# A Framework for Locomotive Bogie Condition-based Maintenance (LOCATE)

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## Abstract

The freight industry is under increasing pressure to reduce costs and improve the reliability of its services. Therefore, the development of intelligent tools and methods for predictive maintenance are needed to optimise the availability of rolling stock, improve the quality of service, and reduce maintenance costs. The framework developed during the LOCATE project aims to address some of these challenges by improving the conditional maintenance of a locomotive bogie (and associated components/subsystems), as one of the main drivers for current maintenance costs of a locomotive is avoiding unnecessary maintenance actions by using predictive maintenance. Several technical challenges also exist which the project has had to address, these include: development of the predictive condition-based maintenance (CBM) framework; statistical degradation modelling of critical failure mechanisms associated with the main components of the locomotive bogie and estimation of hazard rates; development of a mixed-Integer Linear Programming (MILP) approach to tackle the maintenance scheduling problem; development of 'digital twins' for appropriate bogie components; specification of a monitoring system with the capability of providing the necessary information to detect changes in component performance and implementing a CBM framework on an aging fleet of freight locomotives.

Keywords: Railway; Rolling Stock; Asset Management; Condition-Based Maintenance; Predictive Maintenance.

## 1. Introduction

The LOCATE framework typically follows a standard condition monitoring and diagnostic cycle which consists of several activities to establish the key failure mechanisms and critical components/systems, suitable monitoring technologies and strategies that can identify changes in system behaviour that indicate future failures. The three technical work packages (WP3, WP4 and WP5) of the project represent the measured, reference and operational system behaviour. The methodology includes the following steps:

1. Comprehensive understanding of known failure mechanisms of a locomotive bogie and selection of relevant use cases, through assessment of:
    a. Functional failure modes, degradation process and safety/risk profiles
    b. Indicators of health condition (e.g., parameters and limit values)
    c. Relevant maintenance actions and procedures
    d. Operational and technical constraints to these maintenance procedures
2. Development of functional specification for the CBM monitoring system including selection of appropriate sensor technology and post-processing techniques
3. Specification of thresholds and rules based on functional performance of the bogie
4. Definition of decision-making framework for locomotive bogie maintenance and an understanding of the tactical and operational constraints and opportunities for optimisation
5. Implementation of a sound knowledge-map for applying various optimisation methods and tools in the practical maintenance program of locomotive bogies.

This paper provides a summary of the initial work completed during WP5 of the LOCATE project, and reported in deliverable D5.2, and includes a review of the relevant standards and a summary of the condition-based maintenance approach adopted in the LOCATE framework.

## 2. Condition Based Maintenance Framework - A Structured Approach

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. 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) 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]. 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. The LOCATE project is primarily concerned with improving the maintainability of railway systems that supports the indirect benefits from RAMS. LOCATE has 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 beginning to see adoption in other heavy asset industries. The asset management (AM) series of standards, ISO 55000 [3] provides 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. Within the specialisation of prognostic health management (PHM), which can include CBM, a number of key standards have gained widespread adoption in industries such as aviation [6], automotive [7] and others [8].

### 2.1 Condition Monitory and Diagnostics of Machinery and Systems

An extensively adopted standard in PHM used in the CBM is Condition Monitory and Diagnostics of Machinery and Systems, ISO 13374 [10]. The standard specifies 6 functional blocks, the first three 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; 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 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. 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.

### 2.2 System Behaviour

During the initial development phase of the LOCATE project several work packages 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.

## 3. Predictive Maintenance

Preventative maintenance (PM) periodicities are conventionally established on 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, which 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 1(a) below; for illustrative purposes the scaling factor is held at unity.

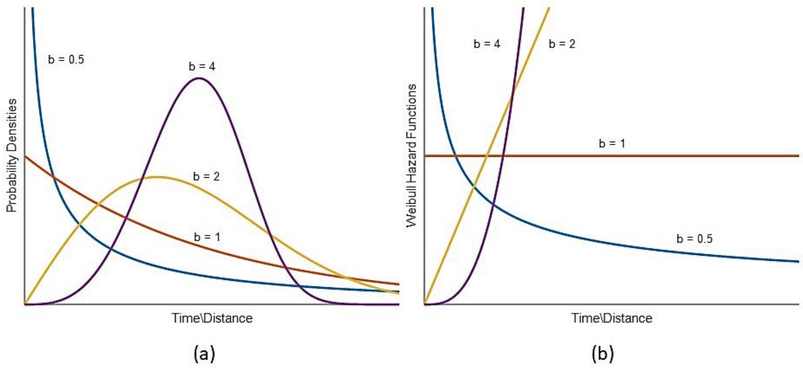


**Figure 1: (a)** Failure distribution and **(b)** Failures Patterns

The hazard Functions, shown in 1(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 can occur due to human error, is described by the blue curve for its conditional probability for failure.

### 3.1 Integrated Approach to Condition Monitoring, Diagnostics and Prognostics (CM&DP)

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 2(a) 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.

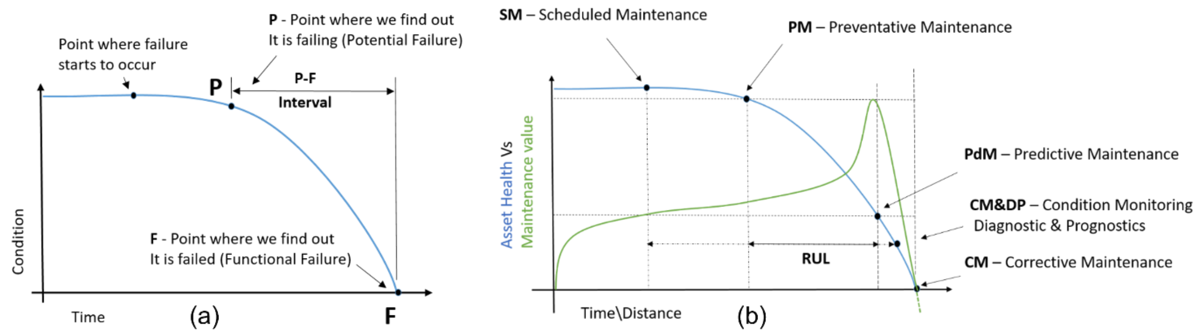


**Figure 2: (a)** Potential Failure and Functional Failure Interval [11][12]; **(b)** Asset health and indicative maintenance value comparison – modified from [13]

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 2(b) 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 a maximum when an optimum RUL is attained by extending routine inspection using remote condition monitoring technology. 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 if exceeded, increasing the risk of a catastrophic failure.

### 3.2. Combining Failure Patterns and Condition Monitoring Data for Prognostics

Failure probability distributions and patterns, as discussed above, are well known in reliability engineering 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 [14]:

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

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 [15] 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 a Failure Mode Symptoms Analysis (FMSA) 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 [16]. 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 consider an imperfect repair known as Proportional Intensity Model (PIM) [17]. 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; furthermore, the P-F interval can be adjusted and updated from conditional data when a CBM programme is in place collecting data.

## 4. 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 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, which can be combined with the operational constraints to support the condition maintenance framework. The failure rates should be reviewed during the demonstrator in collaboration with FGC and provide feedback on the accuracy of the LOCATE system.

### 4.1 Development of Thresholds and Rules

Definition of thresholds and rules, such as the P-F curve identified in Section 3.1, depend on the system/component being assessed, failure modes and type of data monitored. In the LOCATE system, the measured and reference behaviour provides 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-F interval in Figure 2) based on the health status of the system/component. As discussed, 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 are 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) or sensor data (e.g., vibration measurements) which requires some form of post-processing to infer the component/system condition and 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 FMSA, 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 with the symptom(s) and proposed measured or reference data.

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.

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**References**

[1] EU Technical Specification for Interoperability: https://www.era.europa.eu/activities/technical-specifications-interoperability_en
[2] BS EN 50126-1:2017; Railway Applications. The Specification and Demonstration of Reliability, Availability, Maintainability and Safety (RAMS). Generic RAMS Process.
[3] BS ISO 55000:2014; Asset management. Overview, principles and terminology.
[4] BS EN ISO 19650-1:2018; Organization and digitization of information about buildings and civil engineering works, including building information modelling (BIM). Information management using building information modelling. Concepts and principles.
[5] BS EN 81346-1:2009; Industrial systems, installations and equipment and industrial product. Structuring principles and reference designations. Basic rules.
[6] Löhr, A., & Buderath, M. (2014). "Evolving the Data Management Backbone: Binary OSA-CBM and Code Generation for OSA-EAI". PHM Society European Conference, 2(1). https://doi.org/10.36001/phme.2014.v2i1.1487
[7] Holland, S., Felke, T., Hernandez, L., Safa-Bakhsh, R., & Wuensch, M. (2016). "Health Ready Components-Unlocking the Potential of IVHM". SAE International Journal of Materials and Manufacturing, 9(2), 217-223.
[8] Construction; https://www.construction-institute.org/blog/2020/july-2020/cii-and-mimosa-move-interoperability-forward-for-c accessed 02/06/2021
[9] Mining; https://gmggroup.org/interoperability/mimosa-the-open-industrial-interoperability-ecosystem-oiie/ accessed 02/06/2021
[10] BS ISO 13374-1:2003; Condition monitoring and diagnostics of machines. Data processing, communication and presentation. General guidelines
[11] Moubray, J., (1997), Reliability Cantered Maintenance. Oxford: Butterworth-Heinemann.
[12] MIL-STD-2173, (1986), Reliability Centered Maintenance. Washington D.C.: Department of Defense.
[13] Haddad et al., (2012). An Options Approach for Decision Support of Systems with Prognostic Capabilities, IEE Transactions on Reliability, Vol 61, no. 4, December 2012.
[14] Jardine et al., 2006. A review on machinery diagnostics and prognostics implementing condition based maintenance, MechSyst Signal Process; 20:1483–1510.
[15] D. Cox, Regression models and life-tables, Journal of the Royal Statistical Society 34 (2) (1972) 187 – 220.
[16] D. Kumar, B. Klefsjo., (1994). Proportional hazards model: a review, Reliability Engineering and System Safety 44 (2) (1994) 177–188.
[17] D.Lugtigheid, A. K. S. Jardine, X. Jiang., (2007). Optimizing the performance of a repair able system under a maintenance and repair contract, Quality and Reliability Engineering International 23 (8) (2007) 943–960.