The sustainable freight railway: Designing the freight vehicle – track system for higher delivered tonnage with improved availability at reduced cost

SUSTRAIL

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Executive Summary

This report is an outcome of Work Package 4 (WP4) of the EU 7th Framework project SUSTRAIL. WP4 aims to facilitate the need for the railway infrastructure to accommodate more traffic whilst at the same time reducing deterioration of track and wheels through increasing the resistance of the track to the loads imposed on it by vehicles.

One of the goals of this WP is to identify monitoring tools that will move the lower bound of the track resistance probability curve upwards through removing the causes of track failures at discrete locations with low damage resistance.

In this purpose, Task 4.5 includes identification and development of technologies that can be used to monitor track and structures to optimise preventative and intervention level maintenance strategies, thus contributing to optimisation of whole-system LCC.

Data and opinions have been provided for this survey and assessment by various partners involved in WP4: infrastructure managers (NR, NRIC, and ADIF), academic partners (TRAIN, UNEW, LTU, HUD, USFD, and KTH) and suppliers (DAMILL, TATA STEEL, LUCCHINI and MERMEC).

Work Package 4 has also taken input from Work Package 1 (Benchmarking) and Work Package 2 (Duty requirements). The results of WP4 will feed into Business case (WP5) and technology demonstration (WP6).

This study includes:

- Description of limits for axle loads,
- Data collection from IMs,
- Survey on track-based monitoring systems, focus on ALCs
- Technological description and discussion about existing load monitoring systems,
- Description of the JVTC/Damill monitoring station, presentation, available data and interfaces
- Analysis of data from this monitoring station: Statistics on force data, detectable vehicle defects, discussion on limits, potential effect of removal out-of-limits vehicles.
- Data analysis of heavy haul locomotive wheel sets running surface wear,
- Proposition of track condition monitoring for preventive maintenance

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1. INTRODUCTION

The purpose of this work is to assist in sustainable achievement of increased speed and capacity for freight traffic, thus contributing towards making rail freight more competitive. So, it aims to facilitate the need for the railway infrastructure to accommodate more traffic whilst at the same time reducing deterioration of track and wheels through increasing the resistance of the track to the loads imposed on it by vehicles.

One of the goals of this WP is to identify monitoring tools that will move the lower bound of the track resistance probability curve upwards through removing the causes of track failures at discrete locations with low damage resistance.
Diagnostic methods are based on technologies that allow monitoring and inspection of the most important and critical aspects of the railway system. Monitoring is the process of measuring and inspecting an element of the railway system, in order to assess its quality, status, safety, etc.

Some Wayside monitoring can measure values of the vertical force (Q) and sometimes the horizontal force (Y) to determine if the vehicle meets some defined safety limits on imposed loads.

Much work has been carried out in UIC and in other projects on this topic. That was a fruitful input to this task and the work have been built on the knowledge and recommendations made by some previous EC Framework projects (Sustainable Bridges, DRAIL, InnoTrack…).

However, no international conclusions and clear recommendations for safety criteria have been produced, with wide variations between intervention levels and action requirements applied by the member states.

This work includes identification and development of technologies that can be used to monitor track and structures to optimise preventative and intervention level maintenance strategies, thus contributing to optimisation of whole-system LCC.

There is large variations in the way to deal with this topic: There are several different technologies used to measure loads imposed by trains and vehicles on the railway infrastructure. Also, there are implemented in many different ways, and finally, the intervention levels and action requirements applied vary from a member state to another.

In the first part of this report (chapter 2), an overview about the identification of best practices and some existing recommendations for imposed load have been produced. Then, Chapter 3 proposes a survey on track-based monitoring systems, with a focus on axle load checkpoints (ALCs). It contains some functional description of different existing systems, and discussions on the different measurement principles, assessment procedures and intervention concepts. The chapter 4 gives a description of the Swedish monitoring station that provides information of trains running behaviour (e.g. forces, loads). Analysis of data from this monitoring station has been performed, containing statistics on force data, detectable vehicle defects, discussion on limits, on problem of vehicle defects that initiate high forces on the track, and on potential effect of removal out-of-limits vehicles.

The chapter 6 propose a data analysis of heavy haul locomotive wheel sets running surface wear, and the last chapter gives some propositions track condition monitoring for preventive maintenance

2. TRACK SAFETY CRITERIA – COLLECTION OF DATA, DESCRIPTION OF EXISTING UPPER AND LOWER BOUNDS FOR IMPOSED LOAD

The railway track is subject to loads imposed by vehicles passing on it. This causes some deteriorations on the track and also on the wheels, which reduce their life cycle costs. In order to accommodate more traffic, and in the same time ensure the needed safety, imposed loads has to be determined, and then measured and monitored.

Much work has been carried out in UIC and elsewhere which will be a fruitful input to this task. However, no international conclusions and clear recommendations for safety criteria have been produced, with wide variations between intervention levels and action requirements applied by the member states. Furthermore there is no answer about the required precision of the measurement device.

This task has also built on the work undertaken in some previous projects to define Minimum action rules. An overview of the work provide in other projects related to this task has been done (InnoTrack, UIC Axle load Checkpoint (ALC), HRMS, D-Rail).

No specific regulation on imposed load has already been defined. As no specific regulations are existing, different solutions were chosen for limits and alarm values, sometimes based on other existing regulations.

In the framework of this task, a collection of data on track safety criteria, as applied by a range of member states, has been performed to identify best practices, to propose some recommendations and to assess some upper and lower bounds.

As an example, the regulation of RIV was taken to assess unbalanced vehicles, although wheel loads of running vehicles differ from those of standing ones.

With regard to lateral and longitudinal load imbalance, UIC RIV limit static values respectively equal to 1.25 and 3 are found to be appropriate. They don’t include vehicle vibrations due to train-track-interaction.

For the following section, data were collected from the literature and from responses to a specific questionnaire sent to rail infrastructure managers across Europe.

2.1 From the literature

The literature on this subject included European standards and presentations and reports from individual rail infrastructure managers. There are various relevant projects addressing this subject: D-RAIL (EU FP7), InnoTrack (EU FP6), Axle Load Checkpoint and HRMS (both UIC) for which brief summaries are included but final reports have not been made available.

2.1.1 European Standards

EN 15528:2008+A1:2012 Railway application – Line categories for managing the interface between load limits of vehicles and infrastructure [1]. This standard defines a Europe-wide line classification system for IMs in order to manage freight payloads and the vertical load carrying capacity of the track they are running on.

EN 15654-1 Railway applications – Measurement of wheel and axle loads – Part 1: Interoperable ‘in-service’ rail vehicles (Final draft, June 2012) [2]. This draft European

Standard details how the measurement of wheel and axle loads should be carried out, including a set of calibration tests to be performed for each test site in App. B.

2.1.2 INNOTRACK

This FP6 project included a demonstrator wayside monitoring station in Sweden capable of monitoring forces, vehicle identity and steering behaviour, with on-line data accessibility [3].

2.1.3 UIC Axle Load Checkpoint (ALCs)

UIC ‘Axle Load Checkpoints - State of the art’ report presents a scientific and engineering approach to use of axle load checkpoints.

The conclusion of the report determined that ALC are considered by infrastructure managers and vehicle operators to be very useful for providing information on the condition of vehicles as they travel over the network.

Its overall conclusions about using ALC in Europe are:

- ALC give better knowledge about real loads and vehicle behaviour
- Positive influence on safety aspects
- Benefits for vehicle maintenance and service life components
- Reduction of infrastructure maintenance costs
- Need for international regulations for ALC
- Need for European harmonization of limit values
- Need for a European vehicle identification system

2.1.4 HRMS (Harmonisation: Running behaviour and noise on Measurement Sites)

European rail networks use a variety of different way of measuring wheel forces, with different alarm levels and corresponding actions. Many of these systems were developed to meet local or national demands and are often not comparable with each other, leading to interoperability problems. The goal of this UIC project is the harmonization of assessment procedures and limit values for both overloaded wagons and wheel and axle defects for rail vehicles across Europe [4].

2.1.5 D-RAIL

This is an EU FP7 project, completed in November 2014, identifying root causes of derailment, particularly freight vehicles. It aimed to assess both wayside and vehicle-mounted monitoring systems with respect to their ability to identify developing faults which could lead to derailment and also specify appropriate alarm limits and corresponding actions (e.g. speed restrictions and removal from service) [5].

From a derailment prevention point of view, axle load checkpoints were assessed as very beneficial for checking parameters related to derailment. Indeed, they can indirectly indicate wheel flats, uneven loading, skew in vehicle chassis, defect springs, bad steering wheels etc. These systems can cover skew loading, wheel flats, suspension failures, high lateral forces and high angle-of-attack.

Some proposed ranges of these forces are specified in various standards. Some limitations, standards and recommendations, regarding the topic of wheel flange climbing that could lead to a derailment are presented hereafter (more details in [18]):

- ORE (UIC's Office for Research and Experiments) Report B 55/RP 5: wheel-climbing (where the wheel flange climbs up the rail) does not result in derailment if the ratio of the horizontal force (Y) to the vertical force (Q) does not exceed 1.2 and the wheel climb does not exceed 5mm; this limit (Y/Q = 1.2) was later confirmed by the ORE C 138 Committee for mathematical studies of the safety against derailment of freight wagons
- The European Standard EN 14363:2005 Railway applications – Testing for the acceptance of running characteristics of railway vehicles – Testing of running behaviour and stationary tests suggests using a 10% safety factor, i.e., Y/Q < 1.08
- The Uniform Technical Prescriptions (UTP) applicable to Rolling Stock, subsystem Freight Wagons (UTP WAG) [APTU Uniform Rules (Appendix F to COTIF 1999), published by OTIF] specifies limiting values:
    - (Y/Q)lim = 0.8 for large curves R ≥ 250 m
    - (Y/Q)lim = 1.2 for small curves R < 250 m
- However, in the current draft [11.05.2010], this has been changed to:
    - (Y/Q)lim = 0.8 for dynamic on-track tests
    - (Y/Q)lim = 1.2 for stationary tests

The UTP also gives conditions for safety against derailment when running on twisted tracks. A detailed study of the limit has been made recently by Barbosa [Safety of a railway wheel set – derailment simulation with increasing lateral force].
See also the Transit Cooperative Research Program report 'Track- Related Research' [2005, Chapter 5, Flange Climb Derailment Criteria and Wheel/Rail Profile Management and Maintenance Guidelines for Transit Operations].
Another measure used as a derailment indicator is ΔQ/Q, the dynamic change in wheel load divided by the nominal static value, with a threshold value of 0.8.

2.1.6 Denmark

A presentation on Axle Load Checkpoints in Denmark given at the Annual Danish Rail Convention in 2013 outlined their proposed introduction in Denmark where a single test site using the Gotcha system is now operational, as well as the summarising the use of wheel force measurement systems across Europe [6].

2.1.7 The Netherlands

Railinfratrust (RIT) - the Netherlands rail infrastructure operator - have been using the Gotcha wheel impact measurement system for over 7 years with over 45 installations across the network [6],[7].

2.1.8 Switzerland

SBB has 135 operational installations including 24 wheel load checkpoints measuring maximum axle load, brake weight and left-right load displacement. The wheel load checkpoints trigger 600 alarms annually. They are working towards real-time automated cross-border data exchange in order to improve track availability across Europe [8].

2.1.9 Austria

OBB operate wayside train monitoring systems measuring dynamic wheel load for identifying over-loaded wagons and faults with wheels and axles [9]. They are developing cross-border data exchange with SBB (Switzerland) [8], [9].

2.1.10 Finland

According to the 2014 'Finnish Railway Network Statement' report [10], Finland has a total of 8 wheel force measuring stations situated near to the largest railway junction stations and the border stations for rail connections to the east.

Appendix 6 of the report gives maximum permitted axle loads and corresponding speed limits for specific sections of track across Finland. It then goes on to detail actions for dealing with overloaded wagons, summarized below:
The maximum permitted axle loads for the various track sections are 200kN, 225kN or 250kN. Excess loads must be unloaded at the next available opportunity if the maximum permitted load of 225kN is exceeded by > 5% or if the maximum permitted load of 250kN is exceeded by > 2%.
When the maximum axle load of a domestic wagon or a wagon under COTIF agreement is 225 kN, wagons bearing excess weight may be transported at the following speeds:

National track classification	Max. axle load kN	Max. Speed km/h
A*	225	20
B1	235	35
B2	235	50
C1, C2, D	235	80

* On main lines and secondary tracks belonging to the track classification A individual overweight wagons with axle loads exceeding 200 kN but not 225 kN may be transported only on a temporary basis at a speed of 20 km/h. It is not permitted to operate on main lines and secondary tracks of superstructure category A at axle loads exceeding 225 kN.

Overweight wagons must be transported in line with the regulations governing exceptional transport. Before transport the wagon's wheel sets and the rest of the bogie structure must be inspected. Temporary transport of overweight wagons can be considered in case of ad hoc need. Any temporary transport of overweight loads must be notified to the track's maintenance operator with a view to monitoring the condition of the track superstructure.

2.2 Information received from IMs

The on-line survey for Infrastructure Managers included the following questions. Reponses were only received from Network Rail (UK) and Trafikverket (Sweden).

Which proprietary track-based monitoring systems do you use?

Please tick all that apply

- ☐ GOTCHA
- ☐ Wheelchex
- ☐ RailBAM
- ☐ Other: ____

How many trackside monitoring stations do you operate?

____

Do you have any criteria for location of monitoring station? (e.g. track curve radius)

____

Which sensor technologies do you use in your track-based monitoring systems?

Please tick all that apply

- ☐ Strain gauges
- ☐ Fiber optic sensors
- ☐ Acoustic sensors
- ☐ Other: ____

What are your limits and actions for overloaded or unevenly loaded wagons?

Please give all axle load limits and corresponding actions/interventions (e.g. axle load >20t: impose fine of £xx). Please also state if this depends on vehicle type.

____

What are your limits and actions for dynamic impact loads (e.g. due to wheel flats)?

Please give dynamic impact load limits and corresponding actions/interventions (e.g. Wheel load > 400kN: 30km/h speed restriction then removed from service)

____

Do you also measure horizontal forces (Y-force)?

- ○ Yes
- ○ No
- ○ Don't know

If you do measure Y-forces, how do you use the data?

____

2.2.1 Response from Network Rail (UK):

Network Rail operates 31 axle load checkpoints: 28 using the established WheelChex system and 3 implementing the newer Gotcha system.

Table 1:Limits and actions - for locomotives and motor-driven rail cars

Alarm level (dynamic impact load)	Action(s)
250 - 275kN	Communicated to management centre, no action required
275 - 325kN	Out of service at destination, send to workshop
>325kN	80 km/h speed restriction, out of service at destination, send to workshop

Table 2: Limits and actions - for wagons

Alarm level (dynamic impact load)	Action(s)
250 - 275kN	Communicated to management centre, no action required
275 - 325kN	Out of service at destination, send to workshop
325-400kN	60 km/h speed restriction, out of service at destination, send to workshop
>400kN	50 km/h speed restriction, out of service immediately, send to workshop

2.2.2 Response from Trafikverket (Sweden):

Trafikverket has almost 200 wayside train monitoring systems in operation, 27 of which are ALC (they also have 26 pantograph detectors and 143 hot axle box detectors).

Table 3: Limits and actions - for all drive units

Alarm level	Action(s)
>320kN (Peak load) or >220kN (Dynamic load) or >5.0 (Ratio)	'Warning': Continue to destination unrestricted but vehicle must not be used or loaded until wheel has been inspected, corrected and approved by authorized personnel
>350kN (Peak load)	'Low': Continue to nearest suitable location for visual inspection. If no visible wheel damage, continue to final destination with speed reduced by 20%. If visible damage, follow 'High' alarm actions:
>425kN (Peak load)	'High': 10 km/h speed restriction, continue to nearest suitable location where vehicle can be switched out from train.

Table 4: Limits and actions - for wagons and unknown vehicles

Alarm level	Action(s)
>320kN (Peak load) or >200kN (Dynamic load) or >5.0 (Ratio)	'Warning': Continue to destination unrestricted but vehicle must not be used or loaded until wheel has been inspected, corrected and approved by authorized personnel

>350kN (Peak load)	'High': 10 km/h speed restriction, continue to nearest suitable location where vehicle can be switched out from train.

2.3 Summary

The levels and corresponding actions for wheel impact forces varies for different countries, as does the means by which they are measured. Due to lack of response to the request for information, it has been impossible to give an actual range of values or actions.

The level of ALC operation in a selection of European countries is presented in Table 5.

Table 5: Summary of European rail network usage of axle load checkpoints

Country	Infrastructure Manager	No. of axle load checkpoints	Systems used
UK	Network Rail	31	WheelChex (28) Gotcha (3)
Sweden	Trafikverket	27	
Denmark	Banedanmark	1 (test site)	Gotcha
Norway	Jernbaneverket	3	
Spain	Adif	15+	WheelChex
Italy	RFI	10+	
Netherlands	Railinfratrust (RIT)	45+	Gotcha
Swizerland	SBB	24	Gotcha
Germany	Deutsche Bahn	20+	
Poland	PKP PLK	30+	Gotcha
Finland	Liikennevirasto	8	

3. WAYSIDE SENSORS AND MONITORING SYSTEMS

This part describes current and innovative wayside monitoring technologies. A focus is put on the monitoring systems able to provide data on forces and loads. The means by which the data collected from these technologies are used to define limits are also explained.

3.1 Wayside monitoring systems state of the art

Wayside monitoring systems are used to inspect locomotives, wagons and loads. They monitor different train components and physical parameters and can provide early identification of defects.

Hereafter can be found a list of the main wayside monitoring systems:

- Hot box, wheels and brakes detection
- Acoustic bearing defect detection
- Wheel profile and diameter systems - Laser-based wear measurement systems
- Wheel treads condition monitoring detectors
- Brake pad condition detectors
- Bogie performance detectors
- Dragging equipment device (DED)
- Vehicle profile measurement systems
- Wheel impact load detector - Axle load check point (ALC)

This last system deals with the work done in the framework of this task. Generally ALC can reveal overloading and/or unbalanced loading of vehicles, suspension failures and wheel defects such as out-of-round wheels and wheel flats.

3.2 Technology to measure imposed load: Focus on Axle load check point

3.2.1 General description

Axle load checkpoints (ALC) can reveal overloading or unbalanced loading of vehicles and wheel defects such as out-of-round wheels and wheel flats, which increase the risk of rail breaks and the consequent potential for derailment. For derailment prevention, trackside inspection of vehicle forces extends to analysis of curving behaviour and running instability as well. Checkpoints placed on curves, so long as the vehicles do not have the equilibrium speed for the cant, can measure horizontal as well as vertical track forces. Two basic ALC types are presented in Figure 1.

There are a large number of different ALC devices in use around the world. Systems were investigated and assessed in the past and presented in many reports, as reviewed in chapter 2.

ALC provide information on running behaviour of passing trains without the need for stopping trains. In-track ALC installations are designed to allow for grinding, tamping and other maintenance operations without need to dismount equipment.

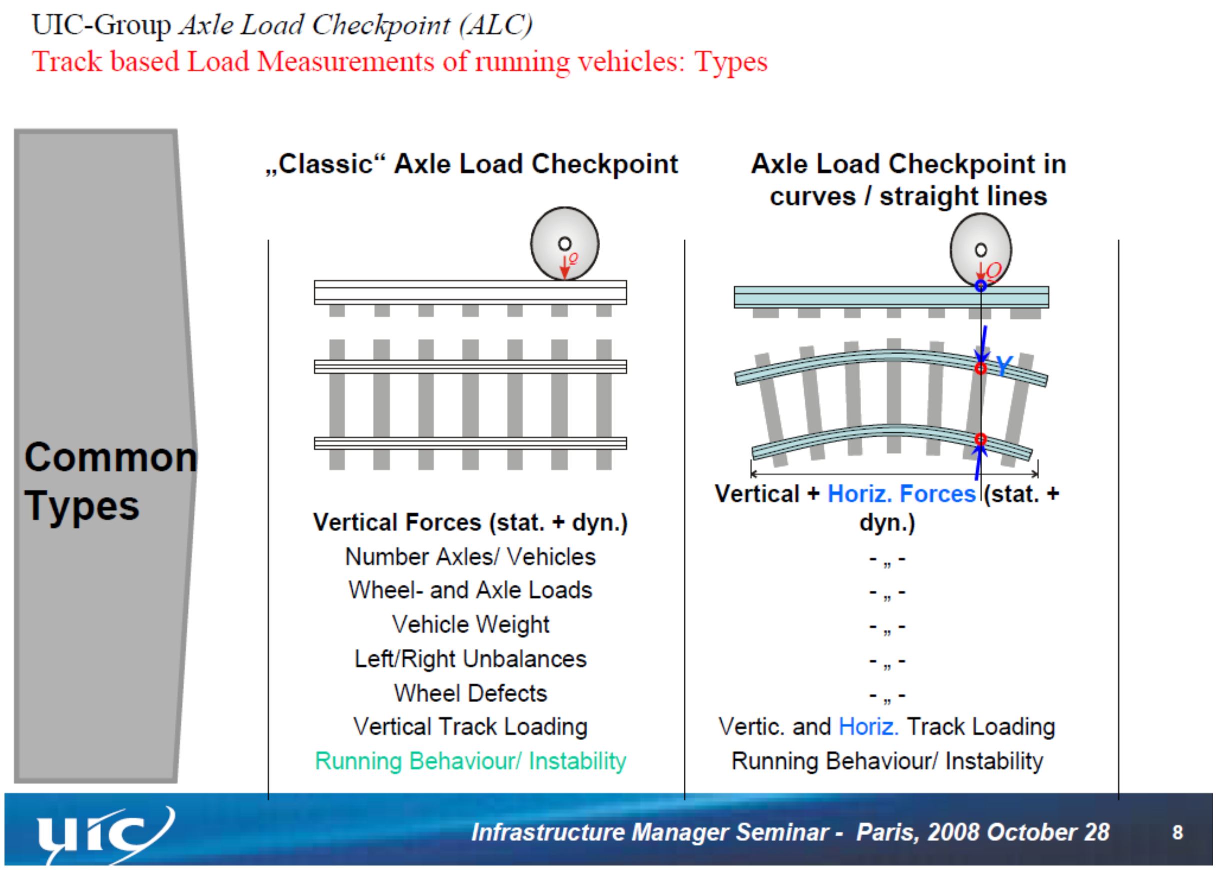


Figure 1: 2 common types of Axle Load Checkpoint

The systems can be designed to handle a very harsh environment. No moving parts and no optical equipment such as cameras or lasers are needed which makes them robust in any weather.

The output from these systems is basically data indexed per axle and automatically generated directly after a train passage.

These systems become more and more common and are available from several vendors on the market. Stabilized or reduced prices are to be expected while functionality is increased.

On-track installations allow for grinding, tamping and other maintenance operations without the need to dismount equipment.

3.2.2 Technological principles used for load measurement

3.2.2.1 Strain gauges and load cells

Strain gauges use wires or conducting foils which change resistance with length. By measuring the change in resistance the strain can be estimated. The gauges are designed to be sensitive to strain changes (material deformation) in a particular direction. The gauge illustrated in Figure 2 would measure strain parallel in the horizontal direction.

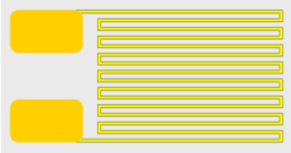


Figure 2: Strain gauge

The relationship between strain and resistance is: δR/R= Sε

δR Change in resistance
R Resistance of unstrained gauge
S Strain sensitivity factor, or ‘gauge’ factor
ε Strain

Load cells convert force into an electrical signal and usually consist of 4 strain gauges in a Wheatstone Bridge arrangement, but arrangements with only one active strain gauge (‘quarter’ bridge) or two active strain gauges (‘half’ bridge) are also possible. Greater precision can usually be achieved through the use of multiple gauges, but placing strain gauges is a difficult procedure, and it is not always possible to find an appropriate surface for placing multiple gauges.

Strain gauges are placed on the surface of the component being studied. The distribution of stress and strain on a surface is two-dimensional, so measurement of strain in more than one direction is often necessary. A single sensor can have multiple strain gauges of different types and orientations, such as the example in Figure 3 where there are three gauges with different orientations. (Typically, two such sensors would be used on opposite sides of a component. The four strain gauges at 45° would create a single ‘full’ bridge used to measure torsion; the two vertical strain gauges would create a single ‘half’ bridge used to measure bending.)

Wheel/rail forces can be determined from measurements obtained by strain gauges. Strain gauges on rails are usually positioned on the rail web and rail foot and used to study the various modes of bending and twisting of the rail as vehicles pass over.

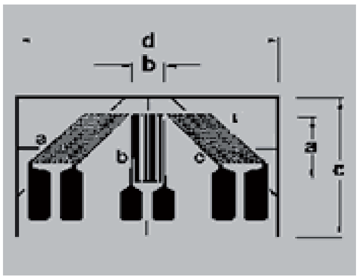


Figure 3: Three measurement grids strain gauges (from UIC ALC)

Strain gauges and load cells are used in axle load check points (ALC). Such strain gauge based systems can be used for the measurements of extensions of the rail: those extensions can result from longitudinal and lateral forces applied on the rail, which cause shear loads on the rails or bendings for example. The principle is that continuously welded rail is usually under tension when it breaks, and a break causes a reduction in the tension. This decrease in tension is detected with strain gauges installed on the web of the rail.

3.2.2.2 Accelerometers

Accelerometers are a mature sensor technology with a range of possible application areas operating at different frequency ranges. Mobile phones use accelerometers to identify orientation with respect to gravity, but most industrial uses of accelerometers are interested in very high frequency vibrations (kilohertz).

On the railway, if the stiffness of a section of track is known precisely, then accelerometer readings can be used to estimate the forces acting on the track. A high-frequency measurement is necessary to capture details of this force. For example, if a vehicle passes at a speed of 30 m/s (108 km/h) this corresponds to approximately 10 wheel revolutions per second. In order to detect out-of-round wheels, the accelerometer frequency would need to be on the order of 1 kHz to capture details as small as 3 cm.

In practice, there are large uncertainties in the structural stiffness of the track and therefore analysis of forces requires careful calibration.

3.2.3 Main components of an ALC

The main parts of an ALC are:

- Components on track for the measurement:
    - Sensors :
        - Strain gauges: An array of strain gauges is used to measure the strains in the rail web and foot to analyze bending and twisting of the rails.
        - Fiber optical sensors: These can be used instead of strain gauges, but are usually used to study deformation over longer spans – strain gauges are used for precise measurement of strain at a point. Some ALC use optical sensors to measure the deflection of the rail between two sleepers, and determine the applied forces from this deflection.
        - Load cells: These can be placed, e.g., between rail and sleeper to measure the vertical force. (The load cells usually have internal strain gauges.)
        - Laser systems: Rail deflection can be analyzed using lasers. These have the benefit that they can be placed away from the track infrastructure.
        - Accelerometers: These are placed on the rails and the motion of the rail is used to determine the applied forces.
    - Cabling of hardware components
- Components at the side of the track:
    - Amplifier
    - Hardware for communication
    - Power supply
    - Processing unit for analysis of measurements
- Software for:
    - Data acquisition
    - Computation
    - Measurement evaluation

3.2.4 Different measurement principles, assessment procedures and intervention concepts.

3.2.4.1 Different kind of ALCs

3.2.4.1.1 Vertical and horizontal forces

There are many different ALC systems already in use. Some assess only vertical forces, some are mounted in curves and derive also horizontal forces and contribute information about the running behaviour of the passing vehicle.

Not only the measurement principle varies, but the length and scatter of sensors differ also.

Beneath systems mounted in tracks with normal conditions specially located ALC are used for vehicle homologation purposes facing higher demands.

3.2.4.1.2 Static or dynamic measurement

They are wayside systems performing either static or dynamic weighing.

Static weighing gives accurate load readings on a parked or slow running vehicle but requires quite complex (expensive) installations with rigid fundaments to prevent unwanted errors due to settlement of the ground. Dynamic scales represent the opposite. They cannot measure forces from a parked vehicle but instead work with relative changes in readings when wheels are passing over them. The installation is less complex (cheaper), less maintenance demanding and these systems can make fast monitoring of axle loads even at high speeds.

The accuracy is less than for a static weighing systems as a system in motion always introduce dynamic variation to the readings but a precision better than 1% can normally be achieved which by far cover the precision required for maintenance or safety purposes.

3.2.4.2 Different measurement lengths

Sensors are normally installed along a track length of minimum 3-5 meters to cover at least 1 wheel circumferences but the length can easily be extended to 20-30 meters if also ride stability and hunting behavior is of interest to monitor.

3.2.4.3 Different operators - different practices

The use of axle load checkpoints can be motivated by different aims and so be operated in different ways.

Most generally, the aims are the protection of infrastructure from high loads, or potentially dangerous vehicles (for example which have a high potential for derailment), or data collection for vehicle maintenance purposes.

From an Infrastructure Manager (IM) point of view, being able to measure the vehicle induced forces different perspectives were the starting point for the activities. Often IM wanted to assess the loading on the infrastructure imposed by running vehicles. Even the protection of the infrastructure from overloads or potentially dangerous vehicles was often the aim.

There are also benefits for train operators: they can monitor the condition of individual vehicles over time; the load information about of their fleet can be used for enhancing their maintenance regimes: preventative maintenance and repair can be scheduled to achieve longer life and decrease LCC, driven by usage and/or deterioration of the structure, rather than the widespread sub-optimal practice of using time-interval based maintenance.

3.2.4.4 Conclusion

As described above one major improvement would be to define precisely the needs of the different users. IM will have different aims than RU. Based on that, the definition of measured values and intervention concepts will follow. From the European perspective it is necessary to homogenize those attempts. This is actually done within the UIC project HRMS (Harmonization Running behavior and noise on Measurement Sites [15]). The task of the engineer is to provide technical solutions, which fulfil those requirements, including the question of measurement reliability and precision.

At the end different measuring systems, including different intervention concepts (e.g. responsibilities, values, data transmission, influence on operation) based on national needs are the result.

3.3 Functional description of existing systems

A review of on-track based measuring systems which are capable of measuring the wheel-rail forces of a passing vehicle has been performed. The primary aim is to identify the most useful outputs for the simulations and whether the resultant predictions can be used to further develop the data processing or threshold warning triggers applied in these technologies. In total, ten measuring systems have been identified, some of these are used primarily in Europe, whilst others are more typically employed in the US or Asia. The review work focuses on the capability of systems to measure derailment indicators and do not discuss or assess all the capabilities of the systems identified (wheel flat detection, out-of-round etc). Full system descriptions are available from the manufacturers' literature.

The following section presents an overview of the systems being studied, their general operating principal, followed by a summary of their key features and how useful each system may be as a derailment risk detector. A commentary has also been provided which highlights the potential for further development of a particular system to improve performance in respect to the prediction of track degradation.

3.3.1 System 1: GOTCHA Weighing in Motion Module

(http://www.gotchamonitoringsystems.com/WIM.php)

Gotcha is a trackside monitoring platform for measuring a wide range of qualitative and quantitative data of passing trains. Gotcha Monitoring Systems obtain real-time information about the state of different aspects of passing vehicles, such as: weight distributions, wheel loads, speed, wheel defects, axle passes, noise emission, axle boxes quality and pantograph. The system is capable of remote reporting and RFID tracking of vehicles and based on a fibre optic measuring system which does not require direct fixing to the rail surface. The Gotcha Weighing in Motion Module (WIM) system is part of the wider ranging Asset Management Platform but is not intended specifically as a derailment risk detector. It currently measures only vertical (Q) forces (see Figure 4), however, in common with other wheel weighing systems, it has the capability to detect variations in static wheel load across a bogie which can be used to identify skew loading and diagonal imbalance - a key factor in a number of cited derailments. This latter feature was added recently to the systems processing for application in the UK, following a freight wagon track twist related flange climb incident. A lateral force measuring capability is under development.

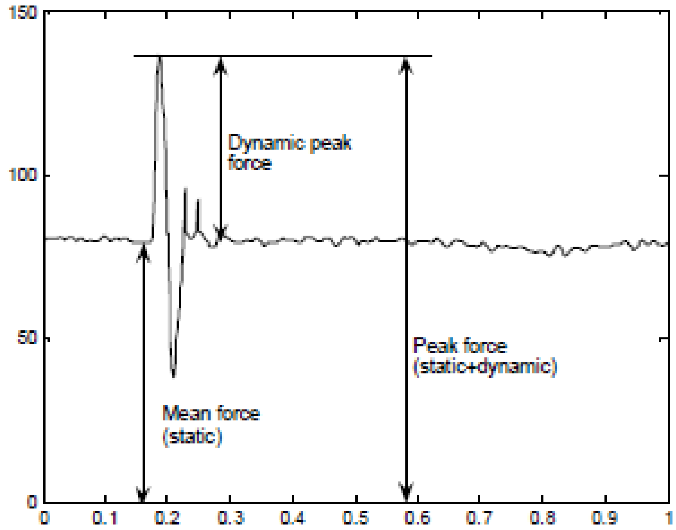


Figure 4: Example of Gotcha System Load Output

Measurement of the individual wheel Q forces under various track, vehicle loading conditions and vertical loading variations across a bogie could be used for the prediction of track degradation. A similar WIM system is also available from LB Foster/Salient Systems (http://www.lbfoster-salientsystems.com/pdf/wim.pdf) and likely other manufacturers can be found.

3.3.2 System 2: Argos Level 3 (Y/Q Derailment Safety and Instability)

(http://www.argos-systems.eu)

The Argos Level 3 system aims to analyse the running performance of vehicles by measuring both vertical and lateral wheel-rail forces without separate earthworks or foundation. In addition the Argos system allows the processing of a number of additional derailment indicators, specifically: the lateral (Y) force, Y/Q ratio and wheelset angle of attack (see Figure 5). It is also capable of measuring general curving forces and hence steering ability of the vehicle. By measuring the combination of lateral and vertical forces, the system can also calculate net centrifugal forces, centre of gravity height and roll-over characteristics.

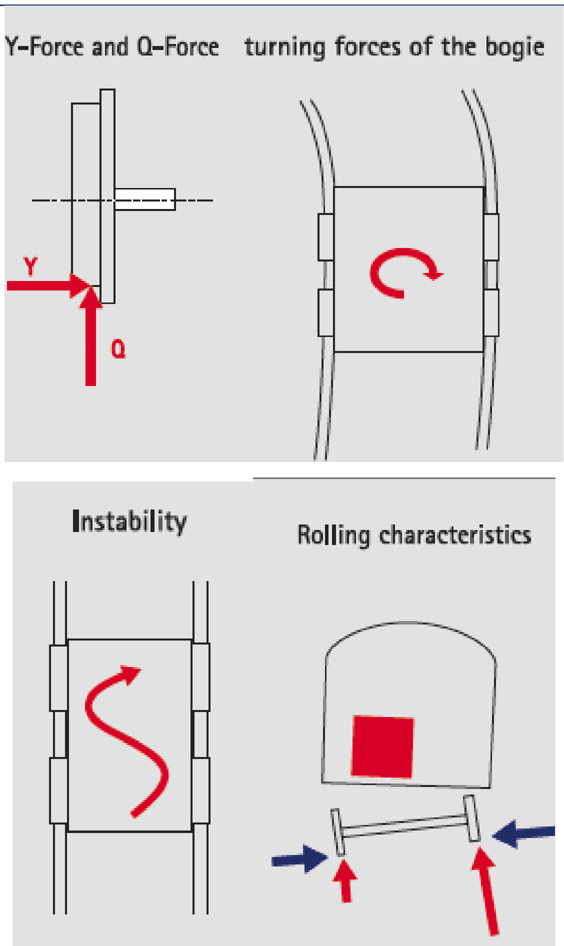


Figure 5: Argos Level 3 – Derailment related Measurements

Having the advantage of being developed as a derailment safety monitor and measuring both vertical and lateral forces, the Argos Level 3 system is a very useful tool in the early prediction of vehicles with increased levels of derailment risk. Outputs to be captured to support the analysis of this system as part of the WP4.4 simulations are Y and Q forces, Y/Q ratio and angle of attack. Sensitivity studies of vehicle skew loading and CofG height will also be used to assess the potential benefits of this system.

3.3.3 System 3: Lasca Mattild

(http://www.innotec-systems.de/index.php/51.html)

The Lasca Mattild system uses a laser based measurement principal which relies on the determination of the gross bending of the rail section to evaluate the vertical wheel-rail forces (see Figure 6). The literature also mentions that the same approach is possible for determination of lateral forces but there is no information regarding any application of this extension. For the purpose of this review, the system will be considered as a vertical only measuring system. The system can measure the usual outputs which can be captured from this type of vertical force measuring system, including static and dynamic vertical wheel loads and associated derived outputs, such as skew loading and diagonal imbalance. Lasca Mattild system has similar technical capabilities to GOTCHA system and shares an ease of mounting to the rail, requiring only a clamping system to the rail foot.

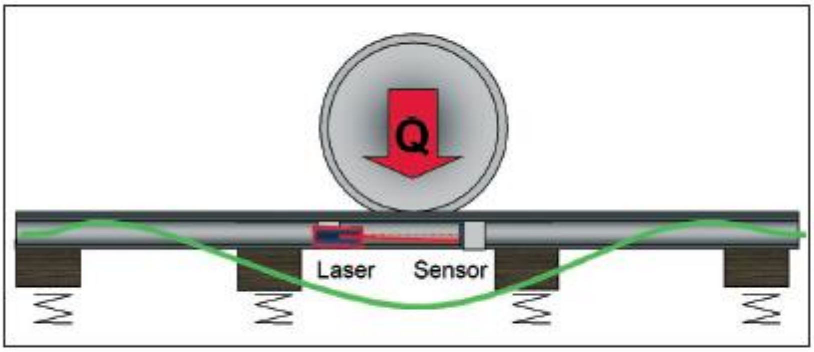


Figure 6: Principle of the Lasca Measurement System

3.3.4 System 4: LB Foster/Salient Systems L/V Detector

(http://www.lbfoster-salientsystems.com/Wireless_LV_Monitor.asp)

The LBF/Salient Systems L/V detector (see Figure 7) is a battery powered wireless strain gauge device which is capable of measuring both vertical and lateral forces. The device requires drilling of the rail web at the neutral axis, which is not always considered the best approach. In common with the other systems studied it also allows remote download and monitoring. The system is essentially a lower cost and simplified solution to that presented in the Argos system. It does not have the additional processing features of Argos, nor the angle of attack detection, predominantly Y, Q and Y/Q monitoring.

Figure 7: LBF/Salient Systems Wireless L/V Detector

3.3.5 System 5: LB Foster/Salient Systems Hunting Truck Detector (HTD)

(http://www.lbfoster-salientsystems.com/Hunting_Truck_Detector.asp)

The LBF/Salient systems Hunting Truck (bogie) Detector (see Figure 8) uses a rail strain gauging method with suitable post-processing to detect vehicles which are exhibiting un-stable hunting motions. The system requires installation in multiple sleeper bays to characterise the wheelset oscillation. This wheelset/bogie motion can induce excessive lateral forces that significantly contribute to the rapid wear of rail and vehicle in a relatively short time. This particular type of degraded vehicle performance is a leading cause of damage to delicate goods. Hunting trucks can also result in severe damage to truck components, thereby increasing the risk of derailment.

Figure 8: LBF/Salient Hunting Truck Detector (HTD)

The LBF/Salient Systems HTD device is aimed solely at detecting hunting motion and therefore does not offer the wider ranging early derailment detection benefits as systems such as the Argos Level 3. Also, derailment directly due to hunting is a fairly low occurrence. However, it remains a risk in terms of degrading the vehicle performance and if possible hunting detection should form part of the post-processing analysis of an on-track wheel-rail force measuring device.

3.3.6 System 6: TTCI Truck Performance Detector (TPD)

(http://www.aar.com/products_services/pdfs/TPD-OnePager.pdf)

The TTCI Truck Performance Detector (TPD) is predominantly aimed at identifying vehicles with poor curving performance and hence can provide indications of high Q and Y wheel-rail forces. The measurement technology is not detailed in the literature but it is likely to be a strain gauge method applied across a number of sleeper bays. The TTCI system fundamentally (see Figure 9) measures Q and Y forces. As a result it should be possible to derive similar output parameters to other dual force measurement devices such as the Argos Level 3 and the LBF/Salient System L/V detector

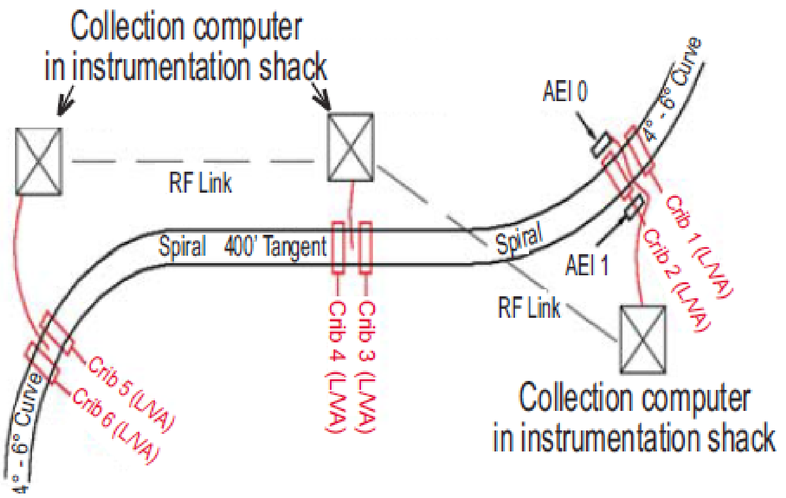


Figure 9: TTCI TPD – Typical Site Installation

3.3.7 System 7: Trackside Intelligence Ltd Wayside Monitoring System

(http://www.trackiq.com.au/wayside-monitoring-system.html)

The Track IQ, Wayside Monitoring System (WMS) is a strain gauged system, coupled with accelerometer measurements. In common with other systems studied the device measures only Q forces. With respect to early derailment risk detection, this limits its application to measurement of variations in static wheel load across a bogie, identification of skew loading and diagonal imbalance.

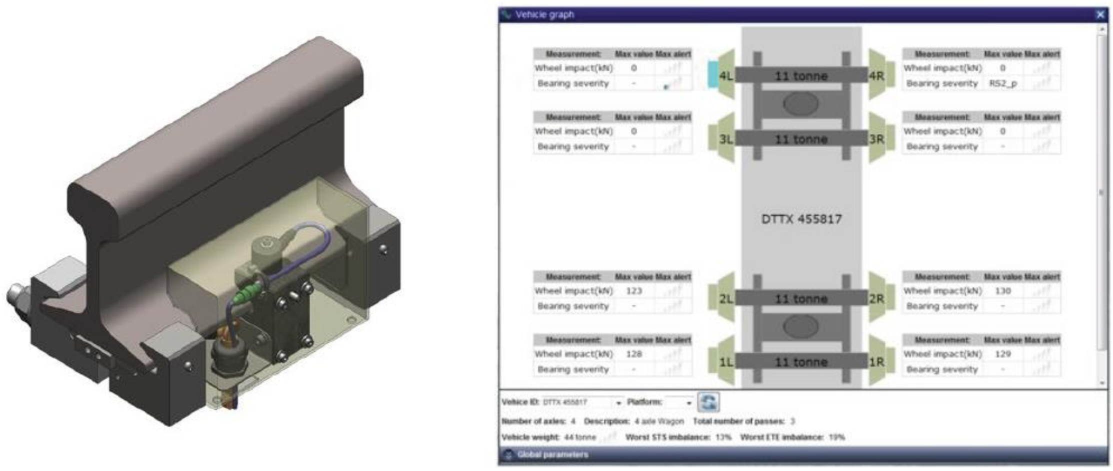


Figure 10: Track IQ, Wayside Monitoring System (WMS)

With reference to Figure 10 above, an advantage of the WMS system is its ability to be readily clamped to the rail foot – this minimises installation and maintenance costs.

3.3.8 System 8: Delta Rail Group - Wheelchex

(http://www.deltarail.com)

Wheelchex is a precise strain gauge based Q force measurement system which requires bonding to the rail under laboratory conditions. It was originally developed as an impact load detector and is a well proven system, with 24 measurement sites operating in the UK (now being phased out in the UK and replaced with the GOTCHA system). It has also been used successfully in Australia and the US.

In common with the other vertical measurement systems studied in this review, the system measures static and dynamic vertical wheel loading and wheel impact data from passing trains, including the average, peak, dynamic ratio and uneven diagonal wheel load on each axle (see Figure 11). Data is recorded in the UK and intervention limits set for these measures. Four levels of wheel impact alarms are currently adopted in the UK, ranging from 350kN (level 1) to 500kN (level 4). Network Rail is also currently investigating alarm limits for wheel imbalance loads following the recent derailment of a freight wagon with abnormal diagonal wheel loads. The Wheelchex system does not support automated vehicle identification via tagging or similar technologies.

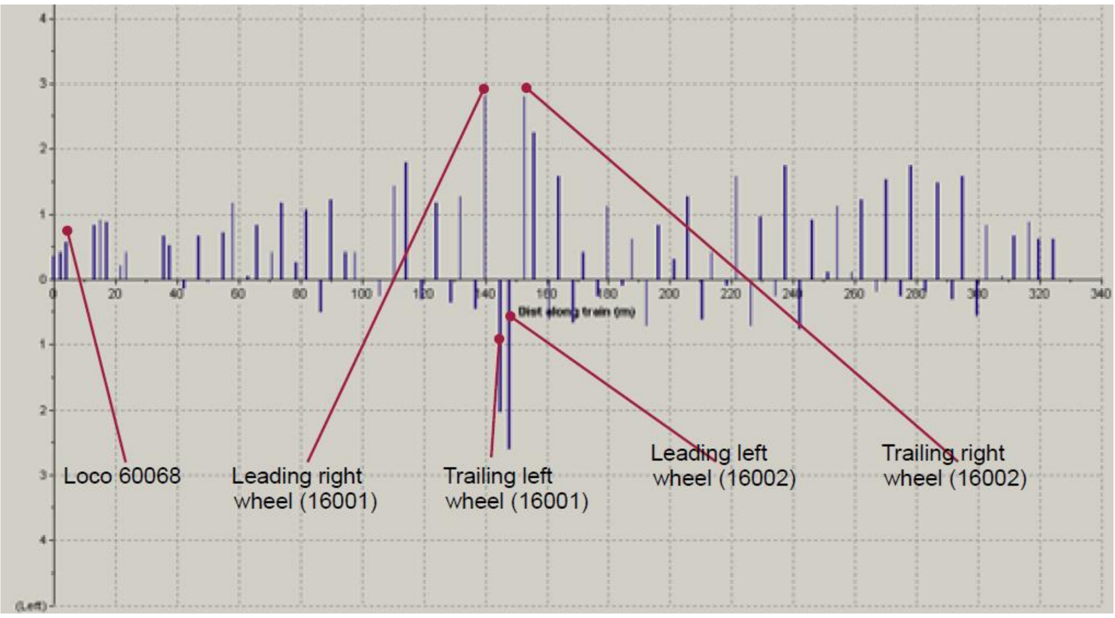


Figure 11: Example of Wheelchex Output for Imbalanced Axles

3.3.9 System 9: Nencki Ltd – Wheel Weighing Machine (WWM)

(www.nencki.ch/railway)

The Nencki WMM fundamentally differs from the on-track based systems presented above in that it is a maintenance depot based device to ensure the on-going derailment safety of vehicles. Adoption of such preventative methods are not common, but the benefits in terms of reducing potential vehicle initiated derailment risk is significant. Via hydraulic actuation of rail sections within the test bed a vehicle twist performance test to EN 14363 can be completed within 30 mins. The system is shown in Figure 12 and the typical Q force output in Figure 13.

Figure 12: Nencki Twist Test System

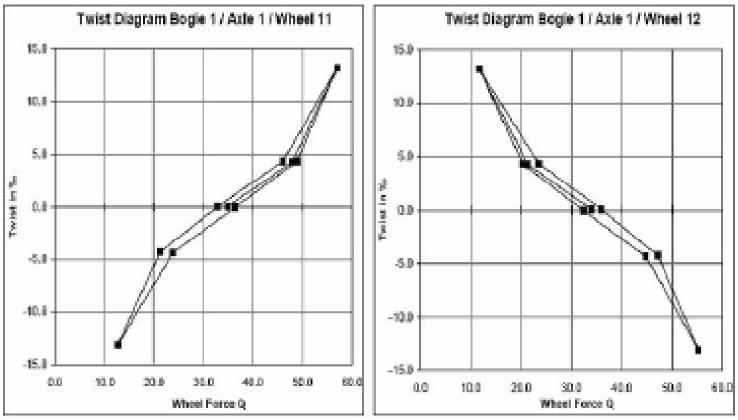


Figure 13: Typical Q force Output

The Nencki system is targeted at operators of large vehicle fleets and is aimed at detecting component failures or errors in bogie overhaul which may influence the vertical wheel unloading under twist. The outputs of the system can be used for on-track (on network) approach to detecting poor twist performance of suspension.

3.3.10 System 10: Metrom Rail - Sentrack

(http://www.metrom-rail.com/sentrack-track-monitoring-system)

In contrast to the majority of systems studied above, the Sentrack system is not a derailment prediction or force measuring device but is used to detect a derailed vehicle. With reference to Figure 14 below, the system employs the following sensors:

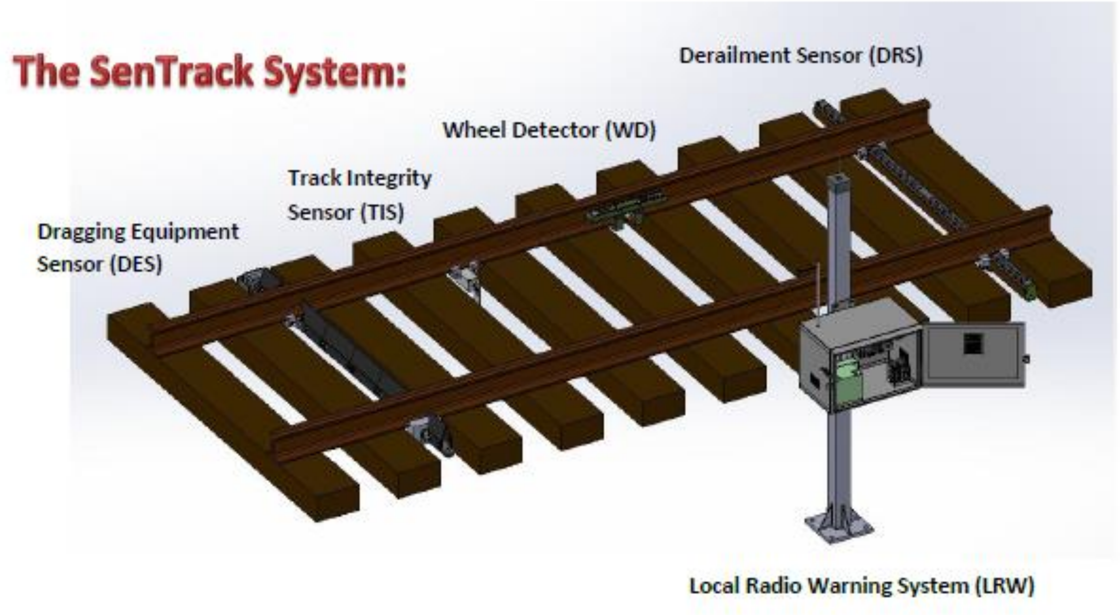


Figure 14: SenTrack Derailment Event Detection System

Track Integrity Sensor (TIS) – The TIS is a sensor secured to both the rail and embedded within the ballast via a probe. In the case of rail deformation or ballast washout caused by a derailed vehicle, the sensor will immediately send an alarm activation for broadcast via the Local Radio Warning System (LWS).

Dragging Equipment Sensor (DES) – The DES detects the speed at which the sensor is struck by dragging objects and in what direction. All details are reported immediately and send an alarm activation for broadcast via the LWS.

Wheel Detector (WD) – The WD is a wheel detection module which interprets axle counts, speed and direction of a vehicle. When an alarm is triggered by any of the sensors in the system, the axle count is added to the broadcast via the LWS.

3.3.11 Synthesis of system features

A wide range of on-track based measuring systems which are capable of measuring the wheel-rail forces of a passing vehicle have been studied, the primary features of each system are summarised in Table 6. It is obvious that there is no single system which is capable of providing all the features identified. System 2, the Argos Level 3 offers the greatest number of features in a single system.

In terms of providing the maximum protection and early warning of derailment risk, it is considered that a system should be capable of measuring both vertical and lateral forces. Measurement of lateral forces provides the additional benefit of early detection of wheel set steering or bogie related issues which lead to high guiding forces (Y). This functionality is offered by Systems 2, 4 and 6.

Table 6: Summary of Primary System Features

System	Q Force	Y Force	ΣY track shifting	Hunting	CofG/Rollover	Veh. ID / monitoring	Derailment detection
1	Yes	No	No	No	No	Yes	No
2	**Yes**	**Yes**	Yes	Yes	Yes	Yes	No
3	Yes	No	No	No	No	Yes	No
4	**Yes**	**Yes**	Possible	No	Possible	Monitoring	No
5	No	No	No	Yes	No	Yes	No
6	**Yes**	**Yes**	Possible	No	Possible	Monitoring	No
7	Yes	No	No	No	No	Yes	No
8	Yes	No	No	No	No	Yes	No
9	ΔQ/Q	No	No	No	No	No	No
10	No	No	No	No	No	No	Yes

It is noted from the review that the most common on-track measuring systems are those which measure only the vertical forces. It is apparent from UK operations and also other member states that whilst these systems are typically used to identify wheel flats/ovality and axle overloading, they often are not used to look at un-even loading or low wheel vertical load. In some cases this data is available from the system but is not used as an alarm by the infrastructure manager (IM). It is recommended that IMs review their on-track mounted wheel load measuring systems and identify whether additional data or measures can be tracked to increase the early detection of possible increased derailment risk.

It may also be beneficial to introduce preventative measures which could indicate any change in a vehicle performance and derailment risk over time. System based on depot ΔQ/Q measurement within twisted track could be adapted to form an on-track ΔQ/Q assessment. The basis of this addition would be to detect deterioration in vehicle ΔQ/Q performance relative to normal operational thresholds. Such a system would require RFID tagging functionality to store threshold ΔQ/Q values for a particular vehicle type.

4. THE JVTC/DAMILL MONITORING STATION

4.1 System presentation

In 2006, JVTC (Luleå Railway Research Center) decided to install a wayside monitoring station on the Swedish iron ore line Malmbanan, see Figure 15. The arrow points at the monitoring site in Sävast, 30km north of Luleå.

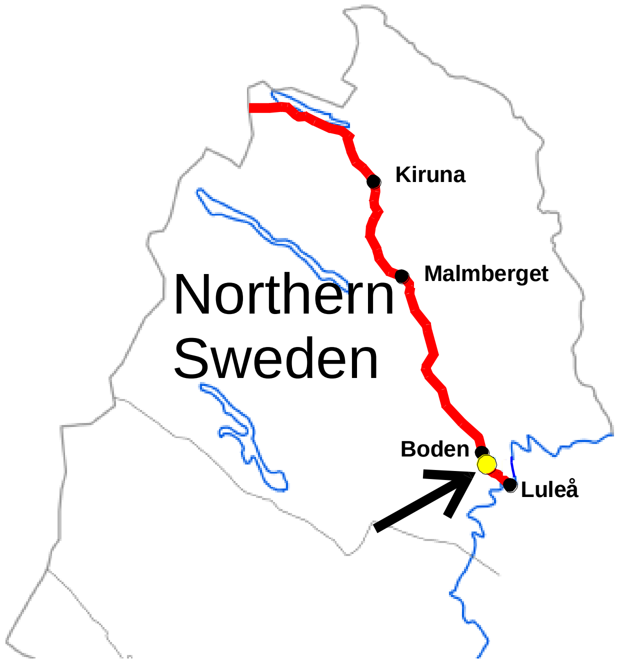


Figure 15: Map of the iron ore line "Malmbanan"

The goal was to support the JVTC research team with empirical data suitable for railway maintenance studies. After some surveys on different monitoring techniques, it was clear that force measurement should be most adequate for this purpose. One of the JVTC partners in 2006 was the company Damill with good knowledge in both monitoring techniques and railway technology. Damill was therefore contracted to build the station. The site was decided to be placed in Sävast, approximately 30km north of Luleå. Main argument for that selection was to find a place where curve radius is quite narrow, where inclination is low and where trains are normally running with constant speed without braking or heavy acceleration. Track geometry data of the JVTC Railway Research Station is:

- Line no. 119
- Track position 1153km + 370m, (368,8/370/371,2m)
- Curve radius -484 m (left turn when running south towards Luleå)
- Cant 110 mm
- Inclination -12 ‰
- Rail type UIC60
- Sleepers Concrete
- Fasteners Pandrol e-Clips

The force measurement system was based on traditional strain sensors put in different patterns on both rails, see Figure 16. No special sleepers are required and the track can withstands standard maintenance intervention such as alignment machines. It was brought into a dedicated bungalow where signal conditioning electronics, computer and internet communication units was placed, see Figure 18. The system data was soon available on a public web page and a RFID-reader was installed so all data from passing iron ore trains could be traced down to a specific vehicle. This was probably one of the first systems in Europe with such combined functionality. From 2006 to 2012 the system was in service with sensors in one position along the track but in November 2012 it was expanded to 3 positions along 2,4 metres of the track. The system has also been recently expanded with dual RFID-readers for the new GS1 standard. Software has also been gradually extended to the current status.

Figure 16: Sensor positions in track.

Figure 17: Minimal system cabinet that contains sensor electronics and optionally also computer and communication electronics.

Figure 18: 2-room heated bungalow for computer and communication electronics.

The JVTC Railway Research Station in Sävast works as a platform for studies of things such as wheel profiles, rail profiles, rail lubrication etcetera. Another area of research is to study and classify vehicles regarding their contribution to the overall track degradation, see references [11] and [12]. This is of interest when talking about differentiated track access charges. The station is owned and fully financed by the JVTC organization while Damill stands for the operative management and service and for the measurement software. The technology used in the station is also sold externally by Damill under the product name StratoForce. The latest versions of the system can, in small installations, work without any bungalow as the equipment is very compact and can be placed in a cabinet on the overhead mast, see Figure 17. Communication is handled by 3G or 4G mobile Internet so the system only needs an external power cable at installation time.

This type of force measurement system is available from several vendors around the world (see part 3.3). They are sometimes called Axle Load Checkpoints (ALC), Truck Performance Detectors (TPD), Truck Hunting Detectors (THD), Wheel Impact Detectors (WID), Wheel Flat Detectors (WFD) or even Wheel Impact Load Detectors (WILD). The names indicate what type of measurements that are in focus for the system but many of the systems can be optionally expanded to measure static wheel loads Q, dynamic wheel loads (telling about wheel defects) and lateral forces Y (telling about bad steering or worn profiles). UIC made a survey of the European ALC-systems in 2011, see part 2.1.3 and reference [13].

4.2 Output variables and output interface

The StratoForce system takes maximum gain of the strain gauges in track. The following output variables are calculated after each train passage:

- Passage time
- Travel direction
- Wheel speed
- Axle count
- Locomotive type
- Static wheel load
- Dynamic wheel load
- Wheel transients
- Lateral wheel forces
- Rail vibration (Wheel generated)
- Angle of attack (AoA)
- Vehicle ID

Some of these variables are unique to StratoForce as they are measured and calculated without the need of any additional sensors in track.

Besides storing the calculated data in an output text file, the system also publishes a daily graph on an Internet page, see Figure 19. Left diagram shows all locomotives and right diagram shows wagons pulled by the locomotive in left diagram. Black and blue dots show the mean values for each train while black and blue lines show minimum and maximum values in that train. This is an extremely compact view of all trains and forces during one day.

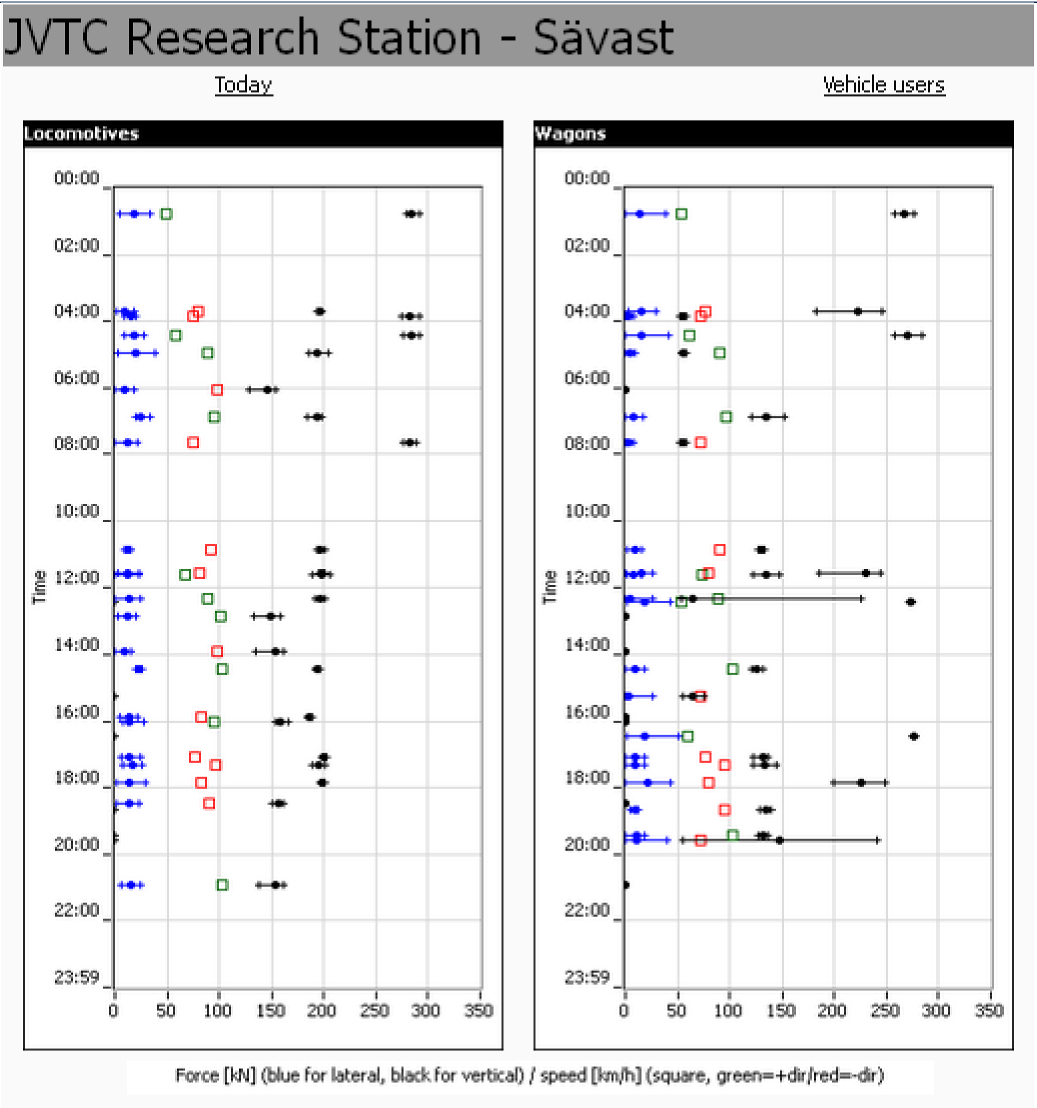


Figure 19: Daily graph showing all passing trains the current day and their forces and speed.

Based on Vehicle ID from the RFID-tags, all data is grouped into vehicle owner lists. These lists represent a top-20 of bad vehicles for the selected car fleet. In Figure 20 we can see an example from the monitor station webpage where axle number 19 in a specific train is in top of the AoA-list. The monitor station is close to a wayside wheel profile measurement station making it possible to check wheel profiles causing high lateral forces and/or high AoA. In the example above, the corresponding wheel profile is shown in Figure 20 right. There is no doubt that the axle with high AoA has worn wheels although not in critical condition. A frequent question about the force monitoring station is if force measurement is really needed when wheel profiles can be measured by a parallel station. The answer is definitely “yes” as wheel profiles are just measured in one spot of the wheel s surfaces and there are several defects not covered by the profile. The lateral forces or AoA can be large without showing defect profiles. That is when the bogies have encountered steering problems and wheels are still not affected but they are about to degrade fast. One typical example of such a phenomena happened in the Sävast monitoring station when a newly repaired wagon had top score in the lateral force list. The wagon was taken to workshop where it was found that it had badly adjusted side bearing pads (too thick). The yaw stiffness was very high.

Besides the web page presentation of data directly by the monitoring station, there is also a FTP –based automatic transfer of data to Luleå University of Technology (LTU) where a database is held. This database makes it easy for researchers to study trends in data from individual cars as well as groups of cars such as a particular car type.

The Figure 20 shows one of the webpage output from the StratoForce system is a “Top-20” list of bad angle-of-attack (AoA) axles during the last 7-day period. The list is filtered to show just one operator at a time. The diagram to the right shows the corresponding wheel profile measured same day on the axle having largest AoA. We can see that the profile conicity is heavily reduced making it difficult for the axle to steer correctly in track.

In the example of the large AoA (Figure 20), the operator of that train runs more than 300 tagged wagons in a 48h closed loop passing the station around 6 times per week. By using top-20 lists regarding large dynamic forces, large lateral forces, large AoA and large wheel induced vibration, the maintenance planning team get a tool to identify vehicles in the 300 wagon fleet that are most urgent to take into the workshop. Of cause there are also parameters not handled by the force measurement station such as wear of block brakes, damper condition, bearing condition, loose or missing components in bogie or couplers or fatigue cracks in wheel web etc. Such parameters still require manual inspection and km-based interventions.

Time	AoA (mRad)	ID	TD	FE	AiT
20141112_17:29:27	7,702	735003433_317445522186	0	A	19
20141110_17:27:50	6,398	735003433_317445521188	0	A	5
20141113_05:22:14	4,946	735003433_317445522186	1	B	38
20141112_17:29:27	4,883	735003433_317445522186	0	A	22
20141107_17:30:59	4,665	735003433_317445522186	0	A	33
20141110_05:14:21	4,362	735003433_317445520552	1	A	7
20141110_05:14:21	4,055	735003433_317445521188	1	B	27
20141110_05:14:21	3,985	735003433_317445521188	1	B	30
20141112_17:29:27	3,888	735003433_317445522186	0	A	21
20141111_05:16:47	3,800	735003433_317445521238	1	A	14
20141107_17:30:59	3,784	735003433_317445522186	0	A	36
20141113_05:22:14	3,734	735003433_317445522186	1	B	37
20141110_17:27:50	3,713	735003433_317445520552	0	B	30
20141107_12:09:49	3,341	735003433_317445522186	1	B	12
20141107_12:09:49	3,326	735003433_317445521196	1	B	30
20141110_05:14:21	3,211	735003433_317445520552	1	A	8
20141113_05:22:14	3,154	735003433_317445522186	1	B	36
20141107_17:30:59	3,069	735003433_317445521196	0	A	15
20141111_05:16:47	3,042	735003433_317445528118	1	A	7
20141107_17:30:59	2,990	735003433_317445522186	0	A	34

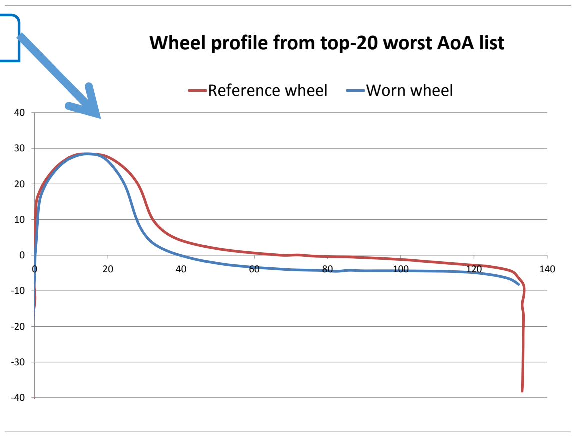


Figure 20: Webpage output from the StratoForce system. “Top-20” list of bad angle-of-attack (AoA) axles during the last 7-day period.

5. DYNAMIC INTERACTION BETWEEN TRACK AND FREIGHT TRAINS

This chapter presents possible vehicle defects that can be detected by an ALC system such as the JVTC/Damill system presented in chapter 4. It also presents typical statistics from that specific system. The data is used to suggest maintenance alarm limits for different parameters that are related to different vehicle defects. Finally, there is a quantitative evaluation of positive effects on the track and vehicle degradation if such limits should be activated.

5.1 Discussion on vehicle defects that can be detected by the system/method

There are many potential defects that can be indicated by measuring forces and angle-of-attack on axles passing a wayside monitoring station. The effect is often indirect, making it difficult to give exact status of the defect component or function but for an overall overview of vehicles condition, it is really a great tool, maybe the currently best system available. Working with forces requires some extra thinking by the analysis team as this is really proactive information. A newly overhauled axle or bogie can generate large forces and people tend to get suspicious about the relevancy. This happens e.g. in the case with thick side pads described in chapter 4.2 or in winter climate when there is a heavy ice build-up in the bogie. There have been studies by TTCI in U.S. telling that 80% of the cases with large lateral forces in 3-piece bogies can be traced down to a root cause with jamming bogie steering. If such a bogie is kept in traffic it will undoubtedly lead to reduced wheel life length.

The researchers at JVTC (Luleå Railway Research Center) want to use the term maintenance alarm limits rather than safety alarm limits. The maintenance alarm limits works on a lower (earlier) level than safety alarms limits and do not require such a precision in the measurement. This statement is based on the assumption that under normal degradation rates, there is time to measure the same vehicle during several passages before action has to be decided.

Table 7 describes the potential defects with description on how the force monitoring station can detect them. Detection does not necessary imply that the exact problem can be defined by the force data only but the listed problem will generate a change in the force profile that can trigger further inspection of the specific vehicle.

Table 7: Vehicle defects that can be detected by the force measurement monitoring stations.

Defect	Sensors/parameter used for detection	Expected parameter reaction
Wheel out-of-roundness	Vertical forces along 3m of track	Sinusoidal variation
Wheel flat	Vertical forces along 3m of track	Short transients, repeated once/rev
RCF surface defect	Vertical forces along 3m of track	Vibration generated into rail
Worn wheel profiles	Lateral forces	Increased absolute magnitude
	Angle-of-attack (AoA)	Increased absolute magnitude
Suspension jamming	Vertical forces along 3m of track	Dynamic variation increased due to high unsprung mass
Increased friction in bogie centre bowl or side pads	Lateral forces	Increased absolute magnitude
	Angle-of-attack (AoA)	Increased absolute magnitude
Skew loading of wagon	Vertical forces	Non-symmetric wheel loads on loaded wagon
Broken suspension	Vertical forces	Non-symmetric wheel loads both on loaded and empty wagons
Skew/twisted wagon frame	Vertical forces	Non-symmetric wheel loads especially on empty wagons
Unstable operation (hunting)	Vertical forces along 10-30m of track	Sinusoidal variation left/right

The table lists many parameters that are really essential for keeping maintenance costs low and safety high of the vehicles. This will also lead to positive effects for the infrastructure. A good condition according to the parameters listed will reduce the impact to the track. According to results published by the recently finished EU-project D-rail, see reference [14], wayside force monitoring stations (ALC) are among the most beneficial investment to do for preventing derailments in Europe. There was a RAMS and LCC-calculation on the benefits of ALC to prevent derailment. With an increase of ALCs in Europe with 120 such stations and calculated over time period 2020-2050, the Benefit/Cost ratio could be as high as 7,80 expressed in NPV (Net Present Value). This is just benefits gained by fewer derailments. To that number should also be added reduced maintenance costs of both track and vehicles and less traffic disturbances du e to reduced wheel/rail forces and fewer wheel flats and vehicle failures although not necessary leading to derailment.

5.2 Statistics on force data collected during 2013.

The wayside monitoring station in Sävast, see chapter 4, accumulates data for every day and in this report one typical month is presented, February 2013. During that month there were a total tonnage of 1,25MGT represented mainly by iron ore trains with 30 ton axle load, heavy steel slabs transportation trains with 22-25ton axle load, other freight trains with 19-22 ton axle, passenger trains with 13-17 ton axle load and finally empty freight and iron ore trains with 6-7 ton axle load. The mean axle load during the month was 18 ton with StD=21 ton while the mean lateral force was 21kN with StD=30kN. Such broadly spread data seem difficult to handle but it gets much better when we split the data into different vehicle types. By using one or several RFID-readers in the monitoring station, this can be easily done.

The total load spectrum is shown in Table 8 and the corresponding lateral force spectrum is shown in Table 9. The standard deviation of the lateral forces shows that the vehicle maintenance conditions introduce a much broader spread than is motivated by load variations. A hypothetical repair of the 5% worst axles regarding lateral forces is also shown in Table 9. The red columns present actual readings of forces on the rail with highest amplitude while the green columns present hypothetical result if the 5% top force axels in each vehicle type would be repaired and put to normal status (i.e. lateral forces reduced to mean value for that vehicle type).

Table 8: Diagram showing the axle load distribution in Sävast during February 2013

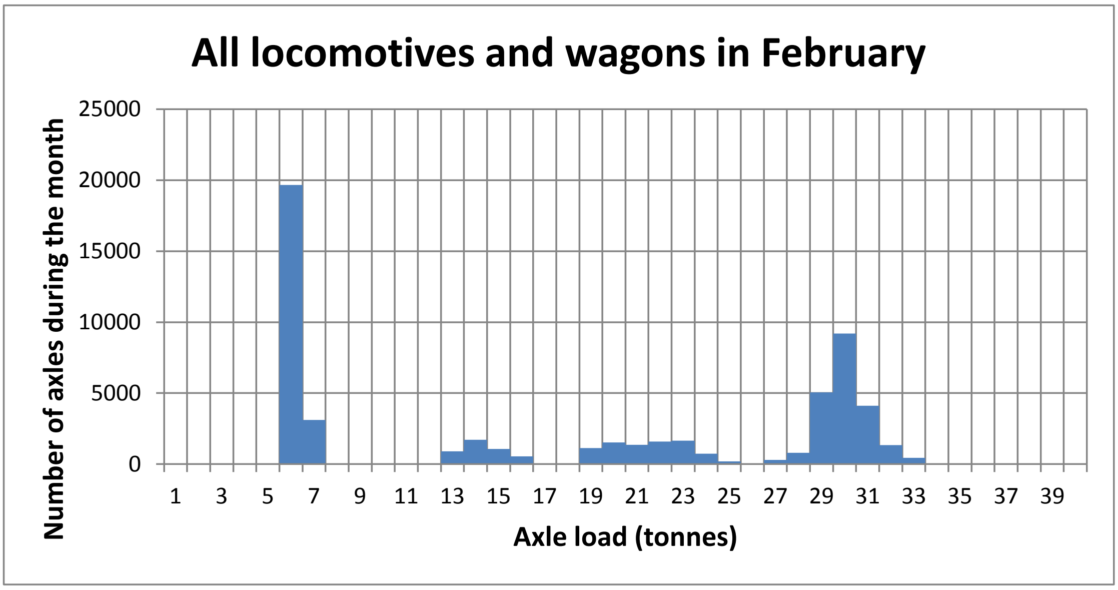
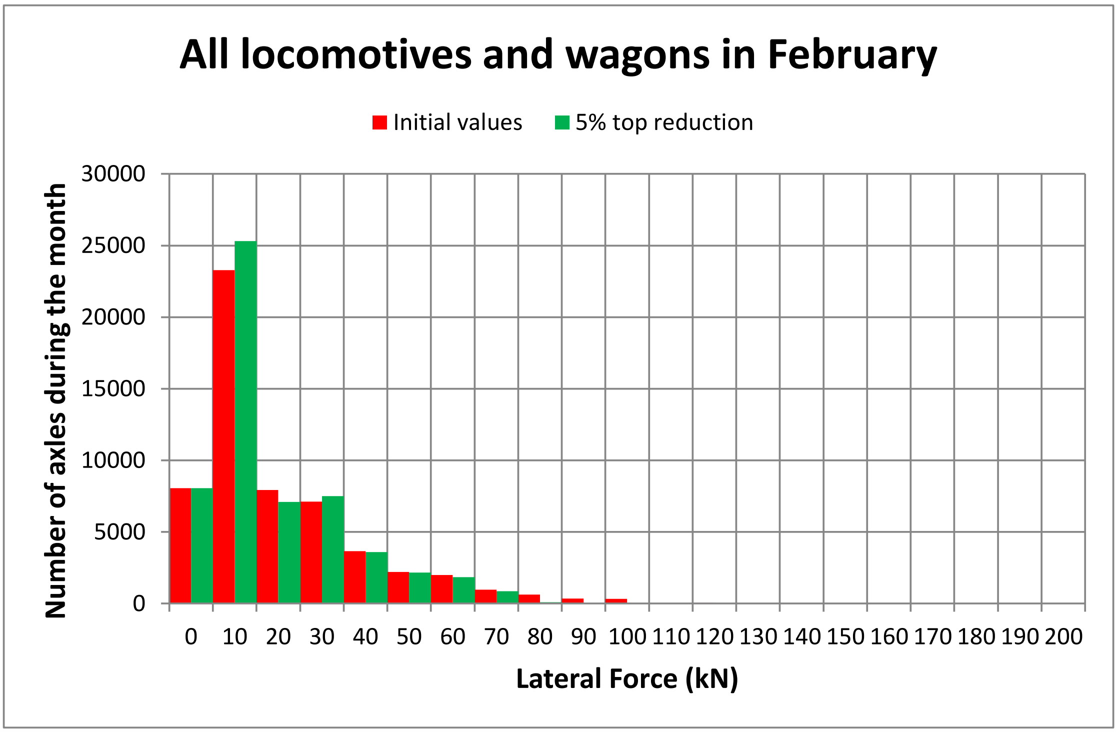


Table 9: Diagram showing lateral force distribution in Sävast during February 2013



The approach to plot vertical load and lateral forces separate as in Table 8 and Table 9 is not optimal for analysis. A much better way is to plot quotient L/V (lateral force/vertical force) for low and high rail wheels.

Table 10 to Table 13 present such data and suddenly the different vehicles produce nearly the same results. Forces on left (low) rail under the locomotives are still in top and this can be explained by their bogies normally having higher yaw stiffness than wagons. Locomotives reach L/V-ratios around 0,5-0,6 while the wagons reach 0,3-0,4 on low rail.

Table 10 shows the quotient L/V (lateral/vertical wheel load) for typical locomotives in Sweden. Data is measured on left (low) rail in the curve. X62 is a commuter train not representing a genuine locomotive but put here as a reference.

Table 11 presents similar data as in previous figure but for right (high) rail. The amplitudes are less than the ones measured on low rail.

Table 12 shows quotient L/V (lateral/vertical wheel load) on left (low) rail for some typical wagons passing the JVTC monitoring station in Sweden.

Table 13 presents similar data as in previous figure but for right (high) rail. The amplitudes are less than the ones measured on low rail which is same behaviour as found on the locomotives.

Table 10: Quotient L/V (lateral/vertical wheel load) on low rail presented for typical locomotives in Sweden

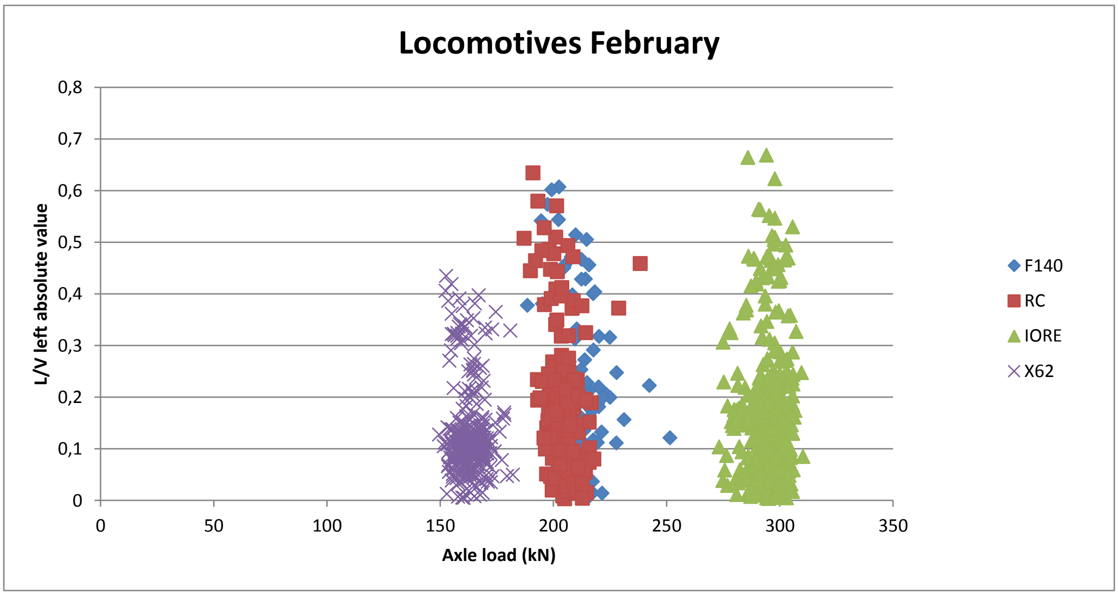


Table 11: Quotient L/V presented for typical locomotives in Sweden for right (high) rail.

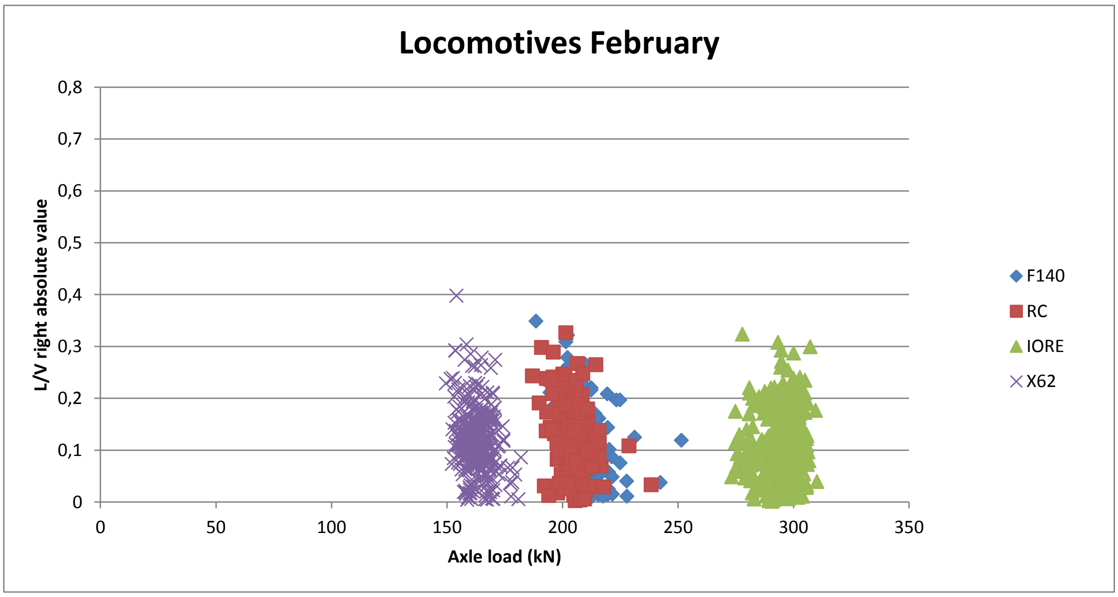


Table 12: Quotient L/V on left (low) rail presented for some typical wagons passing the JVTC monitoring station in Sweden.

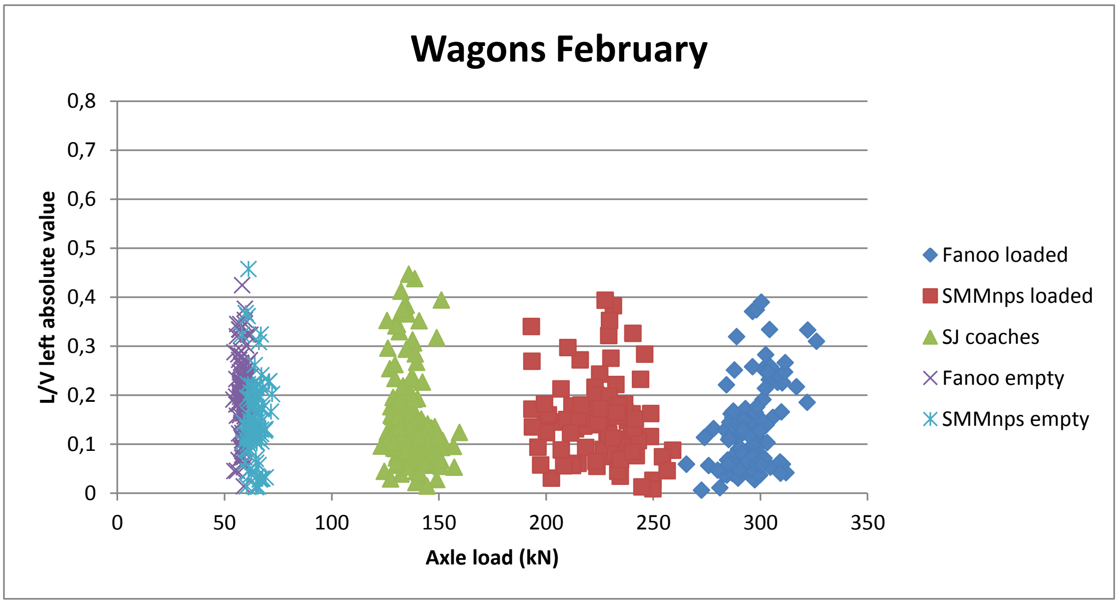
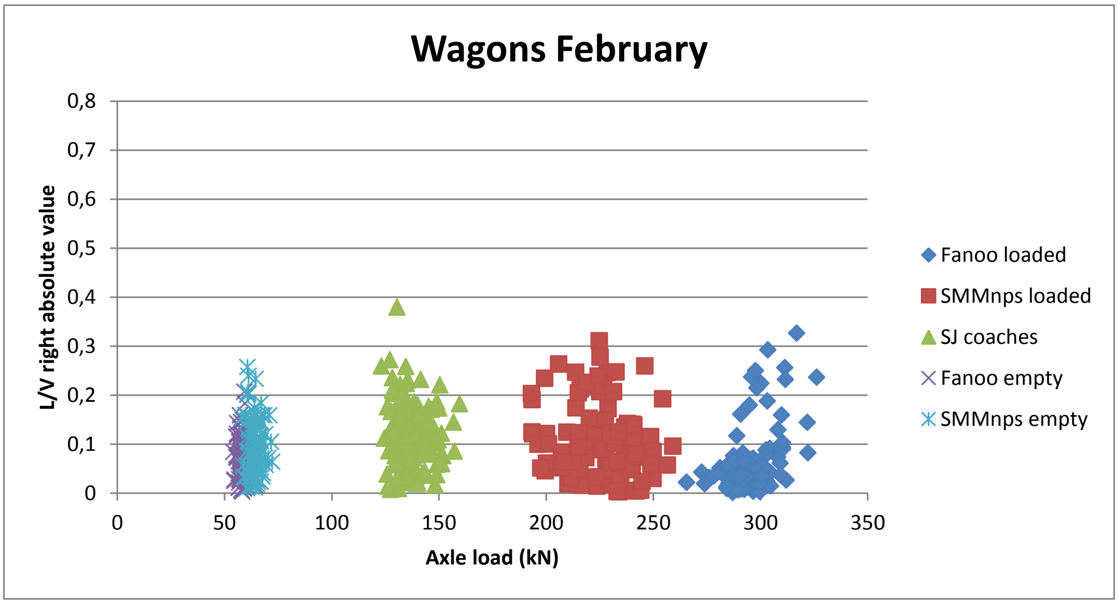


Table 13: Here is similar data as in previous figure but for right (high) rail. The amplitudes are less than the ones measured on low rail which is same behaviour as found on the locomotives.



When we make some statistic calculation on the data we get a table as in Table 14 and Table 15. Statistical tests have been used in this study to verify a normal distribution through goodness of fit tests. We can see that he average values do not differ so much between locomotives and wagons but the standard deviations do. The locomotive bogies have often high lateral forces on leading wheels with L/V-ratios above 0,5 but much less on the trailing axles making the average values drop a lot.

Table 14: Statistics calculated for locomotives and commuter train X62 during two separate months in 2013.

Locomotive	Month	Average L/V left	Standard Deviation L/V left	Average L/V right	Standard deviation L/V right
RC	May	0,25	0,16	0,13	0,08
F-140	May	0,24	0,20	0,14	0,08
IORE	May	0,21	0,15	0,10	0,05
X62	May	0,20	0,13	0,13	0,05
RC	February	0,20	0,14	0,12	0,07
F-140	February	0,20	0,15	0,11	0,07
IORE	February	0,16	0,13	0,11	0,06
X62	February	0,13	0,09	0,12	0,06

Table 15: Statistics calculated for wagons and during two separate months in 2013.

Wagon	Month	Loaded/ Empty	Average L/V left	Standard deviation L/V left	Average L/V right	Standard deviation L/V right
Fanoo	May	Empty	0,20	0,08	0,07	0,04
Fanoo	May	Loaded	0,12	0,08	0,09	0,05
SMMnps	May	Empty	0,22	0,12	0,10	0,06
SMMnps	May	Loaded	0,21	0,15	0,13	0,09
SJ	May		0,20	0,12	0,12	0,06
Fanoo	February	Loaded	0,12	0,08	0,06	0,06
Fanoo	February	Empty	0,16	0,08	0,06	0,04
SMMnps	February	Loaded	0,15	0,08	0,11	0,08
SMMnps	February	Empty	0,15	0,09	0,10	0,06
SJ	February		0,15	0,09	0,12	0,06

In Table 14 and Table 15, slightly higher values in May might be caused by more dry weather and higher friction coefficient.

5.3 Discussion on limits based on collected data

Data from the monitoring station in Sävast give typical values for different vehicles but using them as general values to set limits for other sites is very difficult. The curve radius, cant, humidity, lubrication, rail profiles and train speed are all factors that influence the lateral forces. It seems more adequate to use the output in relative terms and to adapt to each monitoring site. After installation of a new site, the traffic can be studied and individual alarms be set for each vehicle type. When lateral forces are to be measured, the station should be placed in a narrow curve that put extra demand on the steering ability. The radius must on the other hand still be in a range where steering is possible. If it gets too narrow, the lateral force data will not tell about steering ability of the vehicles. The data is instead governed by friction conditions and the rail profile at the site, i.e. local parameters.

Limits for forces are divided into safety limits and maintenance (or service) limits. The latter is supposed to identify an optimal point of time based on economic terms when it is advisable to bring the vehicles into a workshop instead of degrading their maintenance condition further. There are several documents covering safety limits but less on maintenance limits. Two sources of information are the HRMS-report by UIC, see reference [15] and the D-rail report D3.3, see reference [18]. The UIC-report includes discussions on many of the limits set in Europe and, although they vary among different countries, there could be suitable mean values to find that suites most users. A third source is the AAR work in U.S, see reference [16], and indirectly described in reference [17]. The European work may have strong focus on safety limits for all type of vehicles, while the AAR work referenced here has its focus on “track worthiness criteria limits” for freight trains. Another difference is that the European work is based on most data to be measured in tangent track while the U.S work include limits for data measured in curves. This is quite expected as the truck performance detectors (TPD) in curves are much more common in U.S.

Due to the complexity of handling different measurement sources and vehicles, it is beyond the scope of Sustrail WP4 to establish totally new limits for maintenance (service) but by summing up the recommendations from both UIC and AAR and then comparing the results with data read in Sävast, we can find suitable levels for service limits based on force measurement data.

So Table 16 shows the data from the UIC report HRMS and from AAR MSRP, presented together with new proposals of service limits for data from ALC detectors. The yellow fields identify these suggestions.

Table 16: Data from the UIC report HRMS and from AAR MSRP presented together with new proposals of service limits for data from ALC detectors.

Suggested Limit Values

Parameter	Tangent or curve	UIC HRMS report		AAR MSRP	Comment
		Service	Safety	Design Criteria	
Vertical peak load [kN]	T+C	<200	<350		Reduced when 20°C below stress free temp.
Skew load, Diagonal quotient	T	<1,3	<1,7		
Skew load, left/right normally	T	<1,3	<1.7		Reduced by 20% if risk of sloshing
Skew load ,longitudinal front/rear quotient	T+C	<2	<3		
Lateral/vertical wheel load quotient Y/Q	T+C	locos <0,5-0,7 wagons <0,4-0,5	<0,8		Based on Nadal equation
Lateral/vertical wheel load quotient Y/Q, circular curve, 95% percentile	C			<0,8	Can temporarely exceed limit
Lateral/vertical axle sum quotient Y/Q, circular curve, 95% percentile	C			<1,5	Can temporarely exceed limit
Lateral/vertical wheel load quotient Y/Q, transition curve	C			<1,0	
Lateral/vertical axle sum quotient Y/Q, transition curve	C			<1,5	
Minimum wheel load, transition curves	C			>10%	
Twist/Roll, max axle sum L/V quotient	T			<1,5	
Twist/Roll, min vertical load	T			>10%	
Pitch/bounce, min vertical load	T			>10%	
Pitch/bounce, loaded spring capacity usage				<95%	
Dynamic/static wheel load quotient	T	<0,4	<0,6		
Yaw/sway lateral/vertical qoutient, sum of each bogie side	T			<0,6	
Yaw/sway lateral/vertical qoutient, axle sum	T			<1,5	

5.4 The potential effects to track if vehicles with forces outside limits are pinpointed and removed.

The benefits of finding and removing vehicles with high track forces are many. In this report has already been mentioned the reduced risk of derailment but there are also other factors to consider. By doing some brain-storming followed by calculations, we have created a list that is presented in Table 17.

Table 17: Table with benefits achieved when installing ALC monitoring stations.

Benefits from installing and using ALC monitoring systems

Strategy	**Effect**	**Comment**
Repair 5% of the axles and bogies with highest lateral forces	The mean lateral forces will drop 10% implying that also total rail and wheel wear will be 10% less.	Effect calculated by using data from the JVTC monitoring station and a simple friction work model
Repair 5% of the axles with highest dynamic vertical load	Very small effect as long as forces are below safety limit.	Effect calculated by using data from the JVTC monitoring station
Invest in 120 more ALC stations in Europe	Reduced risk of derailment. The Benefit/Cost ratio is 7,80 over 30 years	Effect according to the D-rail project D7.4, ref [4].
Increase the number of force monitoring stations (e.g. ALC)	By reducing the distance between stations, the downtime due to track inspection after defect vehicles (e.g.wheel flats) will be reduced. A simple model would be to assume proportional reduction in downtime.	Budget price according to D-rail D7.4 is €110000 per ALC-station. Based on data from Sweden, a 30km track segment might take more than 60 minutes to check after a severe wheel flat has passed. On single track lines, all traffic is blocked during that time.

6. DATA ANALYSIS OF HEAVY HAUL LOCOMOTIVE WHEEL-SETS' RUNNING SURFACE WEAR

6.1 Introduction

6.1.1 Background

The service life of the train wheel-sets can be significantly reduced due to failure or damage, leading to excessive cost and accelerated deterioration, a point which has received considerable attention in recent literature (Lin, 2013). In order to monitor the performance of wheel-sets and make replacements in a timely fashion, the railway industry uses both preventive and predictive maintenance (Palo, 2013). By predicting the wear (Johansson & Andersson, 2005; Braghin et al., 2006; Tassini et al., 2010), fatigue (Bernasconi et al., 2005; Liu, et al., 2008), tribological aspects (Clayton, 1996), and failures (Yang & Letourneau, 2005), the industry can design strategies for different types of preventive maintenance (re-profiling, lubrication, etc.) for various periods (days, months, seasons, running distance, etc.). Software dedicated to predicting wear rate has also been proposed (Pombo et al., 2010). Finally, condition monitoring data have been studied with a view to increasing the wheel-sets' lifetime (Skarlatos et al., 2004; Donato et al., 2006; Stratman et al., 2007; Palo, 2012).

One common preventive maintenance strategy (used in the case studies) is re-profiling wheel-sets after they run a certain distance. Re-profiling affects the wheel-set's diameter; once the diameter is reduced to a pre-specified length, the wheel-set is replaced by a new one. Seeking to optimise this maintenance strategy, some researchers have examined wheel-sets' degradation data (i.e., the wheel-sets' running surface wear data used in this research) to determine wheel reliability and failure distribution. Furthermore, in previous studies, some researchers have noticed that the wheel-sets' different installed positions could influence the results. To avoid the potential influence of wheel location, Freitas et al. (2009, 2010) only consider those on the left side of a specified axle and on certain specified cars, arguing that "the degradation of a given wheel might be associated with its position on a given car". Yang and Letourneau (2005) suggest that certain attributes, including a wheel's installed position (right or left), might influence its wear rate. Palo et al. (2012) conclude that "different wheel positions in a bogie show significantly different force signatures," but they do not provide case studies.

To solve the combined problem of small data samples and incomplete datasets whilst simultaneously considering the influence of several covariates, between 2012 and 2013, Lin (2013) has explored the influence of locomotive wheel-sets' positioning on reliability using Bayesian reliability inference with Markov Chain Monte Carlo (MCMC, (Congdon, 2001 & 2003)). The results indicate that the particular bogie in which the wheel-set is mounted has more influence on its lifetime than does the axle or side it is on. Since 2013, as a continuous study, both the integrated procedure for Bayesian reliability inference using MCMC and other traditional statistical theories (incl., reliability analysis, degradation analysis, Accelerated Life Tests (ALT), Design of Experiments (DOE)) are applied to a number of case studies using heavy haul locomotive wheel-sets' running surface wear data from Iron Ore Line (Malmbanan), Sweden. The research continuously explores the impact of a locomotive wheel-set's installed position on its service lifetime and attempts to predict its reliability related characteristics. Related studies were supported by Luleå Railway Research Centre (Järnvägstekniskt Centrum (JVTC), Sweden) and Swedish Transport Administration (Trafikverket) between 2012 and 2014 in the study titled "Using Integrated Reliability Analysis to Optimise Maintenance Strategies" and a continuous study titled "Data Analysis of Heavy Haul Locomotive Wheel-sets' Running Surface Wear at Malmbanan". Results from this researches aim to support maintenance strategies by analysing the data from the wheels' running surface wear.

In these studies, data used span January 2010 to May 2013 at Malmbanan, Sweden and data analysis is carried out in four parts. In the first part, an integrated reliability analysis is proposed, developed and tested. This integrated analysis applies Bayesian statistics using Markov Chain Monte Carlo (MCMC) methodologies. In this part, the research also explores the impact of a locomotive wheel's installed position on its service lifetime and attempts to predict its reliability characteristics by using parametric models, non-parametric models, frailty factors, etc. In the second part, comparison analysis for the wheel-sets on two selected locomotives is carried on. It proposes not only the integrating reliability assessment data with both degradation data and re-profiling performance data, but also, its case study compares: 1) degradation analysis using a Weibull frailty model; 2) work orders for re-profiling; 3) the performance of re-profiling parameter; and 4) wear rates. In the third part, corresponding to previous research, data are collected from two specific locomotives at Malmbanan. The corresponding case study undertakes a reliability analysis using both classical and Bayesian semi-parametric frameworks to explore the impact of a locomotive wheel's position on its service lifetime and to predict its other reliability characteristics. Results are used to illustrate how the wheel-sets' running surface wear data can be modelled and analysed using classical and Bayesian approaches to flexibly determine their reliability. In the fourth part, a holistic study is developed by analysing group data from 26 locomotives and 57 bogies at Malmbanan. In this part, data analysis is carried out from both the locomotives and the bogies' perspective. The results suggest that Malmbanan should consider the wheel-sets' data from both the locomotives' and the bogies' point of view. Next, wheel-sets' running surface wear data from a group of 16 bogies' are studied as a whole. More holistic results are drawn from both degradation and wear rate analysis. The report concludes by proposing some recommendations for future research into locomotive wheel-sets' running surface wear data analysis and suggesting some maintenance strategies for Malmbanan.

6.1.2 Description of Data

6.1.2.1 Iron Ore Line (Malmbanan)

The Iron Ore Line (Malmbanan) is the only existing heavy haul line in Europe; it stretches 473 kilometres and has been in operation since 1903. As Figure 21 shows, it is mainly used to transport iron ore and pellets from the mines in Kiruna (also Malmberget, close to Kiruna, in Sweden) to Narvik Harbour (Norway) in the northwest and Luleå Harbour (Sweden) in the southeast. The track section on the Swedish side is owned by the Swedish government and managed by Trafikverket (Swedish Transport Administration), while the iron ore freight trains are owned and managed by the freight operator (LKAB/MTAB). Each freight train consists of two IORE locomotives accompanied by 68 wagons with a maximum length of 750 metres and a total train weight of 8500 metric tonnes. The trains operate in harsh conditions, including snow in the winter and extreme temperatures ranging from - 40 °C to + 25 °C. Because carrying iron ore results in high axle loads and there is a high demand for a constant flow of ore/pellets, the track and wagons must be monitored and maintained on a regular basis. The condition of the locomotive wheel profile is one of the most important aspects to consider.

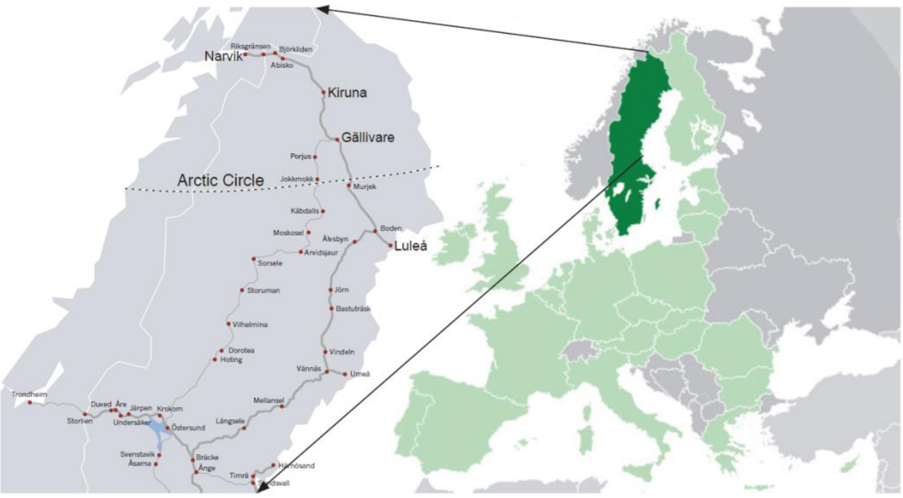


Figure 21: Geographical location of Iron Ore Line (Malmbanan) from Luleå to Narvik

6.1.2.2 Running Surface Wear Data and Re-profiling Parameters

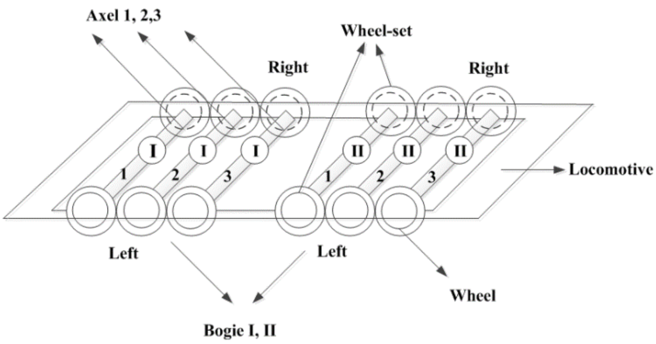


Figure 22: Wheel positions specified in this study

For each locomotive, see Figure 22, there are two bogies (incl., Bogie I, Bogie II); and each bogie contains three wheel sets. The installed position of a wheel on a particular locomotive is specified by the bogie number (I, II-number of bogies on the locomotive), an axel number (1, 2, 3-number of axels for each bogie) and the position of the axle (right or left) where each wheel is mounted.

The diameter of a new locomotive wheel in this study is around 1250 mm. Following the current maintenance strategy, a wheel's diameter is measured after it runs a certain distance. If it is reduced to 1150 mm, the wheel-set is replaced by a new one. Otherwise, it is re-profiled (see Figure 23). Therefore, in this study, a threshold level for failure, denoted as l_0, is defined as 100 mm (l_0 = 1250 mm -1150 mm). The wheel-set's failure condition is assumed to be reached if the diameter reaches l_0. The dataset includes the diameters of all locomotive wheels at a given inspection time, the total running distances corresponding to their "mean time between re-profiling", and the wheels' bill of material (BOM) data, from which we can determine their positions.

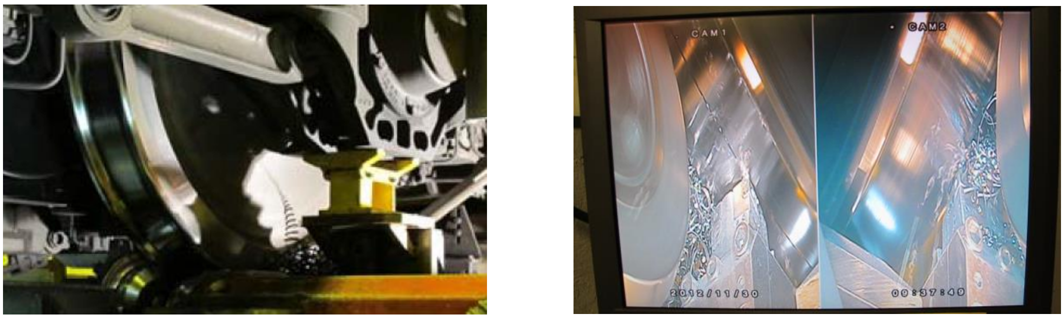


Figure 23 : Locomotive wheel-sets undergoing on-site re-profiling

The measurement tool is SIEMENS SINUMERIK (see Figure 24). During the re-profiling process, the re-profiling parameters include but are not limited to: 1) the diameters of the wheels; 2) the flange thickness; 3) the radial run-out; 4) the lateral run-out. As indicated by Lin (2013), the first parameter is the most important indicator for re-profiling decision making. Hence, the running surface wear data (recorded as diameters in the on-site re-profiling system) are the main parameters adopted for study.

Figure 24: Re-profiling equipment

6.1.3 Objectives and Scope of Work

In this research, data analysis aims to explore the impact of a locomotive wheel-set's installed position (incl. positions of the installed locomotive, bogie, and axel.) on its service lifetime and attempts to predict its reliability related characteristics by using both an integrated procedure for Bayesian reliability inference using MCMC and other traditional statistical theories. In addition, using the Bayesian inference adds flexibility to the analysis as it can accommodate the following aspects simultaneously: 1) Small sample data; 2) Incomplete data set, including censored or truncated data; 3) Complex operational environments. Results from this research will support the locomotive wheel-sets' maintenance strategies through data analysis of wheel-sets' running surface wear.

6.2 Approach and Methodology

As shown in Figure 25, data analysis is carried out in four parts.. The integrated Bayesian analysis framework adopted here is developed by Lin (2013) in the study titled “Using Integrated Reliability Analysis to Optimise Maintenance Strategies”, which Part 1and Part 2 belong to. As a continuous study, which is titled “Data Analysis of Heavy Haul Locomotive Wheel-sets’ Running Surface Wear at Malmbanan”, further research is carried out in two parts (Part 3 and Part 4).

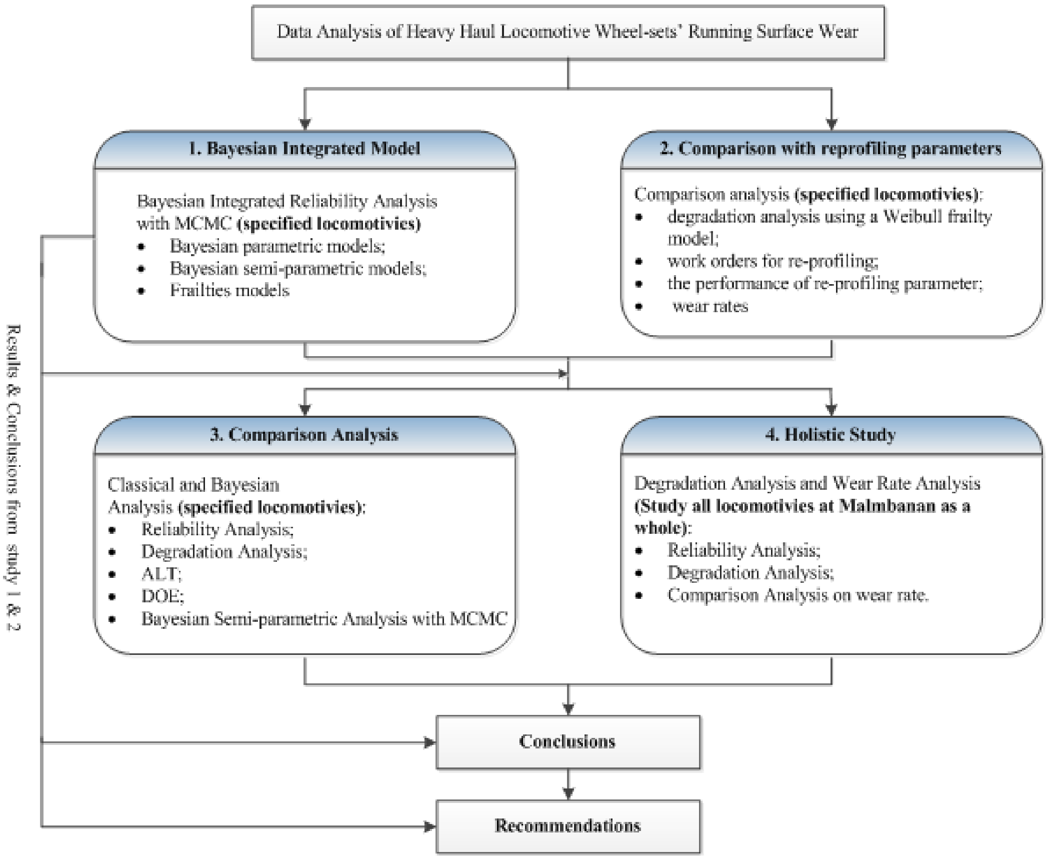


Figure 25: Research Approach and Methodology

6.3 Results and Discussions

6.3.1 An Integrated Procedure for Bayesian Reliability Inference using MCMC

The general procedure begins with the collection of reliability data (see Figure 26). These are the observed values of a physical process, such as various “lifetime data”. The data may be subject to uncertainties, such as imprecise measurement, censoring, truncated information, and interpretation errors. Reliability data are found in the “current data set”; they contain original data and include the evaluation, manipulation, and/or organisation of data samples. At a higher level in the collection of data, a wide variety of “historical information” can be obtained, including the results of inspecting and integrating this “information”, thereby adding to “prior knowledge”. The final level is reliability inference, which is the process of making a conclusion based on “posterior results”.

Using the above definitions, we propose an integrated procedure which constructs a full framework for the standardised process of Bayesian reliability inference. As shown in Figure

26, the procedure is composed of a continuous improvement process including four stages (Plan, Do, Study, Action) and the following 11 sequential steps which are discussed in more detail in Paper I: 1) data preparation; 2) prior inspection and integration; 3) prior selection; 4) model selection; 5) posterior sampling; 6) MCMC convergence diagnostic; 7) Monte Carlo error diagnostic; 8) model improvement; 9) model comparison; 10) inference making; 11) data updating and inference improvement. In summary, by using this step-by-step method, we can create a continuous improvement process for the Bayesian reliability inference.

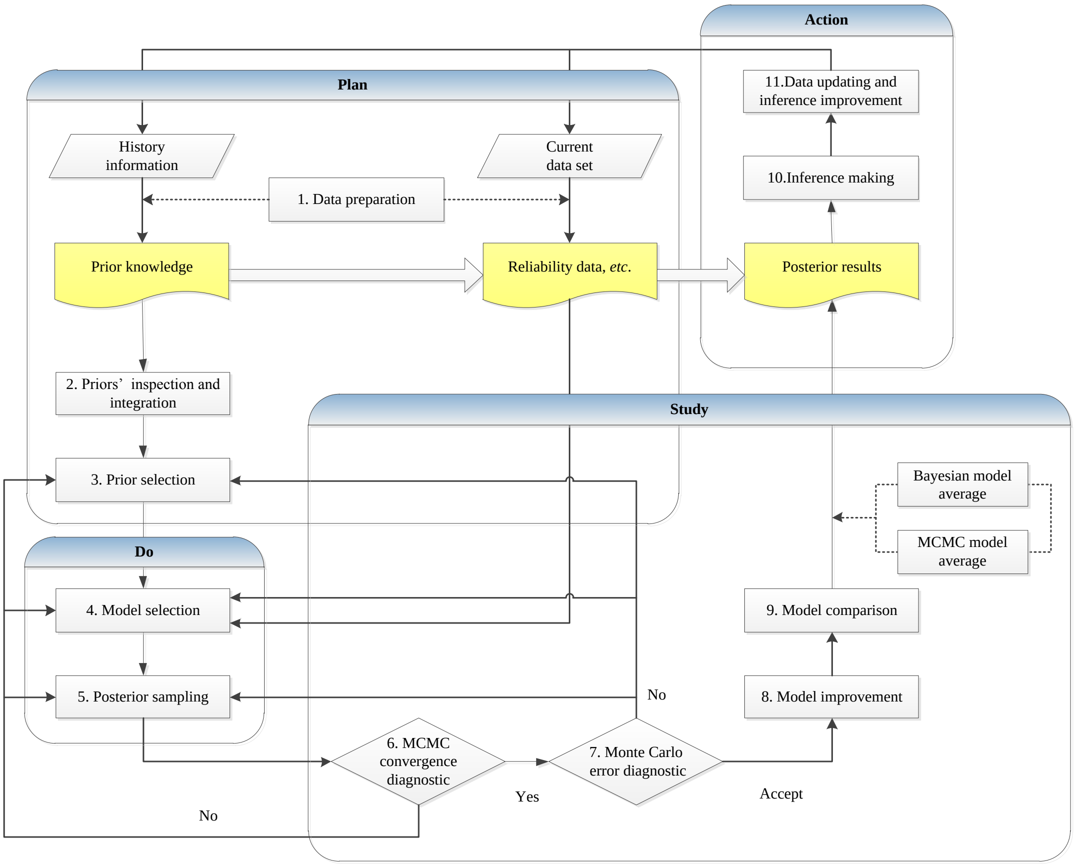


Figure 26: An Integrated Procedure for Bayesian Reliability Inference via MCMC

6.3.2 Bayesian Parametric Analysis for Locomotive Wheel Degradation

This study undertakes a reliability study using a Bayesian survival analysis framework to explore the impact of the wheel's installed position on its service lifetime and to predict its reliability characteristics. The Bayesian Exponential Regression Model, Bayesian Weibull Regression Model and Bayesian Log-normal Regression Model are used to analyse the lifetime of locomotive wheels using degradation data and taking into account the position of the wheel.

In this study, the wheel position is described by three different discrete covariates: the bogie, the axle and the side of the locomotive where the wheel is mounted. By introducing the covariate $\mathbf{x}_i$'s linear function $\mathbf{x}_i^{'}\boldsymbol{\beta}$, these three parameter models are constructed depending on the failure rate λ_i in the exponential model, the log of the rate parameter $\ln(\gamma_i)$ in the Weibull model and the logarithmic mean μ_i in the log-normal models. Following the convergence diagnostics (i.e., checking dynamic traces in Markov chains, time series, and Gelman-Rubin-Statistics, and comparing the MC error with Standard Deviation (SD)), we consider the following posterior distribution summaries (shown in Table 18, Table 19 and Table 20) for our models (Bayesian Exponential Regression Model, Bayesian Weibull Regression Model, and Bayesian Log-normal Regression Model), including the parameters' posterior distribution mean, standard deviation, Monte Carlo error, and 95% HPD (highest posterior distribution density) interval.

Table 18: Posterior Distribution Summaries for Exponential Regression Model

Parameter	Mean	SD	MC error	95 % HPD Interval
β_0	-5.862	0.7355	0.02299	(-7.366,-4.452)
β_1	-0.07207	0.3005	0.007269	(-0.6672,0.5104)
β_2	-0.03219	0.1858	0.003797	(-0.3889,0.3325)
β_3	-0.0124	0.2973	0.00726	(-0.5954,0.5787)

Table 19: Posterior Distribution Summaries for Weibull Regression Model

Parameter	Mean	SD	MC error	95 % HPD Interval
α	10.08	0.9674	0.05559	(8.234,11.76)
β_0	-60.47	5.977	0.3434	(-71.01,-49.16)
β_1	-0.07775	0.306	0.008339	(-0.6845,0.5156)
β_2	-0.146	0.2231	0.005801	(-0.5878,0.2856)
β_3	-0.05026	0.2982	0.007143	(-0.6356,0.5324)

Table 20: Posterior Distribution Summaries for Log-normal Regression Model

Parameter	Mean	SD	MC error	95 % HPD Interval
β_0	5.864	0.05341	0.001622	(5.76,5.97)
β_1	0.06733	0.02174	5.042E-4	(0.02492,0.1103)
β_2	0.02077	0.01373	2.765E-4	(-0.006291,0.04781)
β_3	0.001102	0.02175	5.007E-4	(-0.0412,0.04444)
τ	187.5	39.84	0.3067	(118.3,273.5)

Accordingly, the locomotive wheels' reliability functions can be written as:

- Bayesian Exponential Regression Model:

$$R(t_i \mid \mathbf{X}) = \exp\left[-\exp(-5.862 - 0.072x_1 - 0.032x_2 - 0.012x_3) \times t_i\right]$$

- Bayesian Weibull Regression Model:

$$R(t_i \mid \mathbf{X}) = \exp\left[-\exp(-60.47 - 0.078x_1 - 0.146x_2 - 0.050x_3) \times t_i^{10.08}\right]$$

- Bayesian Log-normal Regression Model:

$$R(t_i \mid \mathbf{X}) = 1 - \Phi\left[\frac{\ln(t_i) - (5.864 + 0.067x_1 + 0.02x_2 + 0.001x_3)}{(187.5)^{-1/2}}\right]$$

Obviously, other reliability characteristics of lifetime distribution, including Mean Time to Failure (MTTF), can also be determined.

Other findings on model comparison, maintenance predictions, and maintenance inspection levels are briefly discussed in the following subsections.

6.3.2.1 Model Comparison

When comparing Bayesian models, both the Bayesian Factor (BF) and Bayesian Information Criterion (BIC) can be used, but for complex Bayesian hierarchical models, this becomes more difficult. Spiegelhalter et al. (2002) have proposed the Deviance Information Criterion (DIC), which utilises the model's deviance to evaluate its measure of fit and the effective number of parameters to evaluate its complexity. We calculate the DIC values for the above three Bayesian parametric models separately, as shown in Table 21.

Table 21: DIC Summaries

Model	$\overline{D}(\theta)$	$D(\bar{\theta})$	p_d	DIC
Exponential Regression	648.98	645.03	3.95	652.93
Weibull Regression	472.22	467.39	4.83	477.05
Log-normal Regression	442.03	436.87	5.16	447.19

Based on Celeux et al. (2006) and the related discussions above, we choose the model with the lowest DIC value. When DIC<5, the difference among models can be ignored. Our results show that the DIC for the Log-normal Regression Model is the lowest (447.19); following the arguments above, it is more suitable than the other two. Using the same model, when we analyse other locomotives' wheels running under similar conditions, we reach similar conclusions. However, when we compare the DIC values for the Weibull Regression Model and the Exponential Regression Model, 477.05 and 652.93, respectively, we see that the performance of the Weibull Regression Model is close to the Log-normal Regression Model, making it a suitable choice in certain specified situations.

6.3.2.2 Maintenance Predictions

All Bayesian parameter models reach a common conclusion: the installation positions influence the wheels' lifetimes. In addition, considering the covariates' coefficients in our case study, we find the following: 1) the lifetime of the wheel installed in the second bogie is longer than that of the wheel installed in the first one; 2) the wheel installed in the third axel has a longer lifetime than that installed in the second axel, and the wheel in the second axel has a longer lifetime than the one in the first axel; 3) the right side wheel's lifetime is shorter than the left side. (Researchers from Norwegian National Rail Administration cited previously concur with this. Using condition monitoring methods on train wheels operating on the same route, they found that the wheel forces on the right and the left sides can be different, even for wheels in the same axel.). Possible causes for the differences include the influence of the topographical complexity, and the position of the locomotive's centre of gravity.

The three Bayesian parametric regression models presented here are all effective in their Markov chain convergence and other diagnostic tools; see, for example, Spiegelhalter et al. (2002) who compare the computation process, including checking Markov chains' dynamic traces, time series and Gelman-Rubin-Statistics, and comparing the MC error with Standard Deviation (SD). However, we prefer the Bayesian Lognormal Regression Model because of its DIC values. The prediction of the locomotive wheels' MTTF, following this model, appears in Table 22.

It should be pointed out that the 95% HPD interval in the Bayesian Lognormal Regression Model for β_2 and β_3 includes 0 (Table 22). This means that although the positioning does have an influence, in some instances, the impact on the wheel's service lifetime is not significantly strong. In our case, the bogies have more impact on service lifetime than axels or sides. Given this knowledge, we can deal with such covariates better in our future research.

Table 22: MTTF statistics based on Bayesian Lognormal Regression Model

Bogie	Axel	Side	μ_i	MTTF($\times 10^3$ km)
I (x_1 =1)	1 (x_2 =1)	Right (x_3 =1)	5.9532	387.03
		Left (x_3 =2)	5.9543	387.46
	2 (x_2 =2)	Right (x_3 =1)	5.9740	395.16
		Left (x_3 =2)	5.9751	395.60
	3 (x_2 =3)	Right (x_3 =1)	5.9947	403.43
		Left (x_3 =2)	5.9958	403.87
II (x_1 =2)	1 (x_2 =1)	Right (x_3 =1)	6.0205	413.97
		Left (x_3 =2)	6.0216	414.43
	2 (x_2 =2)	Right (x_3 =1)	6.0413	422.67
		Left (x_3 =2)	6.0424	423.14
	3 (x_2 =3)	Right(x_3 =1)	6.0621	431.56
		Left (x_3 =2)	6.0632	432.03

6.3.2.3 Maintenance Inspection Level

According to the assumptions in this study, the maintenance inspection level H_2 (where $0 \le H_2 \le H_1$) determines how many lifetime data are "right-censored". Obviously, the higher the maintenance inspection level, the more data are considered "right-censored" and vice versa. For instance, in Figure 27, we show a higher maintenance inspection level (80 mm) and a lower one (20 mm). We denote the area between H_1 and H_2 as Zone I, and the area between H_2 and zero degradation level as Zone II. Therefore, based on the likelihood functions discussed Paper II, the MTTF statistics which are achieved from the higher H_2 (the left picture in Figure 27, where H_2 = 80 mm) will be higher than those obtained from the lower H_2 (the right picture, where H_2 =20 mm), because fewer degradation data are considered right-censored. In other words, the results achieved from the former are more "optimistic", and the results obtained from the latter are more "pessimistic". An extreme condition is to suppose H_2 =0 mm.

For this reason, we can get an interval prediction between "optimistic" and "pessimistic" with different maintenance inspection levels which actually reflect the different risk confidence levels.

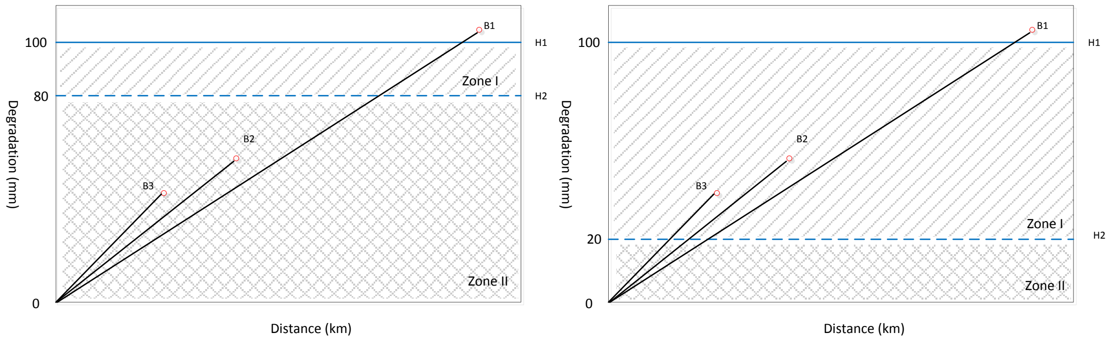


Figure 27: Maintenance Inspection Level with Zone I and Zone II

6.3.3 Bayesian Non-parametric Analysis for Locomotive Wheel Degradation using Frailties

Since semi-parametric Bayesian methods offer a more general modelling strategy that contains fewer assumptions (Ibrahim et al., 2001), Firstly, in this study, we adopt the piecewise constant hazard model to establish the distribution of the locomotive wheels' lifetime. The applied hazard function is sometimes referred to as a piecewise exponential model; it is convenient because it can accommodate various shapes of the baseline hazard over the intervals.

In addition, as mentioned in above paper, most reliability studies are implemented under the assumption that individual lifetimes are independent identified distributed (i.i.d). However, sometimes CPH models cannot be used because of the dependence of data within a group. Modelling dependence in multivariate survival data has received considerable attention, especially in cases where the datasets may come from subjects of the same group which are related to each other (Sahu et al., 1997; Aslanidou et al., 1998). A key development in modelling such data is to consider frailty models, in which the data are conditionally independent. When frailties are considered, the dependence within subgroups can be considered an unknown and unobservable risk factor (or explanatory variable) of the hazard function. We consider a gamma shared frailty, first discussed by Clayton (1978) and later developed by Sahu et al. (1997), to explore the unobserved covariates' influence on the wheels on the same locomotive. In this study, the gamma shared frailties $\boldsymbol{\omega}_i$ are used to explore the influence of unobserved covariates within the same locomotive. By introducing covariate $\mathbf{x}_i$'s linear function $\mathbf{x}_i^{'}\boldsymbol{\beta}$, the influence of the bogie in which a wheel is installed can be taken into account.

The results of the case study suggest that the wheels' lifetimes differ according to where they are installed on the locomotive. The wheel installed in the second bogie has a longer lifetime than the one in the first bogie. The differences could be influenced by the real running situation (e.g. topography), and the locomotive's centre of gravity. The gamma frailties help with exploring the unobserved covariates and thus improve the model's precision. Results also indicate a close positive relationship between the wheels mounted on the same locomotive; the heterogeneity between locomotives is significant as well. We can determine the wheel's reliability characteristics, including the baseline hazard rate $\lambda(t)$, reliability $R(t)$, and cumulative hazard rate $\Lambda(t)$, etc.

The results indicate the existence of change points. As Fig.3.3, Fig.3.4 and Fig.3.5 show, wheel reliability declines sharply at the fourth piecewise interval, while at the fifth piecewise interval, the cumulative hazard increases dramatically. The results allow us to evaluate and optimise wheel replacement and maintenance strategies (including the re-profiling interval, inspection interval, lubrication interval, depth and optimal sequence of re-profiling, and so on). Finally, the approach discussed in this study can be applied to cargo train wheels or to other technical problems (e.g. other industries, other components).

Statistics summaries (Table 23) in this study include the parameters' posterior distribution mean, SD, MC error, and the 95% HPD interval. In Table 23, $\beta_1 > 0$ means that the wheels mounted in the first bogie (as $x=1$) have a shorter lifetime than those in the second (as $x=2$). However, the influence could possibly be reduced as more data are obtained in the future, because the 95% HPD interval includes 0 point. Because $\kappa > 0.5$, there is a positive relationship between the wheels mounted on the same locomotive; in addition, the heterogeneity among the locomotives is significant. Meanwhile, $\omega_1 < 1$ suggests that the predictive lifetimes for those wheels mounted on the first locomotive are longer than if the frailties are not considered; in fact, $\omega_2 > 1$ indicates the opposite conclusion.

Table 23: Posterior Distribution Summaries

Parameter	mean	SD	MC error	95% HPD Interval
β_0	-10.39	2.888	0.2622	(-16.61, -4.79)
β_1	0.3293	0.4927	0.02016	(-0.661, 1.271)
κ	0.563	0.269	0.01038	(0.1879, 1.225)
ω_1	0.1441	0.1374	0.004822	(0.01192, 0.5258)
ω_2	1.866	1.016	0.03628	(0.3846, 4.308)
b_1	0.1361	1.595	0.1037	(-3.196, 3.364)
b_2	0.758	2.182	0.1672	(-3.7, 5.248)
b_3	1.94	2.514	0.2105	(-3.126, 7.342)
b_4	4.447	2.668	0.2389	(-0.5652, 10.48)
b_5	6.342	2.684	0.2415	(1.126, 12.29)
b_6	8.159	2.724	0.2417	(2.843, 14.15)

Baseline hazard rate statistics based on the above results are shown in Table 24 and Figure 28. At the fourth piecewise interval, the wheels' baseline hazard rate increases dramatically.

Table 24: Baseline Hazard Rate Statistics

Piecewise	1	2	3	4	5	6
Intervals($\times$1000km)	(0, 60]	(60, 120]	(120, 180]	(180, 240]	(240, 300]	(300, 360]
λ_k	1.15	2.13	6.96	85.37	567.93	3494.69

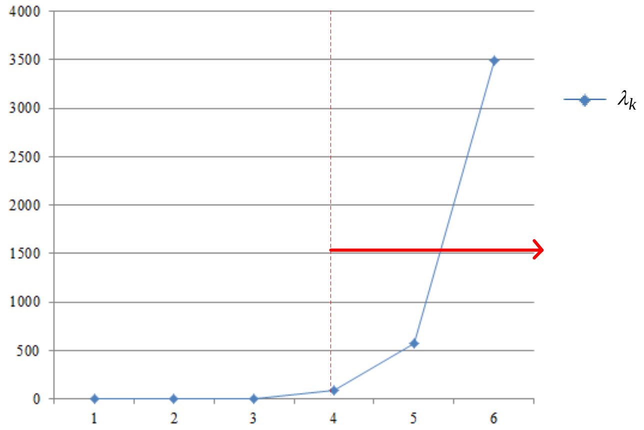


Figure 28: Plot of Baseline Hazard Rate

By considering the random effects resulting from the natural variability (explained by covariates) and from the unobserved random effects within the same group (explained by frailties), we can determine other reliability characteristics of lifetime distribution. The statistics on reliability $R(t)$ and cumulative hazard rate $\Lambda(t)$ for the two wheels mounted in different bogies are listed inTable 25, Figure 29 and Figure 30. Figure 28 and Figure 29 show frailties between Locomotive 1 and Locomotive 2. In addition, for these locomotives, the wheels mounted in the first bogie ($x=1$) have lower reliability and a higher cumulative hazard rate than those mounted in the second one ($x=2$).

Table 25: Reliability and Cumulative hazard statistics

Distance (1000 km)	Reliability $R(t)$				Cumulative hazard $\Lambda(t)$			
	Locomotive 1		Locomotive 2		Locomotive 1		Locomotive 2	
	Bogie I	Bogie II	Bogie I	Bogie II	Bogie I	Bogie II	Bogie I	Bogie II
60	0.999577	0.999412	0.994534	0.99241	0.000184	0.000256	0.00238	0.003309
120	0.998425	0.997811	0.97979	0.97202	0.000685	0.000952	0.008867	0.012325
180	0.992318	0.989338	0.90496	0.870393	0.003349	0.004655	0.04337	0.060285
240	0.881485	0.839169	0.195241	0.103252	0.054785	0.076151	0.709428	0.986101
300	0.350289	0.232678	1.26E-06	6.31E-09	0.455574	0.633245	5.899379	8.200106
360	0.000433	2.11E-05	2.75E-44	2.82E-61	3.363977	4.67591	43.56128	60.54995

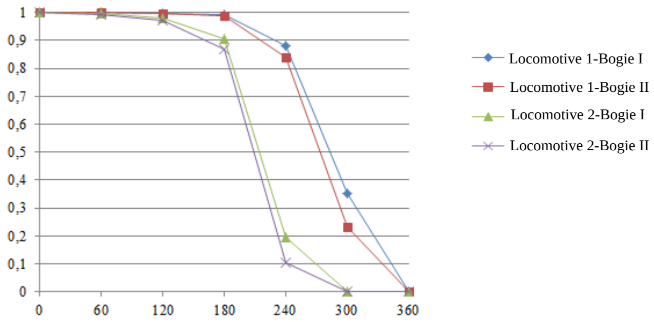


Figure 29: Plot of the reliabilities for Locomotive 1 and Locomotive 2

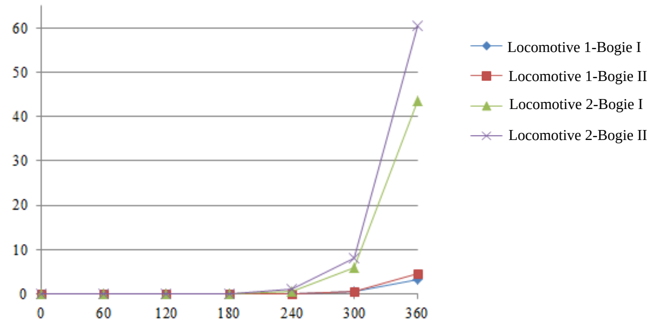


Figure 30: Plot of the Cumulative hazard for Locomotive 1 and Locomotive 2

Figure 29 and Figure 30 show change points in the wheels. For example, the reliability declines sharply at the fourth piecewise interval, and at the fifth piecewise interval, the cumulative hazard increases dramatically. In what follows, several other finds are briefly discussed. These include: lifetime prediction and replacement optimisation, preventative maintenance optimisation, and re-profiling optimisation.

First, determining reliability characteristics distributed over the wheels' lifetime could be used to optimise replacement strategies. The results could also support related predictions for spares inventory.

Second, the change points (Figure 28, Figure 29, Figure 30) appearing in the fourth and fifth piecewise interval (from 180 000 to 300 000 kilometres) indicate that after running about 180 000 kilometres, the locomotive wheel has a high risk of failure. Rolling contact fatigue

(RCF) problems could start at the fifth interval (after 240 000 kilometres). Therefore, special attention should be paid if the wheels have run longer than these change points. Finally, because re-profiling may leave cracks over time and reduce the wheel's lifetime, cracks should be checked after re-profiling to improve the lifetime.

Third, the wheels installed in the first bogie should be given more attention during maintenance. Especially when the wheels are re-profiled, they should be checked starting with the first bogie to avoid duplication of effort. Note that in the studied company, the inspecting sequences are random; this means that the first checked wheel could belong in the second bogie. After the second checked wheel is lathed or re-profiled, if the diameter is less than predicted, the first checked wheel might need to be lathed or re-profiled again. Therefore, starting with the wheel installed in the first bogie could improve maintenance effectiveness.

Last but not least, the frailties between locomotives could be caused by the different operating environments (e.g., climate, topography, and track geometry), configuration of the suspension, status of the bogies or spring systems, operation speeds and applied loads. Specific operating conditions should be considered when designing maintenance strategies because even if the locomotives and wheel types are the same, the lifetimes and operating performance could differ.

Note that in the second part of section 3, we consider a gamma frailty but in a Weibull frailty model. More details appear in the latter paper. The difference between the frailty models used in these paper is that the former is studied in a non-parametric formulate (the baseline hazard rate is piecewise), while the latter is studied in a parametric formulate (the baseline hazard rate is Weibull).

By adopting the same piecewise baseline hazard rate, in the third part of section 3, we got below results (see Table 26).

Table 26: Posterior Distribution Summaries

Parameter	mean	SD	MC error	95% HPD Interval
β_0	-12.08	4.184	0.4019	(-22.17,-4.802)
β_1	0.04517	0.4889	0.02025	(-0.948,0.9669)
κ	0.1857	0.1667	0.008398	(0.008616,0.6128)
ω_1	0.5246	0.2878	0.01401	(0.06489,1.064)
ω_2	1.473	0.5807	0.01596	(0.6917,2.948)
b_1	-0.3764	4.113	0.1619	(-8.316,5.933)
b_2	0.3571	4.95	0.2429	(-8.836,8.181)
b_3	2.272	4.61	0.3029	(-6.4,10.81)
b_4	7.301	4.106	0.3938	(0.2106,17.13)
b_5	5.223	4.225	0.3281	(-3.166,13.41)
b_6	10.03	3.993	0.3802	(2.72,19.3)

In Table 26, $\beta_1 > 0$ means that wheels mounted in the first bogie (as $x = 1$) have a shorter lifetime than those in the second (as $x = 2$). However, the influence could possibly be reduced as more data are obtained in the future, because the 95% HPD interval includes 0 point. In addition, the small value of β_1 (≈ 0.045) indicates that, in this case, heterogeneity among wheels installed in different bogies exists but is not significant. Because $\kappa < 0.5$, heterogeneity among the locomotives does exist but is not significant either. However, the frailty factors obviously exist. For instance, $\omega_1 < 1$ suggests the predicted lifetimes for those wheels mounted on the first locomotive are longer than if the frailties are not considered; meanwhile, $\omega_2 > 1$ indicates the wheels mounted on the second locomotive have a shorter lifetime than if the frailties are not considered.

Baseline hazard rate statistics based on the above results ($b_1, \cdots, b_6$) are shown in Table 27 and Figure 31. At the fourth piecewise interval, the wheels' baseline hazard rate increases dramatically (1481.78). It is interesting that at the fifth piecewise interval, it decreases (185.49) but increases again after the sixth piecewise (22697.27).

Table 27: Baseline Hazard Rate Statistics

Piecewise	1	2	3	4	5	6
Intervals($\times$1000km)	(0, 60]	(60, 120]	(120, 180]	(180, 240]	(240, 300]	(300, 360]
λ_k	0.069	1.43	9.7	1481.78	185.49	22697.27

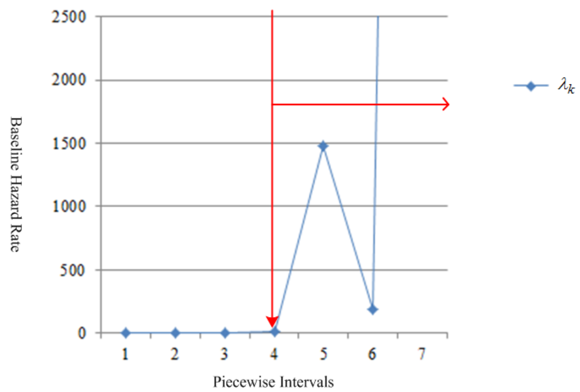


Figure 31: Plot of Baseline Hazard Rate

By considering the random effects resulting from the natural variability (explained by covariates) and from the unobserved random effects within the same group (explained by frailties), we can determine other reliability characteristics of the lifetime distribution. The statistics on reliability $R(t)$ and cumulative hazard rate $\Lambda(t)$ for the two wheels mounted in different bogies are listed in Table 28, Figure 32.

Table 28: Reliability and Cumulative hazard statistics

Distance (1000 km)	Reliability $R(t)$				Cumulative hazard $\Lambda(t)$			
	Locomotive 1		Locomotive 2		Locomotive 1		Locomotive 2	
	Bogie I	Bogie II	Bogie I	Bogie II	Bogie I	Bogie II	Bogie I	Bogie II
60	0.999872	0.999866	0.99964	0.999624	5.57E-05	5.82E-05	0.000156	0.000164
120	0.999466	0.999442	0.998502	0.998433	0.000232	0.000243	0.000651	0.000681
180	0.99458	0.994331	0.984857	0.984162	0.00236	0.002469	0.006627	0.006933
240	0.330536	0.314054	0.044672	0.038695	0.480781	0.502996	1.349964	1.41234
300	0.840949	0.834245	0.614843	0.601179	0.07523	0.078707	0.211236	0.220996
360	8.98E-12	2.77E-12	9.61E-32	3.54E-33	11.0466	11.55701	31.01723	32.4504

For Locomotive 1 and Locomotive 2, Figure 32 shows the plots of reliability and cumulative hazard, respectively.

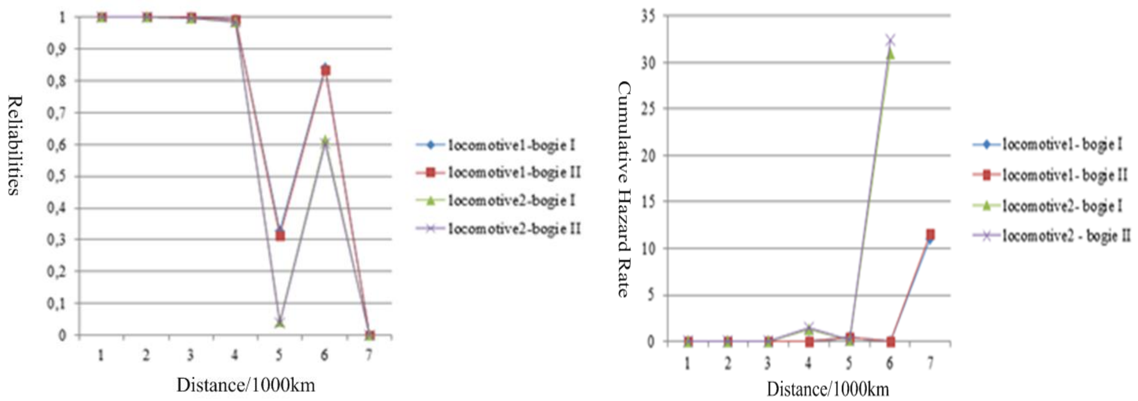


Figure 32: Plot of the Reliabilities for Locomotive 1 and Locomotive 2 (left) - Plot of the Cumulative hazard for Locomotive 1 and Locomotive 2 (right)

It should be pointed that both Figure 32 show change points in the wheels. For example, the reliability declines sharply at the fourth and the sixth piecewise interval. Meanwhile, after the fifth and the sixth piecewise interval, the cumulative hazard increases dramatically.

Table 29: Re-profiling Statistics

No.	Piecewise Intervals*	1	2	3	4	5	6
	Re-profiling	(0, 60]	(60, 120]	(120, 180]	(180, 240]	(240, 300]	(300, 360]
1	Locomotive 1	0	106	144	191	272	309
2	ΔD_1	106	38	47	81	37	51
3	Locomotive 2	33	87	161	204	0	0
4	ΔD_2	54	74	43	189	/	/

* × 1000km

The above results can be applied to maintenance optimisation, including wheel-sets' re-profiling optimisation, lifetime prediction and replacement optimisation, and preventive maintenance optimisation. Before continuing, in Table 29, we list the re-profiling times (running distance/kilometres) for Locomotive 1 and Locomotive 2, in row 1 and 3, respectively. We can see the difference of the re-profiling polices: for Locomotive 1, re-profiling is done, at most, 5 times; the wheel-sets on Locomotive 2 are re-profiled, at most, 4 times. For greater clarification, we list them under the k intervals. For instance, for Locomotive 1, the first re-profiling was performed at 106 000 kilometres, which belongs to the second piecewise interval. We can denote ΔD as the gap from the "current re-profiling" to the next one in each piecewise interval (rows 2 and 4). For instance, for Locomotive 1, the first re-profiling is at 106 000 kilometres, and the next at 144 000 kilometres, creating a gap of 38 000 kilometres (=144 000 – 106 000). For the last re-profiling, we use the boundary of 360 000 kilometres as the "next re-profiling". By comparing ΔD, we can see the running distances of the wheels between profiling. If we do not consider the first interval's statistics (normally, the new wheel is treated as running in a good condition), the largest values appear at the fourth interval for each locomotive, consistent with the findings from Figure 32. Therefore, the re-profiling time will influence the wheel-sets' degradation rate. If the re-profiling was performed earlier than 272 000 kilometres for Locomotive 1, the degradation rate could be reduced, as could the baseline hazard rate. Meanwhile, the reliability in piecewise interval 4 could be increased. This conclusion could also explain why at the fifth interval, the baseline hazard rate decreased while the reliability increased. As discussed above, we recommend improving the re-profiling polices by considering the re-profiling intervals. Now consider the seasonal influence (temperature). In this case, the re-profiling at the fourth piecewise was done between March 2010 and September 2010. Although the degradation rate should be lower than if it were winter, if the time between re-profiling is too long, the baseline hazard rate could increase dramatically and the reliability could decrease. Again, we recommend improving the re-profiling polices by considering the re-profiling intervals, although the seasonal influence should also be included.

It is interesting to see that in Figure 31 and Figure 32, the change points appearing in the fourth piecewise interval (from 180 000 to 360 000 kilometres) indicate that after running about 180 000 kilometres, the locomotive wheel has a high risk of failure. Although the ΔD is sometimes larger (for instance, ΔD_1 equals 106 at the first interval), it is more stable before the fourth piecewise interval. Rolling contact fatigue (RCF) problems could start at the fourth interval (after 180 000 kilometres). Therefore, we recognize the whole period as two stages: one is stable (before 180 000 kilometres), and the second is unstable. Special attention should be paid if the wheel-sets have run longer than these change points (reaching an unstable stage). In addition, because re-profiling may leave cracks over time and reduce the wheel-set's lifetime, we recommend cracks be checked after re-profiling to improve the lifetime.

Although the difference is not that obvious, the wheel-sets installed in the first bogie should be given more attention during maintenance. Especially when the wheels are re-profiled, they should be checked, starting with the first bogie to avoid duplication of effort. Note that in the case study, the wheel-sets' inspecting sequences are random; this means that the first checked wheel-set could belong in the second bogie. After the second checked wheel-set is lathed or re-profiled, if the diameter is less than predicted, the first checked wheel-set might need to be lathed or re-profiled again. Therefore, starting with the wheel-set installed in the first bogie could improve maintenance effectiveness.

Determining reliability characteristics distributed over the wheel-sets' lifetime could be used to optimise replacement strategies. The results could also support related predictions for spares inventory.

Last but not least, the different frailties between locomotives could be caused by the different operating environments (e.g., climate, topography, and track geometry), configuration of the suspension, status of the bogies or spring systems, operating speeds, the applied loads and human influences (such as drivers' operations, maintenance policies and lathe operators). Specific operating conditions should be considered when designing maintenance strategies because even if the locomotives and wheel-set types are the same, the lifetimes and operating performance could differ.

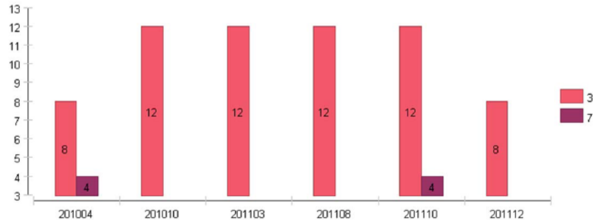
6.3.4 Comparison Study of the Reliability Assessment of Locomotive Wheels

The service life of different railroad wheels can vary greatly. Take a Swedish railway company, for example. For the wheels of its 26 locomotives, statistics show that from 2010 to 2011, the longest mean time between re-profiling was around 59 000 kilometres and the shortest was about 31 000 kilometres. The large difference can be attributed to the non-heterogeneous nature of the wheels; each differs according to its installed position, operating conditions, re-profiling characteristics, etc.

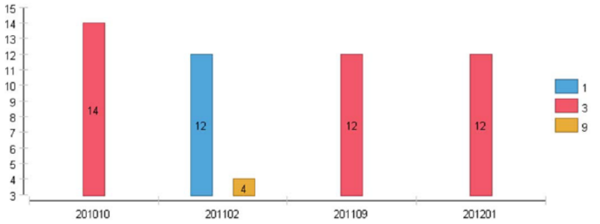
In this study, we compare the wheels on two selected locomotives to explore some of these differences. We propose integrating reliability assessment data with both degradation data and re-profiling performance data. Our case study compares: 1) degradation analysis using a Weibull frailty model; 2) work orders for re-profiling; 3) the performance of re-profiling parameter; and 4) wear rates.

6.3.4.1 Results from comparing re-profiling work orders

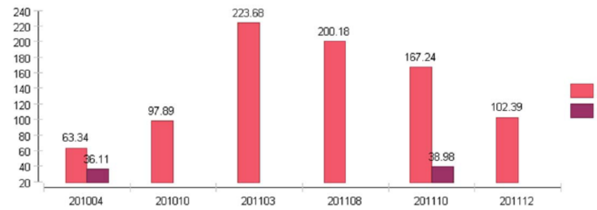
In Figure 33, the work order statistics for re-profiling are listed by date. The colour and the number of the bar represent the type of work order reported in the system. For instance, number 1 (blue) means the reason for re-profiling is a high flange; number 3 (red) represents the RCF problem; number 7 (purple) means the re-profiling is due to the dimension difference between wheels in a bogie; number 9 (yellow) denotes a thick flange. The work orders have 14 categories for re-profiling: high flange, thin flange, RCF, unbalanced wheel, QR measurements, out-of-round wheel, dimension difference in between wheels in same bogie, vibrations, thick flange, cracks, remarks from measurement of the wheel by Miniprof, other defects, to plant for re-profiling, and hollowware. These categories are determined by the operator and are listed in above paper. Take Figure 33(a) for example. By April 2010, the wheels of Locomotive 1 have been re-profiled 12. Eight times it was related to category 3 (RCF problem), and four times it was in category 7 (the dimension difference between wheels in a bogie).



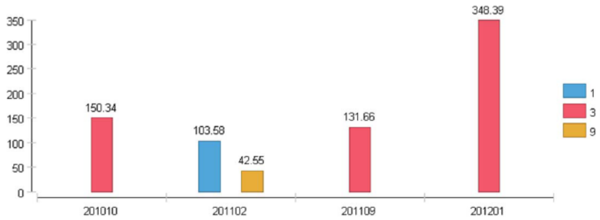
(a)Work order numbers for Locomotive 1



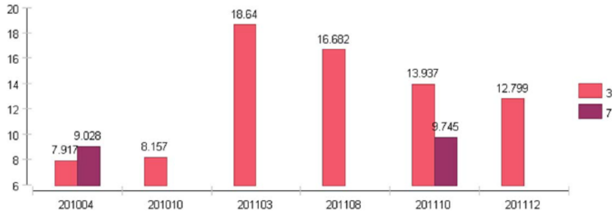
(b) Work order numbers for Locomotive 2



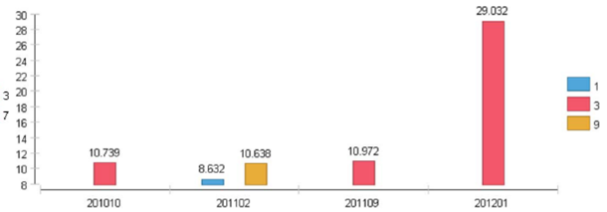
(c)Total re-profiling for Locomotive 1 /mm



(d) Total re-profiling for Locomotive 2 /mm



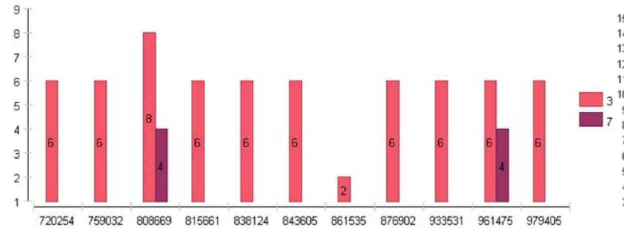
(e)Average re-profiling for Locomotive 1 /mm



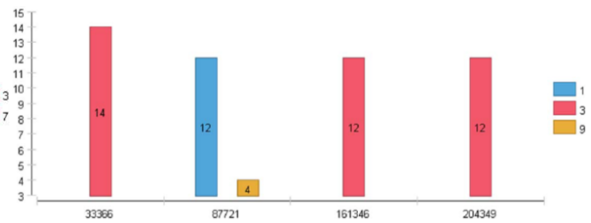
(f) Average re-profiling for Locomotive 2 /mm

Figure 33: Work orders statistics on re-profiling by date

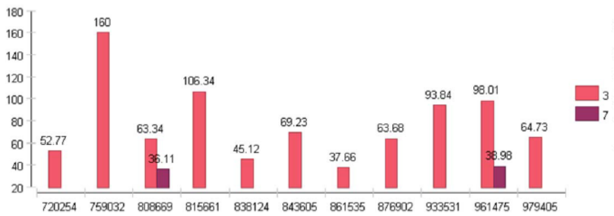
In Figure 33 and Figure 34, the figures on the left side provide the statistics for locomotive 1, while those on the right are for locomotive 2. Note that in Figure 34, the work order statistics on re-profiling are listed by the corresponding bogies' total number of kilometres in operation on the reported date. In Figure 34(b), the wheels have run 87721 kilometres and been re-profiled 16 times, 12 times due to category 1 (high flange) and 4 times due to category 9 (thick flange). It should be pointed out that since October 2010, new wheels have been mounted on both locomotives. However, the selected work orders are from the beginning of 2010; therefore, more re-profiling has been done on locomotive 1.



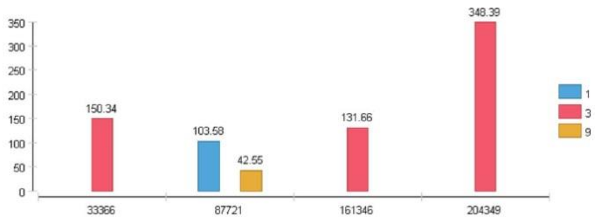
(a)Work order numbers for Locomotive 1



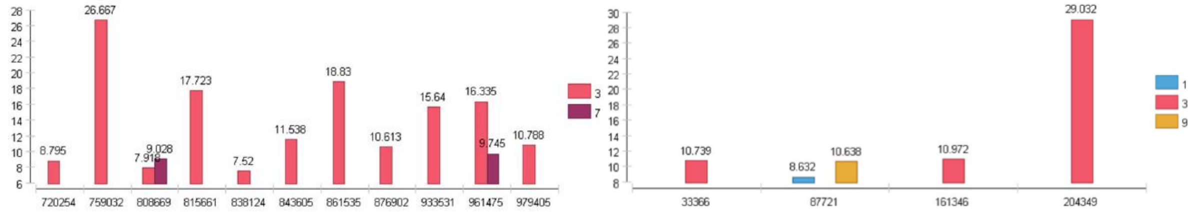
(b) Work order numbers for Locomotive 2



(c)Total re-profiling for Locomotive 1



(d) Total re-profiling for Locomotive 2



(e)Average re-profiling for Locomotive 1 (f) Average re-profiling for Locomotive 2

Figure 34: Work orders statistics on re-profiling by kilometres

For locomotive 1, there are two failure modes: RCF and dimensional differences for wheels in the same bogie. The number of re-profiling work orders due to RCF is 64; the number due to dimensional differences for wheels in the same bogie is 8. Locomotive 2 shows three failure modes, high flange, RCF and thick flange. Again, the dominant failure mode is RCF with 38 re-profilings, followed by high flange with 12 re-profilings and thin flange with 4; see Figure 33 (b). Figure 33 (c) and (d) show the amount of material removed at each re-profiling for all wheels. Even here, the RCF failure dominates with more material lost in re-profiling. Figure 33 (e) and (f) show the mean cut deep for each re-profiling. The RCF failure mode has deeper cuts than other modes; the high flange failure mode has the smallest mean cut depth.

Figure 34 shows the same information but uses the global traveling distance in kilometres (km). It should be pointed out that for Locomotive 1, Figure 34 has more bars on the left hand side because the axels have been changed and the recorded kilometres are different.

Generally speaking, RCF is the main type of work order for both locomotives. What should also be pointed out is that in the work order statistics, natural wear and the amount of re-profiling are considered simultaneously. Yet the trends in the amount of re-profiling are different. For instance, for locomotive 1, there is a decreasing trend for new wheels, while locomotive 2 shows an increasing trend.

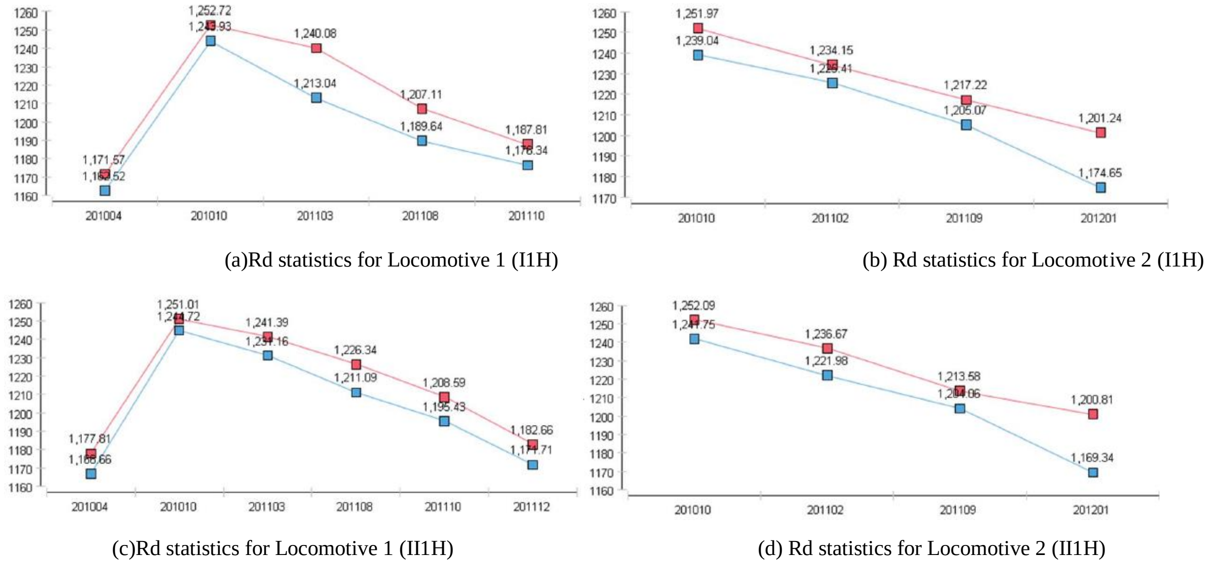
During this investigation, we have discovered a number of problems in the work orders. For example, some reported data cannot be recognised (e.g., some wheels are apparently re-profiled twice on one date; some reported wheel diameters after re-profiling are larger than before re-profiling). We suggest applying related Key Performance Indicators (KPIs) to monitor the re-profiling work and the wheel performance in the future.

6.3.4.2 Results from comparing re-profiling parameters

6.3.4.2.1 Assessment of re-profiling parameters (Rd)

Starting in this section, we only include statistics by re-profiling date. In addition, due to the similarities of the wheels installed in the same bogie, we only list statistics for the chosen wheel within each bogie. The red line represents the statistics obtained before re-profiling; the blue line represents statistics after re-profiling.

Figure 35 shows locomotive 1 on the left hand side and locomotive 2 on the right; for the graphs, the y-axle is the wheel diameter and the x-axle is the re-profiling date. For locomotive 1, the graphs start with the last re-profiling of an old wheel; step two is the first re-profiling with new wheels.



(a)Rd statistics for Locomotive 1 (I1H)

(b) Rd statistics for Locomotive 2 (I1H)

(c)Rd statistics for Locomotive 1 (II1H)

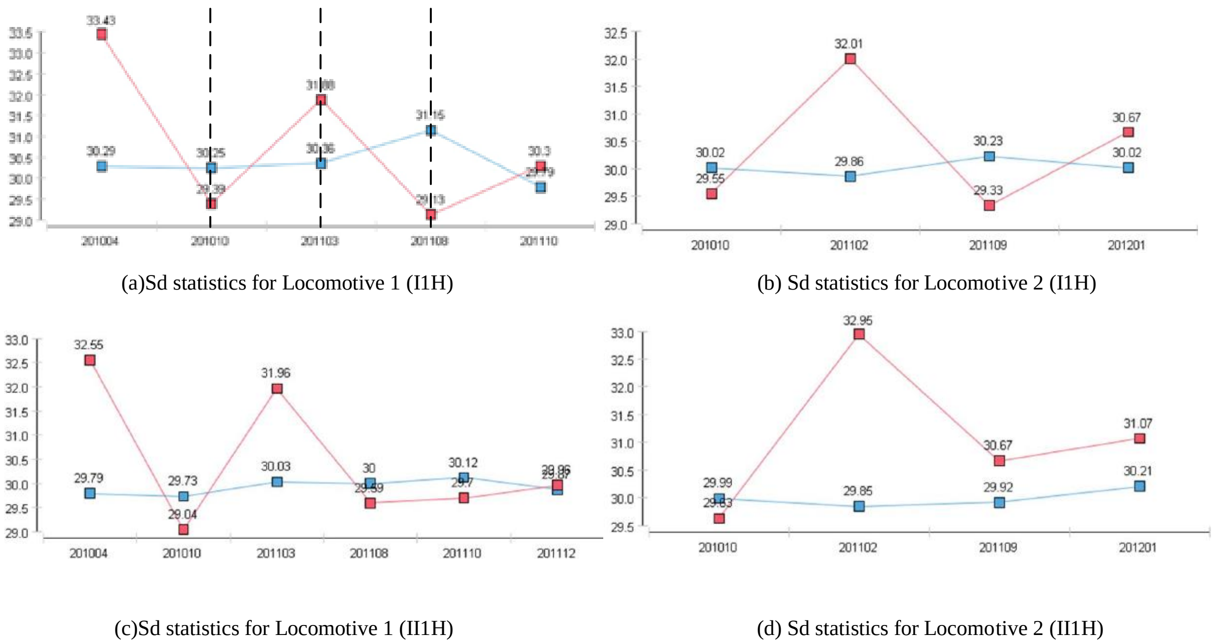
(d) Rd statistics for Locomotive 2 (II1H)

Figure 35: Rd statistics by date (before and after re-profiling): one example (I1H & II1H)

The wheels installed in the same bogie show similar trends in before and after re-profiling (denoted as Δ Rd). Δ Rd is decreasing for locomotive 1 and increasing for locomotive 2.

6.3.4.2.2 Assessment of re-profiling parameter (Sd)

Figure 36 shows some statistics of the Sd for the selected wheels. Locomotive 1 is represented on the left hand side, with locomotive 2 on the right. For both, the flange thickness increases during winter and decreases in summer; this phenomenon is especially pronounced for locomotive 1 and the first bogie and first axle; see the dotted lines in Figure 36(a).



(a)Sd statistics for Locomotive 1 (I1H)

(b) Sd statistics for Locomotive 2 (I1H)

(c)Sd statistics for Locomotive 1 (II1H)

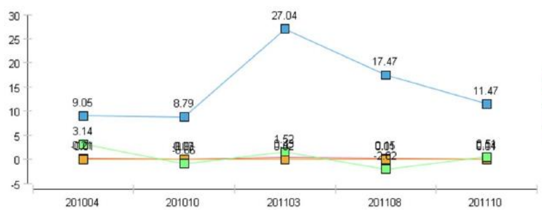
(d) Sd statistics for Locomotive 2 (II1H)

Figure 36: Rd statistics by date (before and after re-profiling): one example (I1H & II1H)

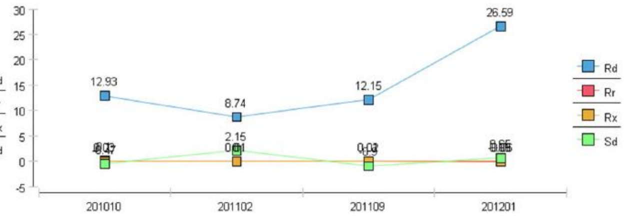
Like the Rd statistics, the Sd statistics for the wheels installed in the same bogie are quite similar. The "after" statistics (in blue) are stable. The "before" statistics (in red) are gradually becoming stable, which means the gap (denoted as Δ Sd) is decreasing. Note that if we check the before and after statistics in different seasons, we see that the red line is decreasing in the summer and increasing in the winter; see Fig.3.12 (a).

6.3.4.2.3 Assessment of re-profiling parameter (ΔRd, ΔSd, ΔRr, ΔRx)

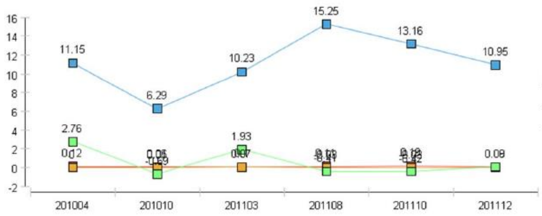
In this section, we simultaneously consider the gaps of the four parameters discussed above: ΔRd (blue), ΔSd (green), ΔRr (red), and ΔRx (yellow).



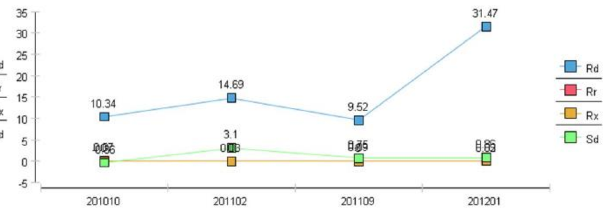
(a) Gap statistics for Locomotive 1 (I1H)



(b) Gap statistics for Locomotive 2 (I1H)



(c) Gap statistics for Locomotive 1 (II1H)



(d) Gap statistics for Locomotive 2 (II1H)

Figure 37: Gap statistics by date (before and after re-profiling): one example (I1H & II1H)

As discussed above, the statistics for the wheels installed in the same bogie are quite similar. Among these four parameters, the changing of ΔRd is the most obvious, with ΔSd coming second. The changing of ΔRr and ΔRx are random and the amount is quite small compared to the first two parameters. Therefore, we suggest applying the first two parameters to monitor the wheels' re-profiling performance in the future.

6.3.4.3 Results from comparing wear rate

Table 30 shows locomotive 1, bogie 1 and the first axle on the right side; Table 31 shows locomotive 1, bogie 2 and the first axle on the right side. The number of re-profiling work orders is different between bogies: bogie 1 has 4 and bogie 2 has 5. The reason for the difference may be that bogie 1 was changed after the fourth re-profiling. The re-profiling at times 1 to 4 was done at the same time for both bogies, extending over 12 months.

As for locomotive 1, Table 30 shows that it has been running for 123.351 km; the mean distance between re-profiling is 41.117 km. The distance after the last re-profiling for bogie 2 was only 17.930 km, less than half of the average distance for re-profiling numbers 1 to 4; see Table 31. Table 30 and Table 31 also show the diameter of the wheel before and after re-profiling and the amount of material removed at each re-profiling. The mean amount of material removed during re-profiling for bogie 1 is 16.193 mm and for bogie 2, 11.176 mm. Remarkably, the amount of re-profiling for bogie 2, step 2 is 27.04 mm, much more than the others; as noted above, the mean is 16.193 mm. If we compare natural wear with artificial wear, the former is between 15 mm and 20% of the total wear. In addition, the total wear rate for locomotive 2, bogie 1, is 0.619 mm/1000 km; for bogie 2, it is 0.393 mm/1000km.

As mentioned, locomotive 1 and locomotive 2 have the same operating conditions (see Figure 37 for the comparison), but the figures in Table 32 and Table 33 show different results. Table 32 shows locomotive 2, the first bogie, the first axle, and the right hand side wheel; Table 33 shows the second bogie, the first axle, and the right hand side wheel. This locomotive has been re-profiled 4 times in 15 months; the mean distance between re-profiling is 56.990 km. The mean amount of material removed for re-profiling for bogie 1 is 15.10 mm; for bogie 2 it is 16.51 mm. The last re-profiling for the first bogie removed 26.59 mm and for the second bogie 31.47 mm. Finally, the total wear rate for locomotive 2, bogie 1, is 0.452 mm/1000 km and for bogie 2, 0.484 mm/1000km

Table 30: Statistics for wear rate: an example (locomotive 1, II1H)

Locomotive	1	Position	I1H		Total/Average
Number of re-profiling	1	2	3	4	4 times
Re-profiling date	201010	201103	201108	201110	12 months
Reported kilometres /1000km	720.254	759.032	815.661	843.605	/
Absolute kilometres /1000km	0	38.778	56.629	27.944	123.351
Diameters (before)/mm	1252.72	1240.08	1207.11	1187.81	/
Diameters (after)/mm	1243.93	1213.04	1189.64	1176.34	/
Re-profiling Amount/mm	8.79	27.04	17.47	11.47	64.77
Natural Wear/mm	0	3.85	5.93	1.83	11.61
Total Wear/mm	8.79	30.89	23.4	13.3	76.38
Re-profiling Amount %	1	0.875	0.747	0.862	0.848
Natural Wear %	0	0.125	0.253	0.138	0.152
WearRate_re-profiling	/	0.697	0.308	0.41	0.525
WearRate_Natural	/	0.099	0.105	0.065	0.094
WearRate_Total	/	0.797	0.413	0.476	0.619

Table 31: Statistics for wear rate: an example (locomotive 1, II1H)

Locomotive	1	Position	II1H			Total/Average
Number of re-profiling	1	2	3	4	5	5 times
Re-profiling date	201010	201103	201108	201110	201112	14 months
Reported kilometres /1000km	838.124	876.902	933.531	961.475	979.405	/
Absolute kilometres /1000km	0	38.778	56.629	27.944	17.93	141.281
Diameters (before)/mm	1251.01	1241.39	1226.34	1208.59	1182.66	/
Diameters (after)/mm	1244.72	1231.16	1211.09	1195.43	1171.71	/
Re-profiling Amount/mm	6.29	10.23	15.25	13.16	10.95	44.93
Natural Wear/mm	0	3.33	4.82	2.5	12.77	10.65
Total Wear/mm	6.29	13.56	20.07	15.66	23.72	55.58
Re-profiling Amount %	1	0.754	0.76	0.84	0.462	0.808
Natural Wear %	0	0.246	0.24	0.16	0.538	0.192
WearRate_re-profiling	/	0.264	0.269	0.471	0.611	0.318
WearRate_Natural	/	0.086	0.085	0.089	0.712	0.075
WearRate_Total	/	0.35	0.354	0.56	1.323	0.393

Table 32: Statistics for wear rate: an example (locomotive 2, I1H)

Locomotive	2	Position	11H		Total/Average
Number of re-profiling	1	2	3	4	4 times
Re-profiling date	201010	201102	201109	201201	15 months
Reported kilometres /1000km	33.366	87.721	161.346	204.349	/
Absolute kilometres /1000km	0	54.355	73.625	43.003	170.983
Diameters (before)/mm	1251.97	1234.15	1217.22	1201.24	/
Diameters (after)/mm	1239.04	1225.41	1205.07	1174.65	/
Re-profiling Amount/mm	12.93	8.74	12.15	26.59	60.41
Natural Wear/mm	0	4.89	8.19	3.83	16.91
Total Wear/mm	12.93	13.63	20.34	30.42	77.32
Re-profiling Amount %	1	0.641	0.597	0.874	0.781
Natural Wear %	0	0.359	0.403	0.126	0.219
WearRate_re-profiling	/	0.161	0.165	0.618	0.353
WearRate_Natural	/	0.09	0.111	0.089	0.099
WearRate_Total	/	0.251	0.276	0.707	0.452

Table 33: Statistics for wear rate: an example (locomotive 2, II1H)

Locomotive	2	Position	21H		Total/Average
Number	1	2	3	4	4 times
Date	201010	201102	201109	201201	15 months
Reported kilometres /1000km	33.366	87.721	161.346	204.349	/
Absolute kilometres /1000km	0	54.355	73.625	43.003	170.983
Diameters (before)/mm	1252.09	1236.67	1213.58	1200.81	/
Diameters (after)/mm	1241.75	1221.98	1204.06	1169.34	/
re-profiling Amount/mm	10.34	14.69	9.52	31.47	66.02
Natural Wear/mm	0	5.08	8.4	3.25	16.73
Total Wear/mm	10.34	19.77	17.92	34.72	82.75
re-profiling Amount %	1	0.743	0.531	0.906	0.798
Natural Wear %	0	0.257	0.469	0.094	0.202
WearSpeed_re-profiling	/	0.27	0.129	0.732	0.386
WearSpeed_Natural	/	0.093	0.114	0.076	0.098
WearSpeed_Total	/	0.364	0.243	0.807	0.484

By comparing the interval of the re-profiling date, we can simply divide each re-profiling episode into seasons (for instance, the summer and warmer times, the winter and cooler times).

In Table 34, we list the statistics for the WearRate_total of all the wheels for the two locomotives. The mean wear rates are 0.516 mm/1000km for locomotive 1 and 0.480

mm/1000km for locomotive 2; in other words, locomotive 1 has a 75% higher wear rate. Axles 1, 2 and 5 have 11.6 % higher wear rate than axles 3, 4 and 6.

Table 34: Statistics for total wear rates

WearRate_total												
	11H	11V	12H	12V	13H	13V	21H	21V	22H	22V	23H	23V
Locomotive 1	0.619	0.607	0.614	0.605	0.542	0.533	0.393	0.404	0.467	0.467	0.467	0.472
Locomotive 2	0.452	0.439	0.448	0.448	0.449	0.448	0.484	0.482	0.568	0.575	0.487	0.476

By comparing the above parameters of the wheels installed in different positions on the locomotives, we reach the following additional conclusions:

- the average wear rate of the wheels on locomotive 1 is greater than for locomotive 2;
- the natural wear is about 10% ~ 25 % of the total wear; the re-profiling is about 75 %~ 90% of the total;
- the natural wear in winter time is slower than in summer;
- the re-profiling rate in winter is faster than in summer;
- the wheels installed on the second axel in the second bogie have an abnormally higher wear rate than the wheels installed in the same bogie but on the other axel; this requires more attention;
- The wheels installed in the same bogie perform similarly.

Generally speaking, the results in this study show that for the two locomotives: 1) under the specified installation position and operating conditions, the Weibull frailty model is a useful tool to determine wheel reliability; 2) RCF is the principal reason for re-profiling work orders; 3) the re-profiling parameters can be applied to monitor both the wear rate and the re-profiling loss; 4) the total wear of the wheels can be investigated by considering natural wear and re-profiling loss separately, but natural wear and re-profiling loss differ depending on the locomotive and the operating conditions; and 5) the bogie in which a wheel is installed influences wheel reliability.

6.3.5 Comparison Analysis with Classical and Bayesian Approaches

6.3.5.1 Data for Comparison Analysis

6.3.5.1.1 Degradation Data

Table 35 and Table 36 present the degradation data for the wheel-sets of Locomotive 1 and Locomotive 2, respectively.

Table 35: Degradation Data of Locomotive 1

Distance (kilometres)	Degradation(mm)											
	Bogie I						Bogie II					
	1	2	3	4	5	6	7	8	9	10	11	12
106613	13.08	13.19	12.11	12.12	12.99	13.04	13.02	13.01	11.94	12.01	13.01	13.16
144207	27.11	27.07	23.01	22.86	25.03	25.09	24.09	24.12	23.95	24.06	26.56	26.55
191468	38.95	38.94	39.11	39.06	39.15	39.17	35.95	35.95	35.88	35.93	36.24	36.04
272697	70.6	70.53	69.94	69.87	69.9	69.9	79.7	79.73	79.73	79.74	79.59	79.76
309426	85.05	85.07	85.09	85.12	85.26	85.27	/	/	/	/	82.87	83.77

Table 36: Degradation Data of Locomotive 2

Distance (kilometres)	Degradation(mm)											
	Bogie I						Bogie II					
	1	2	3	4	5	6	7	8	9	10	11	12
33366	10.96	11.02	10.45	10.54	10.11	10.04	8.25	8.12	/	/	10.06	10.03
87721	24.59	24.56	25.11	25.3	26.68	26.65	28.02	27.99	27.92	28.36	28.05	28.07
161346	44.93	45.16	44.59	44.56	44.63	44.62	45.94	45.89	45.96	45.91	45.98	45.96
204349	75.35	75.12	74.94	75.02	74.7	74.68	80.66	80.76	80.52	80.68	80.87	80.91

6.3.5.1.2 Degradation Path and Lifetime Data

From the dataset (see Table 35, Table 36), we can obtain 3 to 5 measurements of the diameter of each wheel during its lifetime. By connecting these measurements, we can determine a degradation trend. The first step of the analysis is the selection of the degradation model. In their analyses of train wheel-sets, most studies (Freitas et al. 2009, 2010; Lin et al. 2013) assume a linear degradation path. In our study, we plot the degradation data for the locomotive wheel-sets using Exponential degradation, Power degradation, Logaritmic degradation, Gompertz degradation, and the linear degradation path in Weibull++.

The results (see Figure 38– Figure 40) show that the better choices are Gompertz degradation, Exponential degradation, and Power degradation, but the Gompertz model needs a total of more than 5 points to converge. The selection should be based on physics of failure (wear or fatigue). In our study, based on the type of physics of failures associated with wear and fatigue, we select Exponential and Power degradation models.

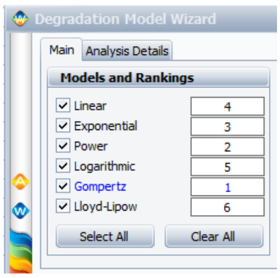


Figure 38: Degradation path analyses

An Exponential model is described by the following function (3.1) and the Power model by the function (3.2) from Nelson (1990):

Exponential:

$$y = b \cdot e^{a \cdot x} \tag{3.1}$$

Power:

$$y = b \cdot x^{a \cdot c} \tag{3.2}$$

where y represents the performance (here, the diameter of the wheels), x represents time (here, the running distance of the wheels), and a, b and c are model parameters to be solved. Figure 39 and Figure 40 show the results of the analysis using a Power function, an Exponential function and the Gompertz degradation path, respectively, for a critical degradation level (threshold level l_0) of 100mm.

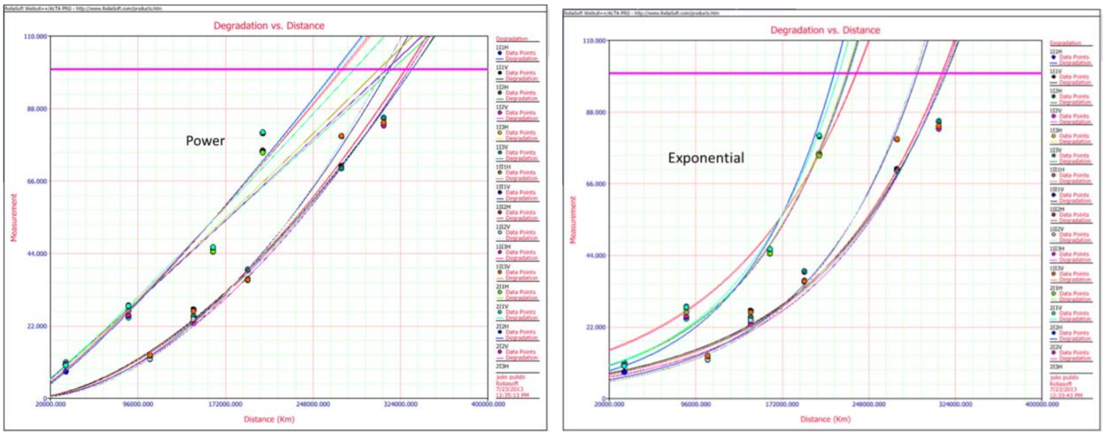


Figure 39: Degradation with Power function (left) - Degradation with Exponential function (right)

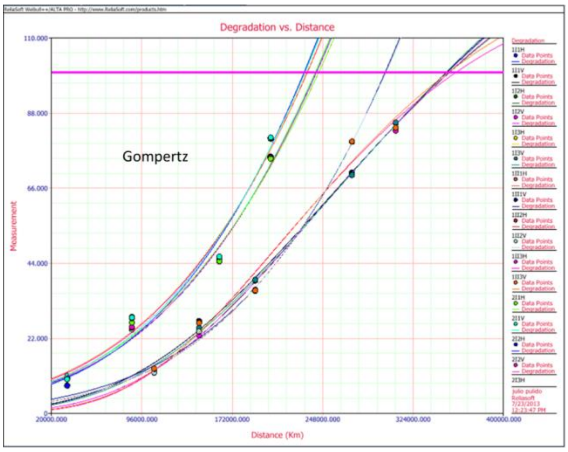


Figure 40: Degradation with Gompertz function

Following the above discussion, a wheel's failure condition is assumed to be reached if the diameter reaches l_0. We adopt the both the Exponential degradation path and Power degradation path for all wheel-sets and set $l_0 = y$. The lifetimes for these wheels are now easily determined and are shown in Table 37. Note: As discussed by Lin et al. (2013), some lifetime data can be viewed as right-censored (denoted by asterisk in Table 37).

Table 37: Statistics on lifetime data

No.	Positions		Lifetime**		No.	Positions		Lifetime**	
	Loco.	Bogie	Exponential	Power		Loco.	Bogie	Exponential	Power
1	1	I	316	334	13	2	I	230	316
2	1	I	316	334	14	2	I	230	317
3	1	I	314	331	15	2	I	230	312
4	1	I	314	331	16	2	I	230	312
5	1	I	316	334	17	2	I	229	305
6	1	I	316	334	18	2	I	228	305
7	1	II	291*	314*	19	2	II	218	269
8	1	II	291*	314*	20	2	II	217	268
9	1	II	289*	310*	21	2	II	237	273
10	1	II	289*	310*	22	2	II	237	274
11	1	II	312	329	23	2	II	222	284
12	1	II	312	328	24	2	II	222	284

* Right-censored data; ** $\times$ 1000 km.

6.3.5.2 Results and Discussions from Classical Approach

Estimating the failure-time distribution or long-term performance of components of high reliability products is particularly difficult. Many modern products are designed to operate without failure for years, tens of years, or more. Thus, few units will fail or significantly degrade in a test of practical length at normal use conditions. For this reason, Accelerated Life Tests (ALT) are widely used in manufacturing industries, particularly to obtain timely information on the reliability of product components and materials. Generally, information from tests at high stress levels of accelerating variables (e.g., use rate, temperature, voltage, or pressure) is extrapolated through a physically reasonable statistical model (e.g. Eiren, Arrhenius, Inverse Power Law), to obtain estimates of life or long-term performance at lower, normal use conditions. ALT results are used in design-for-reliability processes to assess or demonstrate component and subsystem reliability, certify components, detect failure modes, compare different manufacturers, and so forth. ALTs have become increasingly important because of rapidly changing technologies, more complicated products with more components, and higher customer expectations of better reliability.

In some reliability studies, it is possible to measure degradation directly over time, either continuously or at specific points in time. In most reliability testing applications, degradation data, if available, can have important practical advantages (Levin, 2003): particularly in applications where few or no failures are expected, they can provide considerably more reliability information than would be available from traditional censored failure-time data. Accelerated tests are commonly used to obtain reliability test information more quickly. Direct observation of the degradation process (e.g., tire wear) may allow direct modelling of the failure-causing mechanism, providing more credible and precise reliability estimates and a valid basis for extrapolation. Modelling degradation of performance output of a component or subsystem (e.g., voltage or power) may be useful, but modelling could be more complicated or difficult because the output may be affected, albeit unknowingly, by more than one physical/chemical failure-causing process.

In this section, we analyse the degradation data with ALT, considering lifetime data from both the Exponential degradation path and the Power degradation path. The analysis uses a General Log Linear (GLL) life stress relationship. Then, using the Exponential degradation model, we perform a two factor full factorial Design of Experiments analysis. We conclude with a discussion of the findings.

6.3.5.2.1 Results from Accelerated Life Testing (ALT)

Once we obtain the projected failures values for each degradation model, see Table 37, we carry out an accelerated life analysis using the locomotive and bogie as stress factors. The analysis is performed using a General Log Linear (GLL) life stress relationship (3.3) with a Weibull probability function (Meeker and Escobar, 1998).

$$L(\underline{X}) = e^{\left(\alpha_0 + \sum_{i=1}^{m} \alpha_i X_i\right)}$$
(3.3)

This model can be expressed as an Exponential model, expressing life as a function of the stress vector X , where X is a vector of n stressors (Meeker and Escobar, 1998).

For this analysis, we consider stress applications of the model and a logarithmic transformation on X, such that $X = \ln(V)$ where V is the specific stress. This transformation generates an inverse power model life stress relationship, as shown below for each stress factor (Meeker and Escobar, 1998):

$$L(V) = \frac{1}{KV^n}$$
(3.4)

The results of the life data analysis and reliability curves appear in Figure 41.

As shown in Figure 41, the Exponential function for this set of data yields more conservative results and is in line with the field observation when life data are compared at different stress levels as previously defined. Figure 41(b) shows reliability values for Locomotive 2 and Bogie 2; both sides have 95% confidence level.

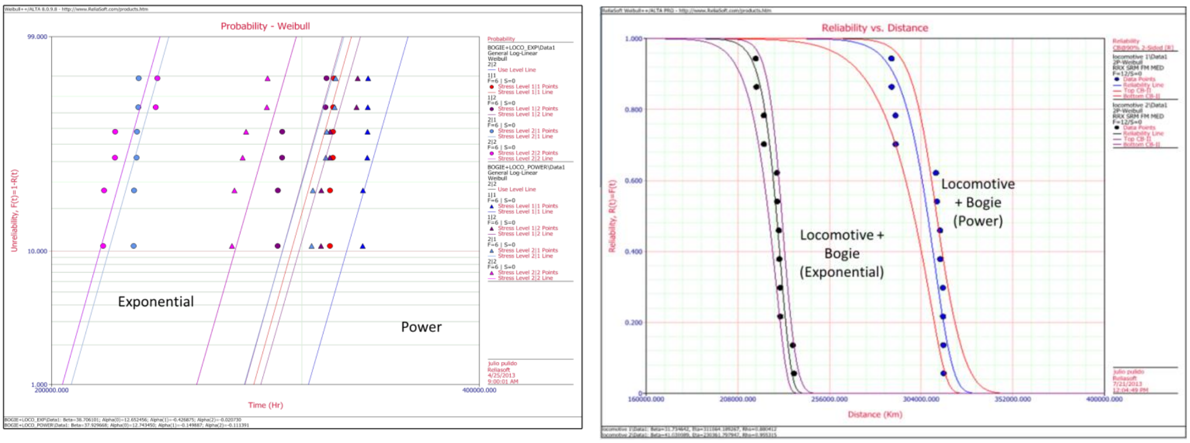


Figure 41: Life Data Analysis (left) - Reliability Curve for Degradation Type (right)

6.3.5.2.2 Results from Design of Experiments Analysis (DOE)

Using the exponential degradation model, we perform a two factor full factorial Design of Experiments analysis and find that the locomotive, bogie and interaction are critical factors (see Figure 42). A review of the life stress relationship between the factors indicates the locomotive is a higher contributor to the degradation of the system than the bogie (Figure 43).

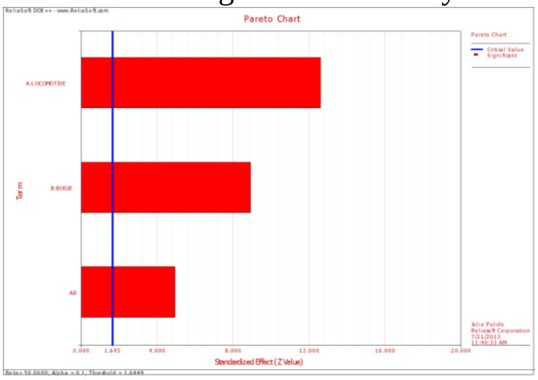


Figure 42: Factors Pareto Chart

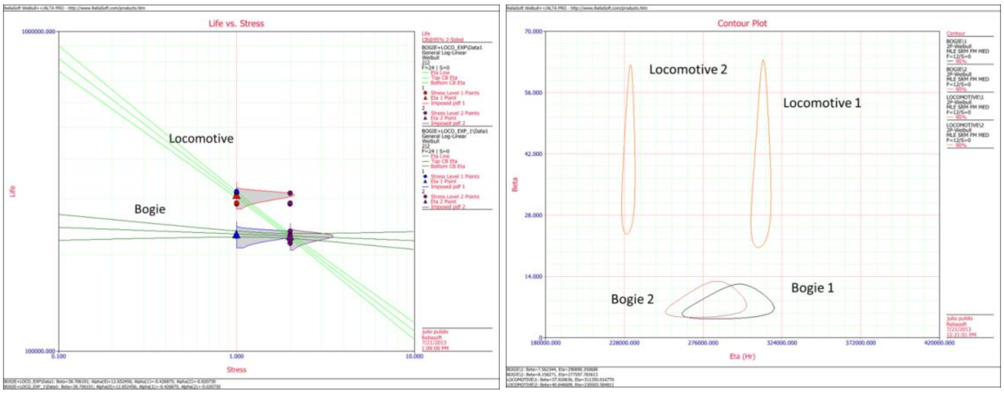


Figure 43: Life vs. Stress (left) - Contour Plot (right)

6.3.5.2.3 Results and Conclusions

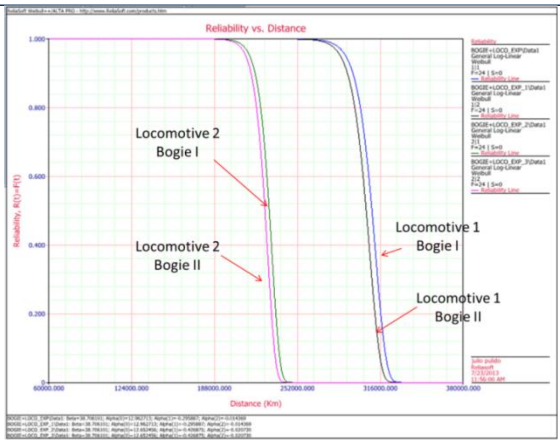


Figure 44: Reliability Curves at each condition

Based on the analysis, we reach the following conclusions. Independent of the Degradation model, the locomotive factor is the more critical stressor, as shown in the data above. Failure modes obtained from the data are similar for the locomotive and for the bogies. Of the two stress conditions, level 2 is the highest for the locomotive and bogie. Figure 44 shows the reliability values at each operating distance and indicates that Locomotive 2 has the highest degradation per distance travelled.

6.3.5.3 Comparison of Classical and Bayesian Approaches

For the sake of comparison, Table 38 presents the reliability statistics using the classical model and an Exponential degradation path, as discussed in Section 3.

Table 38: Reliability statistics using classical model

Distance (1000 km)	Reliability $R(t)$			
	Locomotive 1		Locomotive 2	
	Bogie I	Bogie II	Bogie I	Bogie II
60	1.000000000000	1.000000000000	1.000000000000	1.000000000000
120	1.000000000000	1.000000000000	1.000000000000	1.000000000000
180	0.999999999500	0.999999999100	0.999949988500	0.999912782200
240	0.999963596200	0.999936513100	0.032469287900	0.002535299700
300	0.814489640600	0.699174645800	0.000000000000	0.000000000000
360	0.000000000000	0.000000000000	0.000000000000	0.000000000000

The results of the two approaches show that Locomotive 2 has lower reliability than Locomotive 1. In addition, for both Locomotive 1 and Locomotive 2, before the fourth piecewise interval, the reliability statistics from the classical approach have a higher value; after the fifth piecewise interval, the reliability statistics from the Bayesian approach have a higher value.

6.3.6 Holistic Study of Running Surface Wear Data

As we mentioned above, from the dataset, we can obtain 3 to 5 measurements of the diameter of each wheel during its lifetime. By connecting these measurements, we can determine a degradation trend.

In their analyses of train wheels, most studies (Freitas et al. 2009, 2010; Lin et al. 2013) assume a linear degradation path. In our study, we plot the degradation data for the locomotive wheels using Exponential degradation, Power degradation, Logaritmic degradation, and the linear degradation path in Weibull++. The Gompertz model needs a total of more than 5 points to converge; therefore, it was not considered here. The results show that the better choices are Linear degradation, Power degradation, and Exponential degradation. The selection should be based on physics of failure (wear or fatigue). In our study, we select the linear degradation model.

Let the longitudinal axle represent the performance (here, the diameter of the wheels), and the horizontal axle represe w that the better choices are 3-parameter Weibull and Log-normal distribution. The selection should nt time (here, the running distance of the wheels).

The results sho be based on physics of failure (wear or fatigue). In our study, based on the type of physics of failures associated with wear and fatigue, we select the 3-parameter Weibull lifetime model.

The probability density function (pdf) 3-parameter Weibull distribution is shown in equation (3.6.1):

$$f(t) = \frac{\beta}{\eta}\left(\frac{t-\gamma}{\eta}\right)^{\beta-1} \exp(-\left(\frac{t-\gamma}{\eta}\right)^{\beta})$$

(3.6.1)

where t is the failure time, $\beta > 0$ is the shape parameter, $\eta > 0$ is the scale parameter, and $-\infty < \gamma < +\infty$ is the location parameter or failure-free life. The probability density function of the wheel-sets' reliability in this holistic study is:

$$f(t) = \frac{1.47}{85.8}\left(\frac{t-223.96}{85.8}\right)^{1.47-1} \exp(-\left(\frac{t-223.96}{85.8}\right)^{1.47})$$

(3.6.2)

Other reliability related characteristics could be obtained following equation (3.6.2).

In this holistic study, data analysis is carried out from both the locomotives and the bogies' perspective. The results show that Malmbanan should consider wheel-set data from both points of view. We study the data on wheel-sets' running surface wear for a group of 16 bogies. We derive holistic results from both degradation analysis and wear rate analysis, including the following: first, for the group examined, a linear degradation path is more suitable; following linear degradation, the best life distribution is a 3-parameter Weibull distribution, and the next best is lognormal; second, comparing the wear data of the wheel-sets' running surfaces (including total wear rate, natural wear rate, re-profiling wear rate, the ratio of re-profiling and natural wear) is an effective way to optimise maintenance strategies; finally, more natural wear occurs for the wheels installed in axel 1 and axel 3, a finding that supports related studies at Malmbanan. In addition, there are some problems with data quality in the work orders.

More details can be found in our 2014 report "Data Analysis of Heavy Haul Locomotive Wheel-sets' Running Surface Wear at Malmbanan".

6.4 Conclusions and Recommendations

From the discussion of the research questions, we reach the following conclusions.

First, the proposed integrated procedure for Bayesian reliability inference using MCMC methods has built a full framework for related academic research and engineering applications to implement modern computational-based Bayesian approaches, especially for reliability inference. The suggested procedure is a continuous improvement process with four stages (Plan, Do, Study, and Action) and 11 sequential steps, which can deal with small and incomplete datasets and simultaneously consider the influence of different covariates.

Second, the parametric Bayesian models (including Bayesian Exponential Regression Model, Bayesian Weibull Regression Model, and Log-normal Regression Model, etc.), non-parametric Bayesian models (piecewise constant hazard rate, etc.), frailty models (gamma frailty, etc), as well as the comparison study, are all useful tools for locomotive wheels' reliability analysis using degradation data. Utilising the MCMC technique via the Gibbs sampler can facilitate the integration of high-dimensional probability distributions to make inferences about model parameters and to make predictions.

Third, the results of the case studies show that with the above Bayesian models, we can determine the locomotive wheel's reliability characteristics, including the baseline hazard rate $\lambda(t)$, reliability $R(t)$, and cumulative hazard rate $\Lambda(t)$, etc. The results also allow us to evaluate and optimise wheel replacement and maintenance strategies (including the re-profiling interval, inspection interval, lubrication interval, depth and optimal sequence of re-profiling, and so on).

Fourth, the case studies' results also reveal that, the wheels' lifetimes differ according to where they are installed on the locomotive. The differences could be influenced by the real running situation (e.g. topography), the locomotive's centre of gravity, the braking forces and the curving forces should also be considered.

Fifth, considering frailties can help with exploring the unobserved covariates and thus improve the model's precision. Results indicate a close positive relationship between the wheels mounted on the same locomotive; the heterogeneity between locomotives is also significant. The results indicate the existence of change points which allow us to evaluate and optimise wheel replacement and maintenance strategies.

Sixth, in the comparison study which takes an integrated data approach to reliability assessment by considering both degradation data and re-profiling data, we reach the following conclusion: 1) rolling contact fatigue (RCF) is the main type of re-profiling work order; 2) the re-profiling parameters can be applied to monitor both the wear rate and the re-profiling loss; 3) the total wear of the wheels can be determined by investigating natural wear and/or loss of wheel diameter through re-profiling loss, but these differ across locomotives and under different operating conditions; 4) the bogie in which a wheel is installed is a key factor in assessing the wheel's reliability.

Seventh, other traditional statistical theories (incl., reliability analysis, degradation analysis, Accelerated Life Tests (ALT), Design of Experiments (DOE)) are also useful tools for exploring the impact of the locomotive wheel-sets' installed position (incl. positions of the installed locomotive, bogie, axel.) on their service lifetime and for attempting to predict the reliability related characteristics.

Eighth, the holistic study using data from 26 locomotives and 57 bogies at Malmbanan shows that Malmbanan should consider the wheel-set data not only from the locomotives' but also from the bogies' point of view. For the studied group, a linear degradation path is more suitable; following the linear degradation, the best life distribution is a 3-parameter Weibull distribution, and the second best is lognormal; comparing the wear data of the wheel-sets' running surfaces (including total wear rate, natural wear rate, re-profiling wear rate, the ratio of re-profiling and natural wear) is an effective way to optimise maintenance strategy decision making. The results of the case studies show natural wear occurs for the wheels installed in axel 1 and axel 3; this supports findings in related studies at Malmbanan.

In addition, all case studies' results reveal that, the wheels' lifetimes differ according to where they are installed on the locomotive. The differences could be influenced by such factors as the operating environment (e.g., climate, topography, track geometry), configuration of the suspension, status of the bogies and spring systems, operating speeds and applied loads, as well as human influences (drivers' operations, maintenance policies, lathe operators etc.).

Last but not least, the approach studied in this report can be applied to cargo train wheel-sets or to other technical problems (e.g. other industries, other components).

Based on the research conducted for this report we have the following recommendations:

- Results from this study should be considered for improving daily maintenance strategies.
- Considering the abnormal data found in this project, data quality in both work orders and re-profiling systems needs to be improved.
- In this project, we can only consider one lifecycle's data for each wheel-set due to time limitation. To achieve more convincing results and effectively monitor wheel-set performance, this study should be continuous.
- Results from this study could be used in other research in the internal workshop.

In addition, we suggest the following research:

- In this research, the case studies only focus on locomotive wheel-sets. We should consider more applications, for instance, cargo train wheel-sets, or other technical problems (e.g. other industries, other components).
- The results achieved by this study could be extended to other train wheel-set research topics, e.g., Wheel-set "health diagnostic", RAMS driven Maintenance Strategy Review & Optimization for Rolling Stock Wheels, Precise Maintenance Strategies Making, etc.
- The covariates considered in this report are limited to locomotive wheels' installed positions; more covariates must be considered. These include such factors as operating

environment (e.g., climate, topography, track geometry, the braking forces and the curving forces), configuration of the suspension, status of the bogies and the spring systems, operating speeds and applied loads, etc.

- Results from the study should be studied further. For instance, the piecewise for each re-profiling period should be considered separately.
- In subsequent research, we plan to consider using our results to optimise maintenance strategies and the related LCC (Life Cycle Cost) problem considering maintenance costs, particularly with respect to different maintenance inspection levels and inspection periods (long term, medium term and short term).

7. PROPOSITION OF CONDITION DATA USE FOR PREVENTIVE MAINTENANCE

Wayside monitoring systems give early-warning on defect vehicles and redirect them to a workshop based on economic maintenance limits (still within the safety limits). The wayside monitoring systems can also produce statistics on the track utilisation which is an essential input to track maintenance planning and the prediction of track degradation.

The principles described in this report can also be used for scheduling condition based preventative maintenance and repair, driven by usage and/or deterioration of the structure, rather than the widespread sub-optimal practice of using time-interval based maintenance. Sensors can be utilized to determine what loads have been imparted on a structure, and to assess the resistance or remaining capacity of a structure.

Hereafter we propose some directions to deal with predictive maintenance based on condition monitoring. First, Condition monitoring methods that are employed in other industries and which have potential applications in rail industry are presented. Then, a possible use of a “smart washer” prototype for preventive maintenance of bolts is presented.

7.1 Condition monitoring methods employed in other industries which have potential applications in rail industry

The existing computer simulation tools used to design and assess railway vehicle performance require a detailed knowledge of the vehicle and track parameters. Also the dynamic behaviour of the railway vehicles is highly non-linear and difficult to predict so it is beneficial to use condition monitoring and prediction methods for vehicle dynamic performance employing the parameters of the electrical motor and drive installed on the passenger rail vehicle and locomotive for the freight trains.

Zhao et at (2012) [33] have used a Kalman filter to estimate the creep force and creepage between the wheel and rail and the friction coefficient using the estimated creep force-creepage relationship. The mathematic model of the simplified driving system contains an AC motor, wheel and roller and the simulation model contains the parameters of the actual test rig. It is necessary to measure only the stator voltage, current and speed of the motor which are then processed through a Kalman filter. Residuals between the estimated creepage-creep force curve and those of theoretical values with different friction coefficients are calculated. By calculating the root mean square of the residuals (see Figure 45) and searching for the least root mean square, the friction coefficient is identified. The results have shown that the error is small and the estimation of the friction coefficient is accurate.

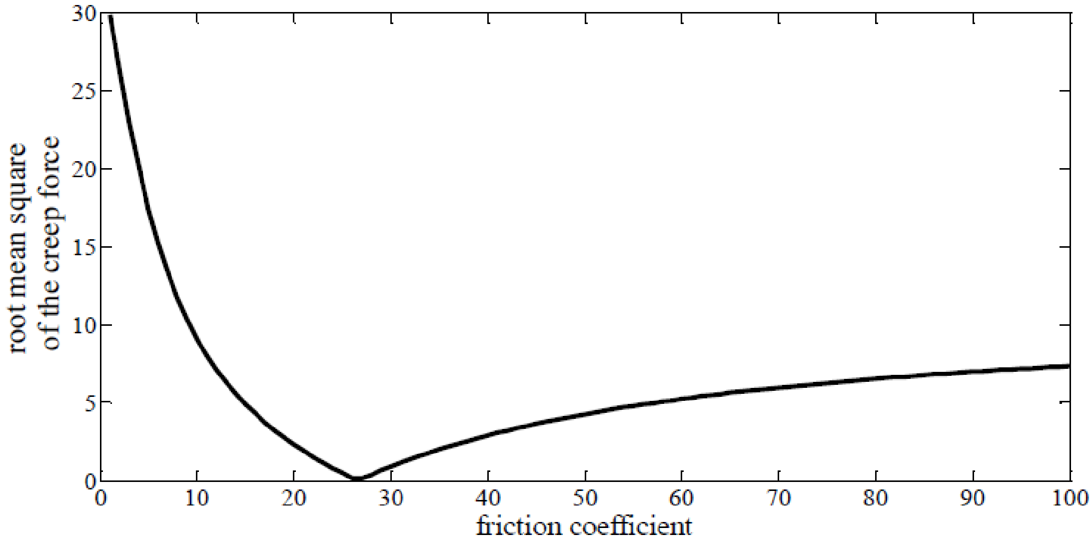


Figure 45: Root mean square value of the creep force (Zhao et al, 2012)

The proposed method can be improved by incorporating techniques used in other industries. Pislaru et al (2012) [34] has performed the gearbox fault detection using the inverter signals to monitor the influence of the mechanical load. The gear faults are time-localized transient events and the existing time-frequency analysis techniques (such as the Short-Time Fourier Transform, Wavelet Transform, motor current signature analysis, empirical mode decomposition, Teager Kaiser Energy Operator, etc.) enable the recognition of the vibration modes but require a lot of computational power. The following variables were measured: the armature current in DC motor (load), speed and torque feedback signals for AC motor (actuator) and speed demand for the inverter. The comparison between measured signals for healthy and faulty gearboxes (see Figure 46) showed that the actuator can be used as a transducer for detecting electrical and electromechanical faults on an inverter-driven motor system. This method can be combined with the method developed by Zhao et al (2012) in order to study the link between the variation of the rail vehicle motor parameters and forces acting on the wheel-rail interface (normal, tangential, creep, etc.)

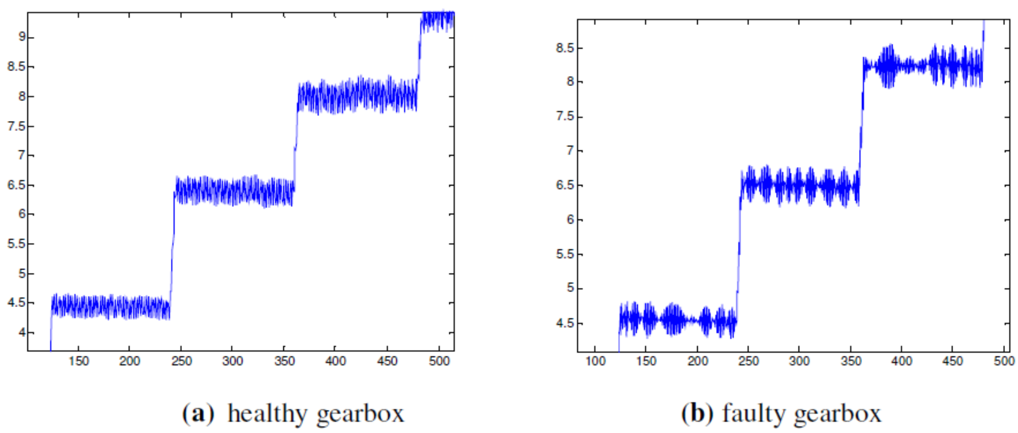


Figure 46: Comparison between the actual AC motor currents (Pislaru et al, 2012)

Gu et at (2011) [35] have used a modified bispectrum analysis of the induction motor current in order to identify and quantify common faults within a two-stage reciprocating compressor.

A study of the nonlinear characteristics of current signals when the motor undertakes a varying load under different faulty conditions was performed. The conventional bispectrum representation of current signal allows the inclusion of phase information and the elimination of Gaussian noise but produces unstable results due to random phase variation of the sideband components. The proposed modified bispectrum allows the combination of both lower sidebands and higher sidebands simultaneously and the identified normalised bispectral peak can be used in association with the kurtosis value of the raw current signal for reliable fault classification results (see Figure 47). This novel approach to the analysis of stator current for the diagnosis of motor drive faults from downstream driving equipment can be used in conjunction with the method developed by Zhao et al (2012) for the development of accurate condition monitoring and prediction methods for passenger rail vehicle and locomotive dynamic performance.

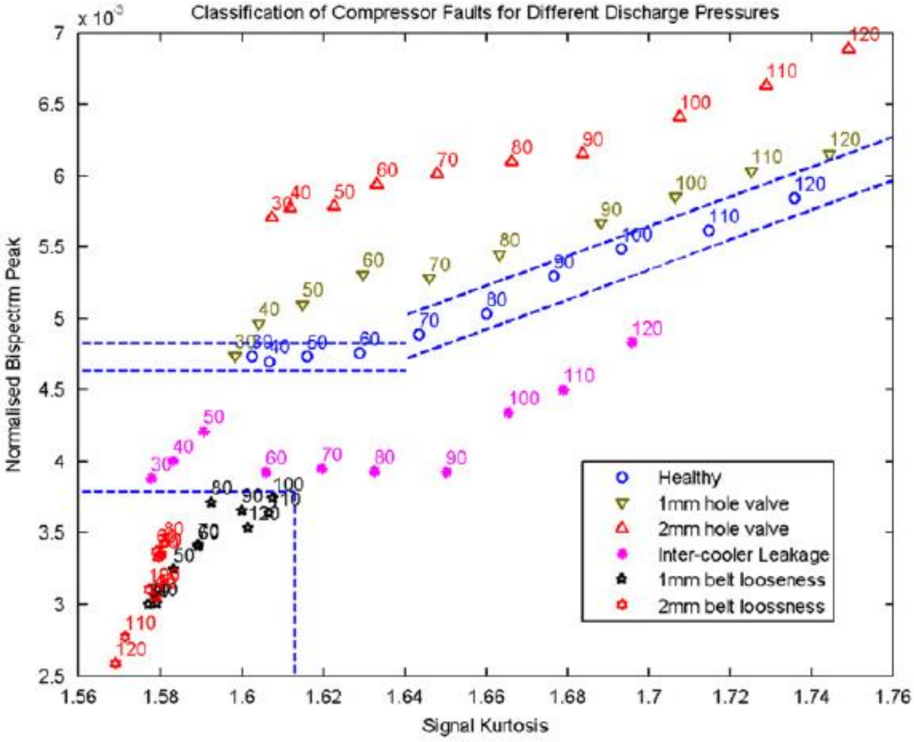


Figure 47: Performance of compressor fault classification at different discharge pressure

The development of future on-board intelligent condition monitoring systems able to perform accurate analysis of the rail vehicle motor current and other parameters and link it with the mechanical causes (wheel-rail forces, suspension, bogie, chassis, wheelsets, etc.) could provide useful information for preventive maintenance decision and planning.

7.2 Possible use of smart washer for preventive maintenance of bolts

Tesfa et al (2012) [36] have developed a clamping force measurement system for the monitoring of the condition of railway track joints. The piezo-resistive based clamping force sensor (packaged as a smart washer) has been developed by using a combination of fragile piezo-resistive sensor elements, elastomers and other components. Several sensor technologies have been studied: capacitive, strain gauge, piezo-resistive (polymer film, fabric). They have been compared based on sensing element performance, electronic circuitry, wireless compatibility, sensor construction implications, sensing element cost. By considering the working environment of the washer, a polymeric material was selected that can resist fluctuations in the environment yet withstand significant loads, applied for long period of time.

Practical lab tests have shown a non-linear relationship between the sensor resistivity and the axial load over the range 20 to 70 kN for compression (bolt tightening) and decompression (bolt slackening) (see Figure 48). These lab results show that the smart washer has the potential to monitor the clamping force of bolted joints, in-situ, as found on the stretcher bars present in all railway points. These achievements were possible due to the University of Huddersfield international expertise in the field of machinery condition and performance monitoring using non-intrusive parameter estimation and model based fault diagnosis methods.

The maintenance can be performed on five fundamental ways on fixed assets. The vast majority of proactive maintenance is performed using Planned Preventive (PPM) and Condition Based (CBM) approaches. The Smart Washer has been designed to facilitate each of these maintenance methodologies. Although it is possible to use PPM and CBM approaches independently and in isolation, it is far more common that the two are used together, because significant additional benefits arise.

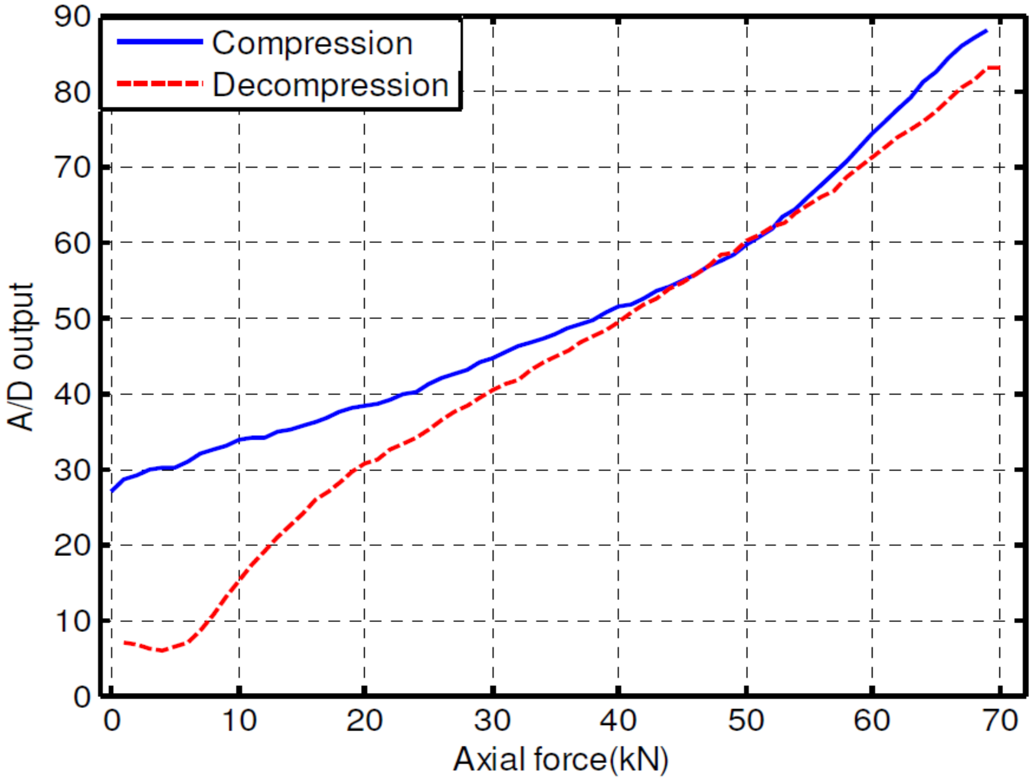


Figure 48: Digital response curve of the washer design as a function of applied axial force

CBM itself can be performed in two basic ways: manual (periodic, off-line) inspection-style data acquisition, and automated (continuous, on-line) monitoring-style data acquisition. The manual condition monitoring of assets permits long-term trending of deterioration and scheduling of maintenance, whereas automated condition monitoring provides (in addition) the round-the-clock integrity assurance of the asset. To prevent confusion it is worth mentioning that modern high-tech maintenance approaches often blur the distinction between PPM and manual CBM because they quite rightly view the manual collection of condition indicating data as itself a PPM task.

The Smart Washer will embody three distinct forms of usage which will give enormous flexibility for use in the widest possible range of maintenance and monitoring applications:

1. Planned Preventive Maintenance – manual regime

2. **Condition Based Monitoring -** manual inspection style – periodic, off-line data acquisition

3. **Condition Based Monitoring -** automated inspection style – continuous, online data acquisition with Fixed Time Interval Monitoring; Monitoring Upon Request and Automated Alerting Upon Threshold.

Each inspection / monitoring tour downloaded to the Smart Washer's hand-held scanner will contain previous measurement history and alert / alarm thresholds for each measurement to be made. By comparing measured data with historical and symptom limit values it will be possible for the scanner to alert the user at the time of scanning if any immediate intervention (e.g. tightening) is required, or if the reading obtained is anomalous when compared to previous data (perhaps prompting immediate further investigation).

- The Monitoring Upon Request automatic-CBM mode will permit a Smart Washer to respond upon demand from the local data collection and transfer point. In this manner the user has the ability to vary the monitoring interval (e.g. tightening the monitoring interval if drift or gradual deviation is detected) and to initiate data collection to suit the need (e.g. convenience, or the proximity of a mobile asset like a track maintenance vehicle).
- The third automatic-CBM mode (Automatic Alerting Upon Threshold) will enable a Smart Washer to operate in an autonomous manner, automatically collecting data at pre-programmed intervals, comparing data values with locally stored (potentially even bespoke, adaptively determined) thresholds and communicating information accordingly to the local data collection and transfer point only if something abnormal is detected. Note that this mode would also include a fixed time interval 'heart beat' signal to provide audit trail confirmation that the Smart Washer is still functioning correctly.

The prototype for 'Smart Washer' has been included as a future innovation in course of validation in WP4 because it requires future developments in order to be tested in the field trails. The proposed innovation will address the following duty requirements specified in WP2:

- modest increase in freight speed – smart washer will provide an audit trail from which the tightness of fasteners can be assessed/trended so the smart monitoring of critical fastenings will generate a huge benefit in terms of operational safety and will significantly reduce the cost of rail infrastructure maintenance when the train speed is increased.
- more reliable insulated rail joints (life*5) – smart washer technology will be capable of monitoring fastener integrity, transferring the data to ensure remote monitoring and enabling the transition from time based planned preventive maintenance to a condition-based approach with integrated audit and quality assurance features.

8. CONCLUSION

The objective of this task was to give recommendations and to propose a guideline for good practice to help Infrastructure Managers (IMs).

This report includes identification and development of technologies and procedures that can be used to monitor track and structures to optimise preventative and intervention level maintenance strategies.
Overall, the existing situation in Europe regarding the monitoring of safety criteria through implementation of automatic inspection and monitoring systems is acceptable.
However, considering the latest technical innovations, researches and developments, there is a significant potential for improvement. Moreover, no international conclusions and clear recommendations for this safety criteria has been produced. The chapter 2 shows that the levels, and corresponding actions for wheel impact forces, varies for different countries, as does the means by which they are measured. The need of international standards for limits and methods is important. Otherwise, there will be problems regarding interoperability.

The chapter 3 describes current and innovative wayside monitoring technologies, with a focus on the monitoring systems able to provide data on forces and loads. The means by which the data collected from these technologies are used to define limits are also explained. It shows that a wide range of different on-track based measuring systems are capable of measuring the wheel-rail forces of a passing vehicle; the most common on-track measuring systems are those which measure only the vertical forces, even if it is considered in this study that a system should be capable of measuring both vertical and lateral forces.

It is recommended that IMs review their on-track mounted wheel load measuring systems and identify whether additional data or measures can be tracked to increase the early detection of possible risks. It may also be beneficial to introduce preventative measures which could indicate any change in a vehicle performance and derailment risk over time.

Then, the analysis of data from the Swedish monitoring station has been performed. After the description of the monitoring system and of its available outputs, some results regarding calculations to define the range of actual loads imposed by trains and vehicles are presented.

In this framework, the chapter 6 presents a data analysis of heavy haul locomotive wheel-set's running surface wear. Some recommendations are proposed and some following research are suggested.

Finally, chapter 7 proposes some directions to deal with predictive maintenance based on condition monitoring: First, by proposing some condition monitoring methods employed in other industries, and which have potential applications in rail industry; then, a potential use of a prototype for preventive maintenance of bolts is described.
From the results of this task, WP5 will investigate how some of these innovative monitoring techniques can be implemented. This WP deals with the Life Cycle Costs (LCC) and Reliability, Availability, Maintainability, Safety (RAMS) analysis of the various concepts developed in the framework of SUSTRAIL.
Finally, WP6 will test, demonstrate and validate in field conditions a selection of the infrastructure and vehicle component upgrade solutions and technologies developed in the project.

9. REFERENCES

[1]. CEN, RAILWAY APPLICATIONS - LINE CATEGORIES FOR MANAGING THE INTERFACE BETWEEN LOAD LIMITS OF VEHICLES AND INFRASTRUCTURE, 2012.
[2]. CEN, RAILWAY APPLICATIONS - MEASUREMENT OF WHEEL AND AXLE LOADS - PART 1: INTEROPERABLE 'IN-SERVICE' RAIL VEHICLES, 2012.
[3]. INNOTRACK, DEMONSTRATOR: VEHICLE CLASSIFICATION BASED ON A WAYSIDE MONITORING STATION - 2010.
[4]. SALINGER, F., L. SCHMITT, AND W. ZOTTL, HRMS - HARMONISATION OF RUNNING BEHAVIOUR AND NOISE MEASUREMENT SITES, IN TRANSPORT RESEARCH ARENA2014: PARIS.
[5]. ULIANOVA, C., ET AL., OVERVIEW OF FREIGHT TRAIN DERAILMENTS IN THE EU. CAUSES, IMPACTS, PREVENTION AND MITIGATION MEASURES. IN TRANSPORT RESEARCH ARENA2014: PARIS.
[6]. THOGERSEN, T. AXLE LOAD CHECKPOINTS (ALC) IN DENMARK. IN THE ANNUAL DANISH RAIL CONVENTION. 2013.
[7]. SUSTRAIL, TRACK DESIGN REQUIREMENTS FOR REDUCED MAINTENANCE - THE SUSTAINABLE FREIGHT RAILWAY: DESIGNING THE FREIGHT VEHICLE – TRACK SYSTEM FOR HIGHER DELIVERED TONNAGE WITH IMPROVED AVAILABILITY AT REDUCED COST, 2012.
[8]. NIETLISPACH, U., WAYSIDE TRAIN MONITORING SYSTEMS AT SBB - BAV MEDIENREISE, SBB INFRASTRUCTURE, 2013.
[9]. SCHÖBEL, A. DEMAND ON MONITORING OF SAFETY RELEVANT PARAMETERS ACCORDING TO EUROPEAN REGULATION. 2010. ZILINA.
[10]. LIIKENNEVIRASTO, FINNISH RAILWAY NETWORK STATEMENT 2014 - FINNISH TRANSPORT AGENCY, 2012.
[11]. INNOTRACK, DELIVERABLE D1.4.10: DEMONSTRATOR - VEHICLE CLASSIFICATION BASED ON A WAYSIDE MONITORING STATION, 2010
[12]. INNOTRACK, DELIVERABLE D6.4.2: MODELS AND MONITORING METHODS FOR LCC AND RAMS RELEVANT PARAMETERS, 40 PP INCL ANNEXES, 2009
[13]. UIC, AXLE LOAD CHECKPOINTS – STATE OF THE ART REPORT, 218 PP, 2011
[14]. D-RAIL, DELIVERABLE D7.4: INDUSTRY GUIDELINES/STANDARD FOR THE IMPLEMENTATION OF MONITORING TECHNIQUES, 100 PP, 2014
[15]. UIC, HRMS HARMONIZATION – RUNNING BEHAVIOUR AND NOISE ON MEASUREMENT SITES, DRAFT 146 PP, 2014
[16]. AAR, MANUAL OF STANDARDS AND RECOMMENDED PRACTICES, (MSRP) C-II CHAPTER 11, 2007
[17]. PARHAM SHAHIDI ET AL., ESTIMATION OF BOGIE PERFORMANCE CRITERIA THROUGH ON-BOARD CONDITION MONITORING, ANNUAL CONFERENCE OF THE PROGNOSTICS AND HEALTH MANAGEMENT SOCIETY 2014, 2014
[18]. D-RAIL, DELIVERABLE D3.3: GUIDELINES ON DERAILMENT ANALYSIS AND PREVENTION, 38 PP, 2013

[19]. ASLANIDOU H, DEY D K, SINHA D. BAYESIAN ANALYSIS OF MULTIVARIATE SURVIVAL DATA USING MONTE CARLO METHODS. CANADIAN JOURNAL OF STATISTICS. 1998, 26: 33-48
[20]. AU S K, CHING J, BECK J L. APPLICATION OF SUBSET SIMULATION METHODS TO RELIABILITY BENCHMARK PROBLEMS. STRUCTURAL SAFETY.2007, 29(3): 183-193

[21]. BERNASCONI A, ET AL. AN INTEGRATED APPROACH TO ROLLING CONTACT SUB-SURFACE FATIGUE ASSESSMENT OF RAILWAY WHEELS. JOURNAL OF WEAR. 2005. 258: 973-980

[22]. BRAGHIN F, ET AL. A MATHEMATICAL MODEL TO PREDICT RAILWAY WHEEL PROFILE EVOLUTION DUE TO WEAR. JOURNAL OF WEAR. 2006. 261: 1253-1264

[23]. BRESLOW N E. COVARIANCE ANALYSIS OF CENSORED SURVIVAL DATA. BIOMETRICS.1974,30:80-99

[24]. CELEUX G, ET AL. DEVIANCE INFORMATION CRITERIA FOR MISSING DATA MODELS. JOURNAL OF BAYESIAN ANALYSIS. 2006, 1(4):651--674

[25]. CLAYTON D G, CUZICK J. MULTIVATIATE GENERALIZATIONS OF THE PROPORTIONAL HAZARDS MODEL (WITH DISCUSSION). JOURNAL OF THE ROYAL STATISTICAL SOCIETY A. 1985, 148: 82-117

[26]. CLAYTON D G. A MODEL FOR ASSOCIATION IN BIVARIATE LIFE TALES AND ITS APPLICATION IN EPI-DEMIOLOGICAL STUDIES OF FAMILIAL TENDENCY IN CHRONIC DISEASE INCIDENCE. BIOMETICKA. 1978, 65: 141-151

[27]. CLAYTON P. TRIBOLOGICAL ASPECTS OF WHEEL-RAIL CONTACT: A REVIEW OF RECENT EXPERIMENTAL RESEARCH. JOURNAL OF WEAR. 1996. 191: 170-183

[28]. CONGDON P. APPLIED BAYESIAN MODELING. ENGLAND: JOHN WILEY AND SONS. 2003

[29]. CONGDON P. BAYESIAN STATISTICAL MODELING. ENGLAND: JOHN WILEY AND SONS. 2001

[30]. CROWDER M. A MULTIVARIATE DISTRIBUTION WITH WEIBULL CONNECTIONS. JOURNAL OF THE ROYAL STATISTICAL SOCIETY B. 1989, 51: 93-107

[31]. DONATO P, ET AL. DESIGN AND SIGNAL PROCESSING OF A MAGNETIC SENSOR ARRAY FOR TRAIN WHEEL DETECTION. JOURNAL OF SENORS AND ACTUATORS A. 2006. 132: 516-525

[32]. FREITAS M A, ET AL. RELIABILITY ASSESSMENT USING DEGRADATION MODELS: BAYESIAN AND CLASSICAL APPROACHES. PESQUISA OPERACIONAL. 2010,30 (1):195-219

[33]. ZHAO Y., LIANG B. IWNICKI S. (2012) ESTIMATION OF THE FRICTION COEFFICIENT BETWEEN WHEEL AND RAIL SURFACE USING TRACTION MOTOR BEHAVIOUR. *JOURNAL OF PHYSICS: CONFERENCE SERIES. 2012*. 364(1), 012004. ISSN 1742-6596 2012

[34]. PISLARU C., ET AL. FAULT DETECTION OF GEARBOX FROM INVERTER SIGNALS USING ADVANCED SIGNAL PROCESSING TECHNIQUES. *JOURNAL OF PHYSICS: CONFERENCE SERIES. 2012*. 364 (1), 012080. ISSN 1742-6596 2012

[35]. GU F. ET AL. ELECTRICAL MOTOR CURRENT SIGNAL ANALYSIS USING A MODIFIED BISPECTRUM FOR FAULT DIAGNOSIS OF DOWNSTREAM MECHANICAL EQUIPMENT. MECHANICAL SYSTEMS AND SIGNAL PROCESSING. 2011. 25 (1), 360-372 . ISSN 0888-3270 2011

[36]. TESFA ET AL. (2012) ‘A CLAMPING FORCE MEASUREMENT SYSTEM FOR MONITORING THE CONDITION OF BOLTED JOINTS ON RAILWAY TRACK JOINTS AND POINTS. *JOURNAL OF PHYSICS: CONFERENCE SERIES. 2012*. 364 (1), 012021. ISSN 1742-6596