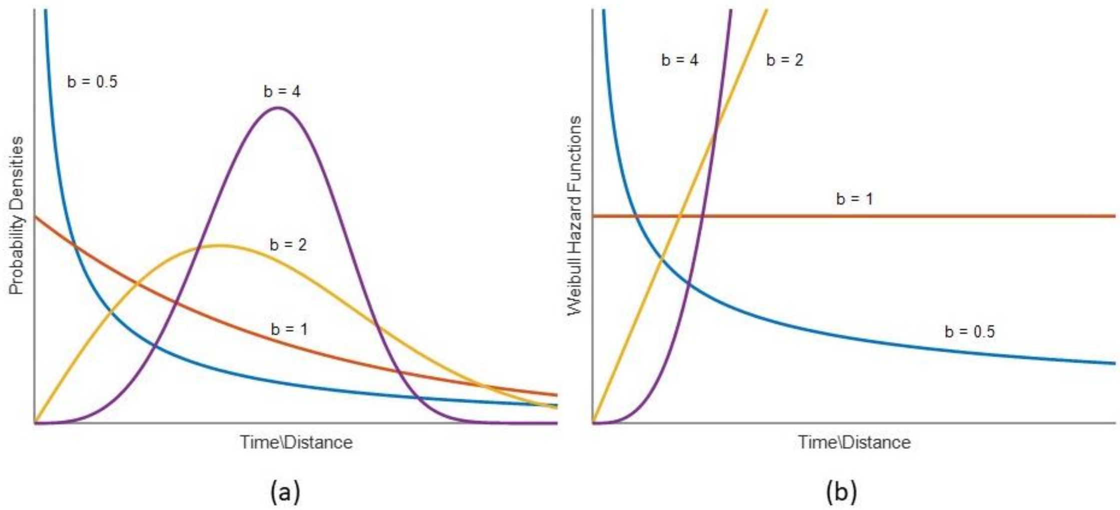

Figure 9 (a) Failure distribution and (b) Failures Patterns

The hazard Functions, shown in Figure 9(b), describes the failure patterns associated with each distribution. These patterns can be age-related or non-age-related degradation. Typical failure patterns such as that seen for fatigue are described by the linear decay associated with the left-skewed distribution and linear failure pattern, shown in yellow. Age-related failure is typically described by the purple pattern, where degradation becomes pronounced towards the end of the component life. Random failures, such as those associated with bearings, is generally described by the constant failure pattern in red, where a failure is likely to occur in a relatively small percentage of the sample distribution. Infant mortality, sometimes seen when a component is sent for periodic overhaul due to human error, is described by the blue curve for its conditional probability for failure.

<u>Integrated Approach to Condition Monitoring, Diagnostics and Prognostics (CM&DP):</u>

The probability of failure discussed above indicates that in many instances there is little or no relationship between how long an asset has been in service and its remaining life. However, even though many failure modes are not age-related, there is usually some warning that failure is beginning to develop. Figure 10 illustrates the typical stages of failure; this is known as the P-F curve and describes how a component degrades, usually at an accelerated rate, to Functional Failure (point F) if the failure is not detected when it begins to show signs (Potential Failure, point P).

The P-F interval is directly proportional to the inspection interval. It is usually sufficient to select a task frequency equal to half the P-F interval. This ensures the failure will be detected before it accelerates to functional failure. For instance, if the P-F interval for a failure mode is 2 weeks it is sufficient to inspect it once a week; but if the checks are done once a month, then the failure might be missed completely. Conversely, if the component is checked daily then it is an overuse of valuable resources. This is known as the nett P-F interval which is selected to ensure failure is detected whilst not being an inefficient use of resources.

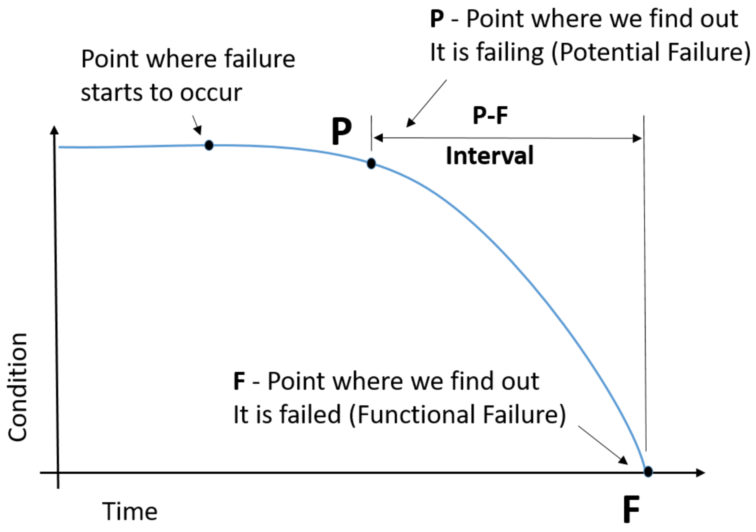

Figure 10 Potential Failure and Functional Failure Interval [11][16]

Clearly, condition monitoring can have a useful impact on the inspection intervals through automatically detecting and describing the failure modes, freeing up resources to be directed to more cost-effective and urgent tasks. Figure 11 compares the asset health and the value of maintenance as a component degrades. As can be seen by the green line, the value proposition of PdM is at its maximum when an optimum RUL is attained by extending routine inspection through the use of remote condition monitoring technology.

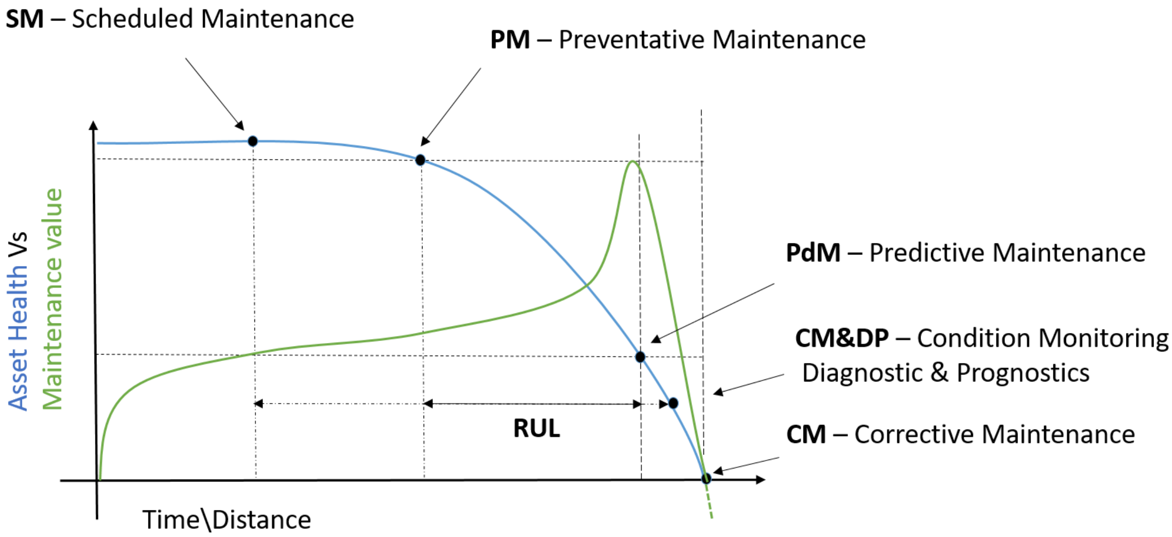

Figure 11 Asset health and indicative maintenance value comparison – modified from [31]

<u>Caution on extending RUL:</u>

Using CM&DP it is possible to extend the RUL safely to ensure that a failure mode is not permitted to damage the component beyond repair whilst still extracting optimum life from the component without unnecessary inspection or overhaul. The caution here is how far down the curve can the RUL be extended without stressing the component beyond the inherent threshold for which the component was designed to withstand, therefore increasing the risk of a catastrophic failure.

Combining Failure Patterns and Condition Monitoring Data for Prognostics

Failure probability distributions and patterns, as discussed above, are well known in reliability analysis used for PM of rolling stock. However, CBM can provide additional measures of condition from sensors that can be combined with the conditional probability of failure to give a more accurate estimate of RUL. A mathematical model based on both the conditional probability of failure and condition data can be built using a time-dependant proportional hazard model (PHM) as described by the following equation [32]:

$$h(t) = h_0(t) \cdot e^{(y_i \cdot x_i(t))}$$

Where $h_0(t)$ is the Weibull parametric hazard function, $x_i(t)$ are covariates as a function of time and y_i are model coefficients.

The PHM's were first proposed by Cox [33] and are one of the most extensively used models in prognostics. As previously discussed the P-F curve can be obtained from operational experience, given that this is subjective, it is better if the P-F curve were estimated using an FMSA (Appendix A) combined with a set of regression parameters from condition monitoring data which would then provide a reasonable degree of certainty in the estimated P-F interval for a particular component from the failure modes listed in the FMSA. It should be noted that PHM depends on the assumption that after repair, a component is returned to a 'good as new' condition by perfect repair or replacement. This assumption can introduce significant error in RUL estimations [34]. Proportional hazard models were very effective and took account of the complexities associated with practical reliability analysis; however, this body of work has been superseded by more advanced prognostics models that take into account an imperfect repair known as Proportional Intensity Model (PIM) [35].

It should be noted that in all PM regimes failure data is typically unavailable as the functional failure is avoided at all costs. It is conceivable that a qualitative study to estimate the P-F interval through the development of a questionnaire to retain the expert domain knowledge of the FGC engineers will provide these estimates for the failure modes presented in the table in Annex A; furthermore, the P-F interval can be adjusted and updated from conditional data when a CBM is in place collecting historical data.

6.4. Discussion

The aim of this deliverable is to define a set of specifications for the development of initial thresholds and decision support rules. To provide context to the LOCATE project, a wider discussion has been provided on dependability, reliability, maintainability, and supportability. However, the focus has remained on the definition of thresholds and rules to enable the intrinsic reliability of rolling stock to be maintained. The relevant European standards and literature on condition monitoring and diagnostics have been reviewed to develop methods for threshold selection and the relevant standards and literature for prognostics have been reviewed to assist in developing decision support rules. The ISO 17359 for condition monitoring and diagnostics of machines and ISO 13373 describing the 6 levels of processing are instrumental in the development of the framework for monitoring threshold and decision support rules in this deliverable. The tried and tested, standardised approach for machine condition monitoring is very desirable and promises enormous potential if used effectively. However, its application in rolling stock condition monitoring and predictive maintenance is challenging due to the complex nature of rolling stock systems and their operating condition, also closely related to the environmental and economic constraints the assets must be managed within.

Clearly, the potential for the application of diagnostic and prognostics is enormous, however, there remain significant gaps to translate machine CM&DP standards to rolling stock. This deliverable has identified strategies that industries such as oil & gas, automotive, and others, have successfully applied machine CM&DP to their asset management processes effectively. The MIMOSA standard and associated Open System Architecture for CBM frameworks have been found to be very useful in this regard with significant value being afforded in bridging the gap between machine CM&DP to CBM for rolling stock.

Reliability Centred Maintenance, especially its application in the aviation industry, known as MSG3, was investigated in a S2R crosscutting innovation programme (IP) projects called SMARTE, which showed that considerable benefits and transferrable techniques and methods for rolling stock maintenance could be derived from further alignment to MSG3 and its foundation in RCM. This deliverable has also offered a wider discussion on reliability and maintainability studies around conditional probabilities of failure and hazard functions from failure patterns discussed in 6.3 to understand how thresholds in terms of alerts and alarms are established from manufacturers recommendation based on the principles of the most reliable and industry-wide adopted standards.

The next deliverable in this series, D5.3, will make significant efforts to employ the failure rates defined in the FMECA produced during D3.2, adapted from the INNOWAG project. The tactical optimisation models in D5.3 will also begin to address the challenges of managing the RUL of a component with condition data using failure distribution modelling from manufacturing data and a generalised piecewise linear approximation model for optimisation of the tactical maintenance, which is ultimately designed to assist the higher-level decision support for asset management.

Figure 12 below is an example of the items which might be expected from the failure modes for rolling stock components. The standard approach applied to rolling stock can be seen to have clear advantages. Data tagging is employed for identification, which together with the other processes shown in the boxes could be an example of how critical information for condition monitoring, diagnostics and prognostics might be applied in a rolling stock depot. It is conceivable that the boxes shown in this example might be presented to a maintenance practitioner in a depot, providing them with the necessary information to make effective decisions to extend RUL of a component such as the wheelset; this includes information about condition of the component, providing a health index, a diagnosis and recommended actions based on several possible outcomes from several prediction scenarios for RUL. This approach would not stop at providing recommendations on only the wheelset, but rather the system would have a view of all component health conditions and provide an estimate of the capacity of the locomotive to complete its mission profile within the fleet of locomotives.

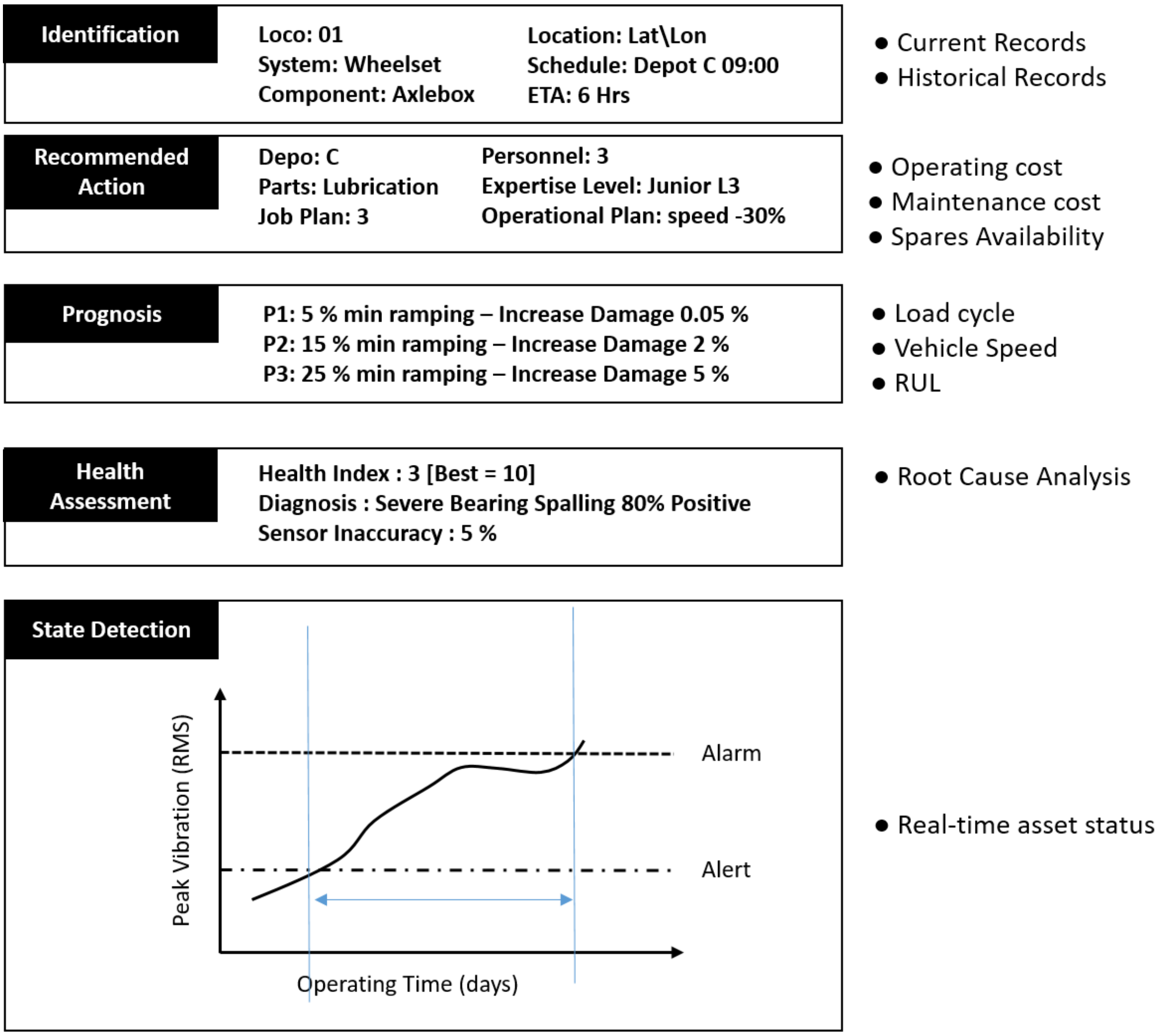

Figure 12 Diagnostics and Prognostics Information for Decision Support

P-F Curve and Component Survival Data

The discussion on PdM in Section 6.3 highlighted the relationship with the estimated time to failure (ETTF), the maintenance interval and the P-F Curve that are central to RCM, MSG3 and CM&DP. It is important to distinguish between reliability data provided by the manufacturer and the experience of operational conditions which reflect the maintenance requirements more accurately than supplier recommendations. It is however accurate to say that the reliability data can provide a conservative estimate of schedule for maintenance to assure dependability but at a higher cost for maintenance. The purpose of a CBM programme is to assure dependability through condition monitoring, diagnostics, and degrees prognostics; although not always clearly stated prognostics has two elements, the ETTF (also known as the RUL) and importantly the associated confidence limits for the prognosis. The more refined the degradation models and more advanced the prognostic models the better the confidence in the projections for RUL. An example of Weibull probability densities and hazard functions for typical failure patterns was suggested by D5.2 and adopted by Task 5.3. Addionally, an example of the proportional hazard model linking conditional data from sensors was provided in section 6.3 of this deliverable outlining its limitations and providing other more recent model suggestions.

Manufacturers recommendations for maintenance intervals are based on survival data. This is the standard approach in establishing the periodicities for SM and PM. However, the return on investment for CBM is in increasing the confidence of an entity in charge of maintenance (ECM) to extend maintenance intervals without impacting safety, environmental, operational and economic concerns for the organisation. Reliability methods provide a good approach for estimating the point before a potential failure is detected on the P-F curve. Beyond this point, it is CM&DP that provides confidence to the organisation that the wider safety and business concerns are considered and maintained.

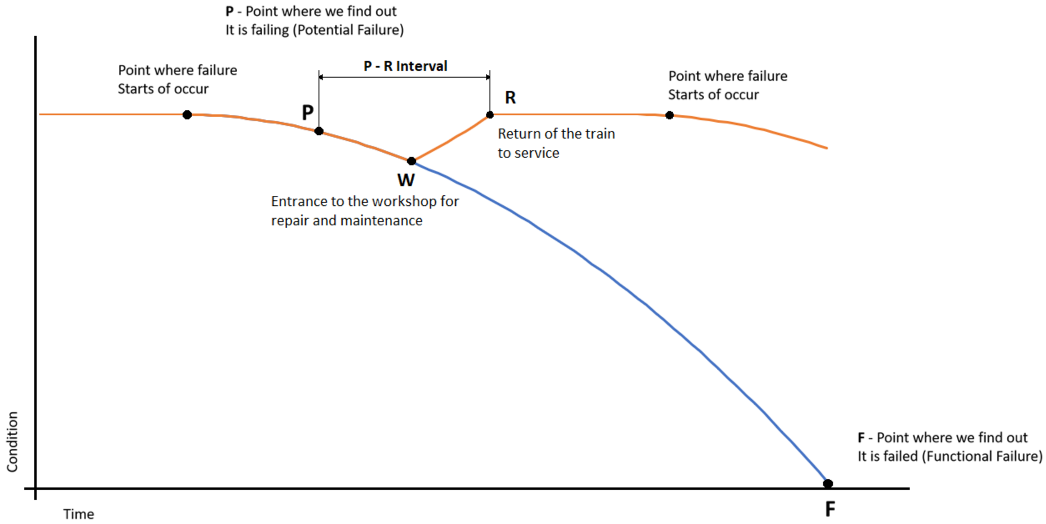

Figure 13 FGC Maintenance Interval using P-F interval

The current PM programme at FGC is demonstrated by Figure 13 above. The point of potential failure (P) is identified through, what is known in RCM and MSG3 as, on-conditions tasks, such as when the operating crew on a locomotive detect a fault through human senses or when routine scheduled, or preventative inspection reveal a potential failure. At the earliest convenience without impacting the concerns discussed above, the vehicle is sent to the workshop and put back into service after the repairs are made. It is clear to see from the illustration that the component represented in the figure, with proper condition monitoring, could potentially be in a degraded but operable state. Condition data in this instance could allow the decision to keep the asset in operation based on empirical information of the asset and therefore allowing traceability and accountability in the decision were safe yet economic.

As demonstrated by the P-F curve presented in Figure 13, for each failure mode that can potentially be detected by the LOCATE system, the average time needed to organise the corresponding repair is required (identified as the P-R interval in Figure 13). This information can typically be obtained from the maintainer following inspection of the component condition. Once this interval is identified, a threshold (P) can be defined which corresponds to the condition of the component at the time when an alert is required to the fleet management to provide sufficient time to organise the required maintenance (W). In addition, a second threshold must be established corresponding to the time after which the risk of a failure in service is intolerable (F), considering the operational and safety risk.

Diagnostics and Prognostics

The relationship between diagnostics and prognostics has been evaluated for this deliverable and prognostics is highly reliant on diagnostics; however, there is little consensus on what the demarcation between the fields lies. It is sufficient to say that diagnostics is descriptive and so retrospective relying on historical data to identify the damage, isolate and quantify it empirically. Whereas prognostics is concerned with predicting the damage yet to occur and providing consequential information on the effects of actions that should or should not be taken to preserve the function of the system. Despite the ambiguities in the literature regarding how the two fields are interrelated, in terms of the D5.2 diagnostics is firmly in the realm of assisting and better understanding how monitoring thresholds should be set and prognostics has most value in helping organisation to set the rules for making effective decisions.

Role of prognostics and the selection of appropriate models

As discussed in Section 6.2, that the prognostics techniques used in LOCATE project have employed knowledge-based approaches using first principle models in the reference behaviour work package (WP4) through the building of digitals twins. This is combined with a multi-pronged data-driven approach that initially obtains baseline profiles from a preliminary monitoring campaign for calibration of the model parameters. A second longer measurement campaign is planned to obtain condition monitoring data from the data acquisition system on the locomotives which will build a better understanding of the linear piecewise degradation models built in D5.3 to support the tactical planning of maintenance in Task 5.5.

7. Conclusion

Currently, FGC adopts an on-condition based maintenance regime, where inspections are undertaken and specified intervals with defined thresholds. If one of these limits is reached an intervention to correct the problem should be made as soon as possible. The LOCATE project proposes to replace this with a predictive maintenance system for the bogie of the FGC's locomotives. This system will continuously monitor the bogie and the performance will be compared to reference data obtained from a digital twin. Failures will be anticipated and the time before the failure affects the locomotive operations shall be estimated, based on the defined thresholds and rules. The scheduling of this operation (D5.3) must be done to limit the impact on the availability of the fleet.

To define the threshold and rules, it is initially proposed that the failure rates defined in the FMECA (WP2) and/or manufacturing data (if available) are utilised to provide the most accurate representation of the failure rates of the components (accounting for any variation between components/operation). These should be combined with the condition data to provide an estimate of RUL. These can be combined with the operational constraints, from D5.1, to support the condition maintenance framework (D5.3). The failure rates should be reviewed during the demonstrator in collaboration with FGC and provide feedback on the accuracy of the LOCATE system (to be covered in deliverable D6.2 LOCATE Predictive Maintenance Framework) .

7.1. Development of Thresholds and Rules

Definition of thresholds and rules, such as the P-F curve identified in Section 6, depend on the system/component being assessed, failure modes and type of data monitored. In the LOCATE system, the measured and reference behaviour provide an indication of the health status (or performance) of the system/component. Thresholds/rules are required to provide an indication of when maintenance is required, with sufficient time for maintenance to be scheduled (e.g., P-R interval in Figure 13) based on the health status of the system/component. As identified in Section 6 this requires an understanding of the relationship between performance and degradation to support the prediction of the estimated-time-to-failure (or RUL) and definition of the P-F curve.

The type of thresholds used is dependent on the type and format of measured/reference behaviour data. For example, data could include physical measurements of the actual condition of a component/system (e.g., wear measurement of a wheel profile) and sensor data (e.g., vibration measurements) which require some form of post-processing to infer the component/system condition or functional performance. If the physical condition of the component/system is monitored, then changes in the measured data can be tracked to detect potential failure which can be linked to industry (safety) and company (performance) limits. In the latter case, features in system performance, e.g., peak frequencies which change with degradation (e.g., symptoms) need to be identified and there are challenges in terms of identifying the type and severity of a fault and recommending the most appropriate maintenance action.

To support the definition of initial thresholds and rules in the LOCATE project, existing standards and techniques for condition monitoring and prognostics have been reviewed. Techniques, such as failure mode symptoms analysis, were shown to provide useful information for identifying the symptoms which potentially lead to a particular failure, the current means of detection and thresholds which trigger a maintenance action. In discussion with FGC and the LOCATE Advisory Board, this technique has been applied to each of the selected use cases to link the main failure modes identified in the FMECA developed during WP2 (D2.3) with the symptom(s) and proposed measured or reference data.

The expanded FMECA can be found in Annex A. This includes details of the current detection method and existing (or typical) thresholds and rules that are applied to each of the use cases. In LOCATE, these will be replaced with information (either physical measurements or data features) from the measured or reference data developed during WP3 and WP4 (to be covered in deliverable D6.2 LOCATE Predictive Maintenance Framework).

An estimate of the P-F interval, in time or distance, for all the identified failure modes would have been a valuable addition to the FMSA table presented in Annex A. However, in the current preventative maintenance regime adopted by FGC, the failure modes are not permitted to remain in the system past the potential failure point (P). This concept is not natural in the current regime therefore no records of extending RUL or scheduled maintenance intervals exist. It is envisaged that once the CBM system is in place and the maintenance transitions to a PdM regime, failures modes will be tracked more closely and a better understanding of the limits and threshold to support the confirmation of the initial P-F intervals defined in D5.3.

The summary table presented in Annex B represents the RAMS table using the FMECA process in which the failure modes and causal factors are linked to symptoms. The table in Annex A represents more closely an FMSA analysis that extracts descriptors from the symptoms for each failure mode. Deliverable D5.3 can make use of the information included in Annex A and B to better understand how the failure modes are interlinked within the component, e.g. if a failure mode for a particular component is linked in a series or has an independent growth curve due to the complexity of the number of elements in the component. The symptoms and descriptors, defined in Annex B, can also lead to better degradations models and a list of covariates for use in the regression models which are linked to the reliability data for a component and will also provide D5.3 with useful information for the linear piecewise approximations of condition data (covariates). An example of Weibull probability densities and hazard functions for typical failure patterns was suggested by D5.2 and adopted by Task 5.3. Addionally, an example of the proportional hazard model was provided in section 6.3 of this deliverable outlining its limitations and providing other more recent model suggestions.

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Annex A – Failure Mode Symptoms Analysis

A detailed list of the failure modes of the bogie is given in annex A.

System	Component (s)	Failure mode(s)	Cause(s)	Symptom(s)	Descriptor (s)	Parameter(s)	Failure Prognosis	Failure Diagnosis
Bogie frame		Deformation	Impact damage and fatigue	Offset wheel loads (bogie twist)	Features: strain\ crack detection using SHM harmonic component analysis	Bogie\Axlebox	Condition based moving PDF \ evolution of parameters	VT\MT\UT
		Twist		High levels of vibration		Acceleration\ IMU\ strain gauge		Operator
		Cracking		High levels of bogie strain/stress				Parameter change
Suspension	Primary	Coil spring – deformed/dislodged, cracked, broken	Wear, fatigue, impact damage	Abnormal vibrations	Features: change in vertical stiffness from baseline \ SD correlation between bounce, roll, pitch	Bogie\Axlebox		VT \
	Secondary	Dampers - fluid leak		Poor ride performance / bogie stability		Acceleration\IMU\ displacement		Operator
		Insufficent height		Insufficient vehicle height				Parameter \ change \
								Historical data
Axlebox	Casing	covers with crashes, breaks, fissures or	Wear and tear, grease quality (contamination), leakage of grease,	Abnormal vibrations. Increases in bearing		Bogie\Axlebox		

		overheating	fatigue, corrosion	temperature and noise				
		leak of grease				Acceleration. Temperature gradient above ambient/thresho ld		
		excess of grease						
		control devices not fastened						
		control devices damaged						
		overheated, damaged, missing or unfastened elements				Carbody\Bogie\ Axlebox		
		water inside				Acceleration		
		grease in bad condition colour, quantity, density						
		sealing joints weak, deteriorated						
		condition and torque of attachments holding coupled devices			Features: enveloped acceleratio n, temperatur e			VT \
	Union	state of the						

	Elements	plates and their holders						
		fixing torque of the holding screws to low				Pressure		Torque measurement\
	Bearings	insufficient closing strength						Parameter
		level of wear						Change\
		state of the lubricant grease						
		condition and torque of attachments holding the bearings						Historical data
Wheelset	Axle	visible impacts	In-service wear, manufacturing/maintenance error, wheel slide, wheel-rail forces	Bogie stability (equivalent conicity related)	Features: RMS, mean, peak, frequency peak, kurtosis, crest factor, skew etc.			VT
		fatigue cracks	Impact damage, corrosion, pitting	Abnormal vibrations				Profile measurement
		fatigue cracks		Increased stresses in axle				Ultrasonic inspection
	Wheels	cracks and notches on the wheel tread		Increased vibration				Operator
		flats						Parameter change
		build up od material in case of CBB						
		wheel out of round						

		wear of the profile over threshold equivalent conicity exceeds						
		wheel diameter < minimum						
		internal distance between wheels too important						Historical data
Braking	Cylinder & Rigging	System fluid leaks	Wear and tear	Loss/variation in braking force	Features: pressure exceedance from baseline			VT
		wear (block/pad)	System malfunction	Noise				TCMS
Traction engine	Motors and Collector	Cracked collector brushes	High temperatures (environmental)	Pollution	Features: motor current profile against motor speed			VT
		wear to gears	Wear and tear	Noise				
				High engine temperature				

Figure 14 Failure Mode Symptoms Analysis

Annex B – RAMS Table Summary

System	Failure mode(s)	Cause(s)	Symptom(s)	Current detection method	LOCATE
Bogie frame	Deformation, twist, cracking	Impact damage and fatigue	Offset wheel loads (bogie twist) High levels of vibration High levels of bogie strain/stresses	Visual inspection	(1) FGC have never had any problems with bogie frames and likelihood of occurrences are low. Therefore, potentially not important to detect bogie frame faults and not likely to see any benefits from such measurements during the project. (2) Failure modes difficult to infer from measured data, strain gauges could provide useful information but influenced by gauge locations etc. (3) Digital twin may provide some information - measured data used to support validation (4) Monitoring of bogie stability / vibration might indicate problems in other components/systems.
Suspension	Coil spring - deformed, cracked, broken Dampers - fluid leak, deformation	Wear, fatigue, impact damage	Abnormal vibrations Poor ride performance / bogie stability Insufficient vehicle height	Operator / drivers reports Visual inspection	(1) Use of accelerometers mounted on axlebox and bogie frame to detect changes in suspension performance. (2) Displacement sensor to indicate abnormal variations in suspension heights. (4) Development of a model-based parameter estimator to support identification of faults and inputs to the digital twin. (3) Digital twin will also provide some useful information, in relation to reference behaviour in normal and degraded condition.

Axlebox	Bearing failure	Wear and tear, grease quality (contamination), leakage of grease, fatigue, corrosion	Abnormal vibrations Increases in bearing temperature and noise	Visual inspection Torque measurement	*Note - axle box is replaced as complete unit (rather than repaired), less need to identify specific failure modes.* (1) Monitoring of axlebox (bearing) vibration and temperature. (2) Identify changes in vibration / temperature. (3) Link axlebox vibration signatures to bearing condition (WP4). (4) Predict remaining useful life (RUL).
Wheelset	Wheel tread damage (flats, cracking, OOR) Wheel wear (diameter differences, profile shape) Axle fatigue	In-service wear, manufacturing/maintenance error, wheel slide, wheel-rail forces Impact damage, corrosion, pitting	Bogie stability (equivalent conicity related) Abnormal vibrations Increased stresses in axle Increased vibration	Visual inspection Profile measurement Ultrasonic inspection	*Note - Better control of vibration induced by wheel defects might help to reduce degradation on other components (e.g., suspension, bogie frame etc.).* (1) Assessment of amplitude and frequency content of axlebox accelerations. (2) Link axlebox acceleration to wheel condition (WP4). *Note - Although consequences of axle failure are large, it is not clear how many failures FGC have reported and what the benefits from detecting this failure mode are. Not sure the measured data or digital twin would replace NDT or extend periodicity due to the safety implications.* (3) Digital twin may provide information on strain range / fatigue cycles of axle.
Braking	System fluid leaks, wear (block/pad)	Wear and tear System malfunction	Loss/variation in braking force Noise	Visual inspection	(1) Noise measurements
Traction engine	Cracked collector	High temperatures (environment	Pollution Noise	Visual inspection	(1) Comparison of measured current from engines - peak value and variations between engines.

	brushes, wear to gears	al) Wear and tear	High engine temperature		