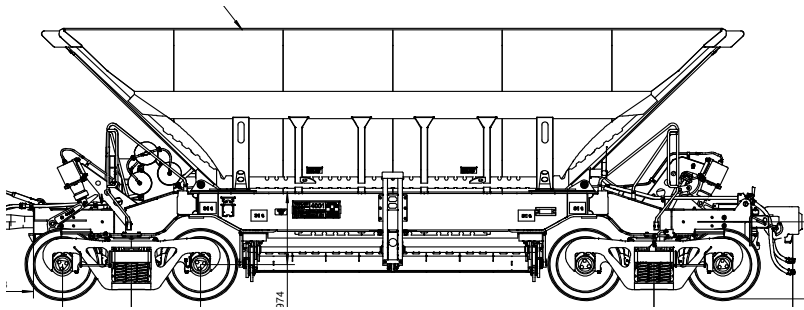


# Condition-Based Maintenance for Effective and Efficient Rolling Stock Capacity Assurance

*A Study on Heavy Haul Transport in Sweden*



Mikael Palo





Condition-Based Maintenance  
for Effective and Efficient  
Rolling Stock Capacity  
Assurance

*A Study on Heavy Haul Transport in Sweden*

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## PREFACE

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The research in this thesis was carried out from 2009 to 2013 within the research subject Operation and Maintenance Engineering at Luleå Railway Research Centre (Järnvägstekniskt Centrum, JVTC) at Luleå University of Technology. It was sponsored by Swedish Transport Administration (Trafikverket) and LKAB mining company, through Hjalmar Lundbohm Research Centre (HLRC).

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Mikael Palo  
Luleå, 2014



## ABSTRACT

---

All businesses need equipment to deliver services or manufacture goods. Over time, this equipment will degrade, but with proper maintenance, the degradation can be controlled, and failed equipment can be restored to operational status. Run-to-failure maintenance is performed when equipment or systems break down. In preventive maintenance, equipment is maintained as a precautionary measure to prevent failure. Finally, condition-based maintenance recommends maintenance actions based on the condition of the asset.

The railway is a superior mode of transport if capacity, speed and environment are the main criteria; it also plays a crucial role in heavily crowded regions. The condition of the wheels and the rails affects railway safety, and infrastructure regulators and managers are always trying to reduce potential risk areas. The wheel-rail interface triggers most of the cost for maintenance.

The railway wagons in this research use a time-based maintenance strategy, a strategy which does not fully consider the actual health of the asset. However, by using condition data from observations, along with diagnostics and prognostics, an effective condition-based maintenance strategy can be planned effectively way and executed efficiently.

The results of this research suggest the efficacy of using automatic condition monitoring systems to increase the amount of available data for analysis and maintenance support planning, rather than depending on a system where operators or maintenance personnel do the measurements. The results also indicate that continuous monitoring of lateral forces will decrease the risk of derailment.

Condition monitoring data can support maintenance preparation, assessment, and improvements and help to form a continuous improvement loop. This, plus a condition-based maintenance strategy, will lead to capacity assurance.

### KEYWORDS:

*Railway, Maintenance, Condition Monitoring, Condition-based Maintenance, Decision-support, Wheel Wear, Wheel Profile, Heavy Haul, Rolling Stock*



## LIST OF APPENDED PAPERS

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- PAPER A M. Palo, J. Ling, and P.-O. Larsson-Kråk,  
*"Maintenance performance improvement for rolling stock wheels,"*  
Published in Chemical Engineering Transactions, Vol 33, 2013
- PAPER B M. Palo and H. Schunnesson,  
*"Condition monitoring of wheel wear on iron ore cars,"*  
Published in COMADEM, Vol 15, No 2, 2012
- PAPER C M. Palo, H. Schunnesson and U. Kumar,  
*"Condition monitoring of rolling stock using wheel/rail forces,"*  
Published in Insight, Vol 54, No 8, 2012
- PAPER D M. Palo, D. Galar, T. Nordmark, M. Asplund and D. Larsson  
*"Condition monitoring at wheel/rail interface for decision-making support",*  
Accepted for publication in Journal of Rail and Rapid Transit
- PAPER E M. Palo, P.-O. Larsson-Kråk and J. Lin  
*"Life cycle cost model for rolling stock freight wheels",*  
Submitted to journal



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## INDEX AND ACRONYMS

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AoA	angle of attack
$C_A$	acquisition cost
CBM	condition-based maintenance
$C_{CM}$	cost for corrective maintenance
$C_I$	inspection cost
CM	condition monitoring
CMMS	computerised maintenance management system
$C_{PM}$	cost for preventive maintenance
$C_R$	risk cost
DSS	decision-support system
Fanoo	Fanoo iron ore wagon
LCC	life cycle cost
m	meter
N	newton
OOR	out-of-round
PoF	physics of failure
qR	flange gradient
RCF	rolling contact fatigue
RUL	remaining useful life
$S_d$	flange thickness
$S_h$	flange height
TBM	time-based maintenance
TPD	truck performance detector
TH	tread hollow wear
UAD	UAD-model iron ore wagon
UNO	UNO-model iron ore wagon



Part I

SUMMARY



## INTRODUCTION

---

All businesses, including the mining industry, manufacturing, and transportation, need equipment to deliver services or manufacture goods [Murthy et al. 2002]. According to Murthy et al. [2002] such equipment is becoming increasingly expensive and complex, with companies' subject to heavy losses if it is not fully operational.

A common problem in a large and mature industry is that not all assets are the same age or used in the same environment [Kumar et al. 1992]. Therefore, the analysis of failure data must reflect these issues.

Equipment degradation can be controlled and failed equipment restored to operational status through the use of proper maintenance procedures [Murthy et al. 2002]. Although maintenance strongly affects reliability, it can represent a major operating cost [Jardine et al. 1996] and historically, maintenance activities have been regarded as a necessary evil by different parts of management within an organisation [Tsang 1995].

### 1.1 RAILWAY

The railway played a key role in the industrial revolution and the development of modern industrial society [Lagnebäck 2007]. The railway is a superior mode of transport if capacity, speed and environment are the criteria; it also plays a crucial role in heavily populated regions [Ekberg and Kabo 2005].

Railways use the low resistance of movement between wheel and rail and the effective guidance by the rail, to be an energy efficient and reliable mode of transport for freight and passengers. However, the development of fast or heavy trains affects the vehicle-track dynamic interaction [Chaar 2004, Iwnicki 2006].

Safety is the most important attribute of quality of service and operation for railways [Patra et al. 2009]. The condition of wheels and rails has a great impact on railway safety. Therefore, having railway vehicles, especially wheels, in an acceptable condition is a major concern for both train operators and infrastructure managers, for example, above safety limits or within a risk or an economical framework. Both infrastructure regulators and managers try to reduce the number of potential risk areas that can lead to accidents.

## 1.2 RAILWAY WHEELS

The lifetime of wheels is limited by wear and rolling contact fatigue (RCF) [Braghin et al. 2006, Dirks and Enblom 2011]. Wheel profiles have seen few changes in 150 years but these have recently become very significant [Iwnicki 2009]; see Fig. 1.1 for a picture of the wheel/rail interaction. Wheel and rail profiles are designed to meet certain desired properties of conicity, gravitational suspension stiffness, and resultant contact stresses [Tournay and Mulder 1996]. The wheel and rail enter service and change shape over time.

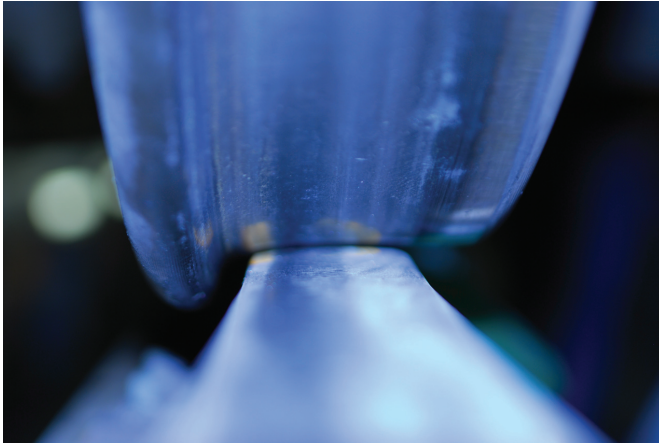


Figure 1.1: Wheel and rail contact

In the 1960s, various organisations began to adopt a more complex “worn” profile, consisting of a series of curves mimicking the shape to which wheels tended to wear in the hope of avoiding the initial rapid phase of wheel wear [Pearce 1996]. The surfaces of the wheel-rail are subjected to high stick, sliding, and contact stresses in rolling contact [Chang et al. 2010]. The change in rail profiles is a major maintenance cost driver [Iwnicki 2006, Verneresson et al. 2010]. In fact, the wheel-rail interface incurs most of the cost of maintenance for both railway vehicles and infrastructure.

## 1.3 SWEDISH RAILWAY

The history of the Swedish railway network goes back to the 1850s. From the start, the national government sponsored the main national lines [Hasselgren 2012]. Up to the late 1930s, all other lines were supplied by private companies, co-owned by local governments, comprising up to 70 % of the total system. The national government invested in the rail-road system through loans and grants to the privately owned railroads.



The entire Swedish network was nationalised in 1939, with the establishment of the Swedish State Railways [Åhren 2008]. Nationalisation was a way to unify the oversized and badly structured railway system, which included many local railroad corporations along with the National Railroad agency [Hasselgren 2013]. In 1988, the ownership of the infrastructure and traffic operation was separated, and this started the deregulation process [Alexandersson and Hulten 2008]. Today, there are several stakeholders in the Swedish railway network [Palo et al. 2013]; see Fig. 1.2 for an example.

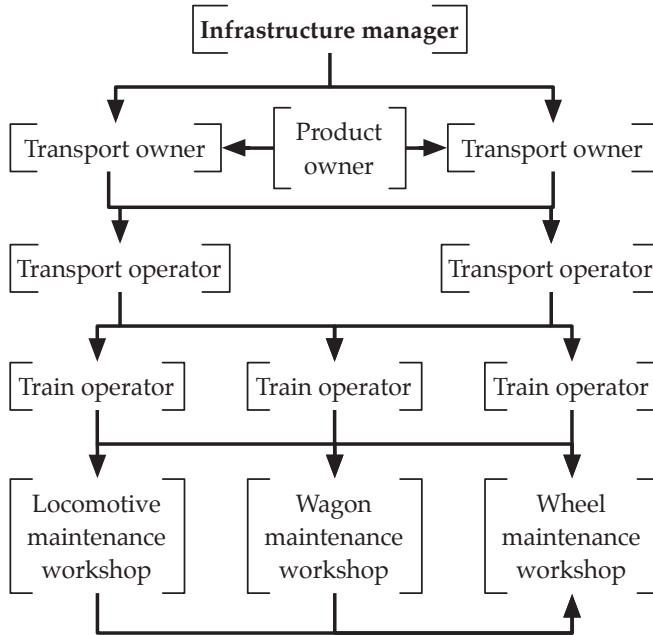


Figure 1.2: Stakeholders within the deregulated Swedish railway network

Many railway assets, such as wheel sets, suffer from increasing wear and tear during operation. The importance of maintenance and, therefore, of maintenance management has grown in recent years [Dekker 1996]. Today's railways face increasing pressure from stakeholders and owners to improve safety, capacity, and reliability – while controlling expenses and tightening the budget [Morant et al. 2012].

In the early days of the railroad, the materials and infrastructures were designed to support the load and speed of the rolling stock, but the increased load and speed that started in the 1950s caused more wear on wheels and rails [Fröhling 2007, Kilburn 1964]. In the early years, maintenance personnel manually inspected the infrastructure and the vehicles [Zarembski et al. 2003], but as technology advances, condition monitoring (CM) and analysis tools to evaluate the railway load are increasingly embraced by the industry [Fröhling 2007, Zoeteman 2004].

Traditional inspection techniques used in the railroad industry such as drive-by visual inspection, are not as accurate and reliable as more rigorous and quantitative inspection methods [Stratman et al. 2007].

### 1.4 MAINTENANCE

Maintenance can be defined as the combination of all technical and administrative actions, including supervising actions, to retain a technical system in, or restore it to, a state in which it can perform a required function [Dhillon 2002, International Electrotechnical Commission 2004]. The driving force behind a maintenance decision is not the failure but the consequence of the failure [Kumar 1998].

One maintenance technique is run-to-failure, whereby maintenance is performed when equipment or systems break down. Another technique is preventive maintenance, as for example time-based maintenance (TBM), which takes place at periodic intervals regardless of the health status of the physical asset. Both techniques can be very costly in a complex system with high requirements for quality, availability, and reliability. Thus, condition-based maintenance (CBM) is a better maintenance option [Jardine et al. 2006].

The planning and execution of consistent maintenance and maintenance support requires certain essential processes, shown in Fig. 1.3. Each internal or external organisation using this process should tailor it to the specific needs and context for which the maintenance and maintenance support are being applied. One example is for the case of several stakeholders involved in the maintenance process.

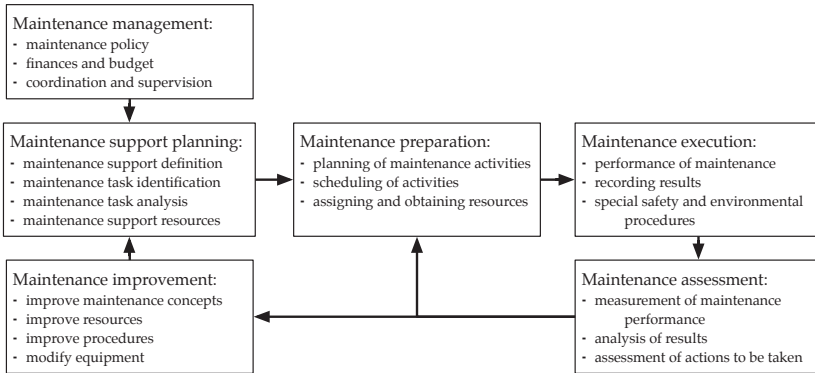


Figure 1.3: General maintenance processes [International Electrotechnical Commission 2004]

## 1.5 CONDITION-BASED MAINTENANCE

CBM is a maintenance strategy that recommends actions based on the information collected through performance measurements, such as CM [Jardine et al. 2006], and is designed to detect the beginning of a failure [Tsang 1995]. It enables maintenance decisions to be made based on the current state of the equipment, avoiding unnecessary replacements and taking maintenance actions whenever there is indication of a failure [Jardine et al. 1997].

In his review paper, Jardine et al. [2006] discusses the three key steps of CBM: data acquisition, data processing and maintenance decision making. In Fig. 1.4, for details see Paper D, the first and last steps are clearly defined; data processing requires several steps, however. First there is a need to preprocess the data to calculate additional parameters and put the data in a format that is accessible. At this point, the data can be uploaded as information to specified servers to reveal trending, compare thresholds and make the appropriate decisions.

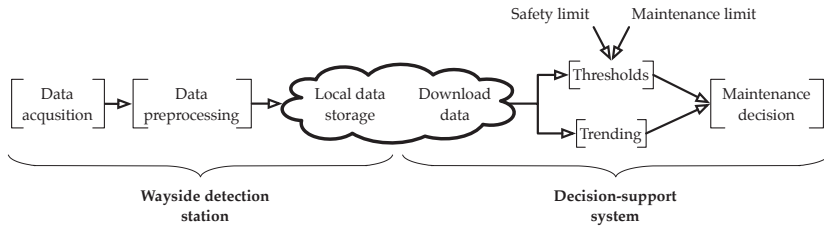


Figure 1.4: Illustration of condition monitoring data to decision

In Fig. 1.4, the trending, thresholds, and maintenance decisions are connected in a loop to ensure continuous improvement within a decision-support system (DSS) and to follow the general maintenance process shown in Fig. 1.3.

## 1.6 CONDITION MONITORING

The traditional aim of CM has been the early prediction of failures by monitoring critical parts or components in a system [Kumar 2008b]. CM can provide information on the current state of the system using both diagnostic variables and environmental conditions that may affect the future life [Banjevic 2009]. This information can be used for prediction, prognostics, and maintenance activity planning. CM can be defined as the continuous or periodic measurement and interpretation of data to indicate the condition of an item to determine the need for maintenance [Milne 1992]. This is normally carried out with the item in operation, in an operable state or removed, but not when it is subject to a major strip-down.

Monitoring can be executed with various levels of automation, from relying entirely on human senses to assess the condition to fully automated and integrated monitoring systems that measure and analyse, e.g., vibrations, temperatures, pressures etc [Bengtsson 2006]. Continuous monitoring is usually done by sensors mounted on the machine that trigger an alarm when a fault is detected [Jardine et al. 2006]. Continuous monitoring is often very expensive and inaccurate due to noise in the signals. Periodic monitoring is more cost effective and can provide more accurate diagnosis using filtered and/or processed data.

1.7 MAINTENANCE MANAGEMENT AND DECISION-SUPPORT

Maintenance management includes the planning of maintenance strategies and the implementation of those strategies [Patra 2009]. The various maintenance strategies must be jointly optimised with the operating loads on the asset, since the load degrades the asset and maintenance actions control this degradation [Murthy et al. 2002]. The overall business objectives also need to be considered in operating and maintenance decisions.

Sufficient and efficient decision support is crucial for the maintenance decision making [Jardine et al. 2006]. There are two main categories of maintenance decision support in a CBM program, diagnostics and prognostics. Diagnostics refers to the detection and isolation of faults or failures, while prognostics is the process of predicting the future state of the item or system; this prediction is based on the current and historic condition [Vichare and Pecht 2006]; see Fig. 1.5. Prognostics can be done at any time during the life of an item; for example, it can determine the expected life length from first use.

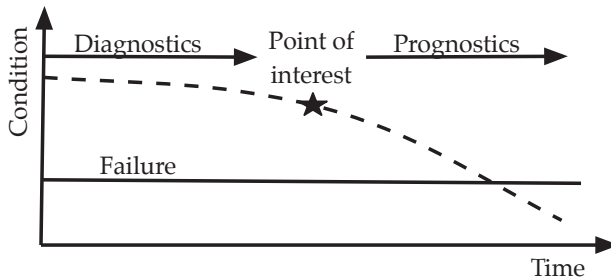


Figure 1.5: Relationship between, diagnostics, present, and prognostics

For decision making it is important to identify the factors causing degradation, measure these factors and develop a life cycle cost (LCC)-model for maintenance action intervals and renewals [Chattopadhyay et al. 2005].

### 1.7.1 *Prognostics and diagnostics in decision-support*

As Jardine et al. [2008] states: “The classical age replacement strategy recommends replacing an item either at failure or when it reaches a certain age”. An optimal replacement policy can be defined as a rule for replacement or leaving an asset in operation until the next decision opportunity, depending on the monitoring results [Jardine et al. 1997].

CM data can be classified as direct and indirect [Si et al. 2011]. Direct data describe the state of the system directly, for example, the wear of crack sizes. Indirect data can only partially or indirectly describe the state of the system, through conversion or transformation. Examples include vibration or oil analysis.

Including good CM data and event data (past recorded failure data) together with the current diagnostic information for maintenance decisions can improve prognostics and maintenance policy [Banjevic and Jardine 2006, Si et al. 2011]. A CBM task triggered by a threshold limit is easy to manage; these tasks have no diagnostic power for predicting when an alarm level will be reached [Tsang 1995].

If abnormal operating conditions are reported from the monitoring system, the next step is to locate the source of the deviation [MacGregor and Cinar 2012]. Using a model-based diagnostic system, a recorded condition can be compared to the model, and the fault behaviour can be predicted [Yam et al. 2001].

The main task of prognostics is to calculate future health state and estimate the remaining useful life (RUL) [Niu et al. 2010]. RUL can be defined as the length of time from the current time to the end of the useful life [Jardine et al. 2006, Si et al. 2011]. RUL is very useful when the lifetime of the asset is a random variable and difficult to predict [Banjevic 2009, Si et al. 2011]. CM provide information about the operating environment, current working age, and asset health according to specified variables.

For a prognosis model, data or knowledge of fault propagation and failure mechanisms must be available [Jardine et al. 2006]. There are several different approaches to prognostic modelling. In the first approach, physics of failure (PoF), the modelling is based on the identification of potential failure modes and failure mechanisms for the product at a specified loading condition [Gu and Pecht 2008]. The second is data-driven and uses historical data on failure mechanisms for the component to build a model [Schwabacher 2005]. These two modelling approaches can be combined to create a hybrid-model, using both diagnostics and prognostics together with set boundary conditions.

### 1.7.2 *Tools for decision-support*

Performance measurement can support efficient and effective decision making [Stenström 2012]. There are many ways to measure performance

[Neely et al. 1995], but the important thing is for decision makers to give it a relative measure.

Several factors drive the need for information to assist maintenance management [Labib 2004]. The first is the amount of information and the second is data lifetime. A computerised maintenance management system (CMMS) is a very useful platform for data collection and analysis and also for decision analysis to achieve world-class maintenance [Labib 1998]. Most existing off-the-shelf CMMS are greedy for data but seldom provide output in terms of decision-support [Jardine et al. 1997, Labib 2004].

DSS are technological solutions able to support complex decision making and problem solving [Shim et al. 2002]. The theory has evolved significantly since its early development in the 1970s [Shim et al. 2002, Zoeteman 2004]. By definition, DSS theory revolves around the issue of providing flexibility in analytic support, even though it is intended for repetitive use.

LCC is a method to identify cost drivers and to collect the cost data of a system, module or component over its whole lifetime [Ekberg and Paulsson 2010]. The analysis possible with LCC allows the comparison of different systems and delivers the necessary information for decision making on technical and economic strategies and designs [Nissen 2009]. LCC is known for being able to deliver quick results on total cost of ownership with limited input data [Zoeteman 2004]. It can be used as a tool to make cost effective decisions on investment, renewal, maintenance, and to optimise the performance of the asset [Patra 2009].

## THESIS APPROACH

---

Chapter 1 discusses maintenance, CBM, CM, maintenance management, decision-support, and the railway. The decision-support tools mentioned in that chapter, along with diagnostics and prognostics, can be used for maintenance management and planning, as shown in Fig. 1.3. This chapter describes the problem, states the goal and research questions, and presents the scope and limitations.

### 2.1 PROBLEM DESCRIPTION

In the railway industry, the capacity of the rolling stock is a measure of the railway's overall availability. TBM is a very simple maintenance policy but there is still a possibility of reducing failures. To use CBM, there must be a gradual loss of function, but there is a good possibility of finding and fixing the problem before the capacity is reduced.

The mining industry is dependant on the ability to move products from the mine to the customer. This transport often includes the railroad, resulting in heavy loads and long trains. These long and heavy trains increase stresses in the wheel/rail interface [Fröhling 2007]. Ideally, the stress-state should be managed as a system, in and of itself [Roney 2005].

The railway industry often uses TBM as a maintenance strategy, based either on tonnage or kilometres travelled [Lagnebäck 2007]. Given today's demands of higher availability, however, there is a need to look for alternative strategies.

The most expensive component on a freight wagon that needs periodic replacement is the wheel [Fröhling and Hettasch 2010]. Fig. 2.1 provides an example of the health state as a function of time for the two failure modes of wheels: RCF and wear. Most failure modes for the railway wheel have a gradual loss of function; see Fig. 2.1.

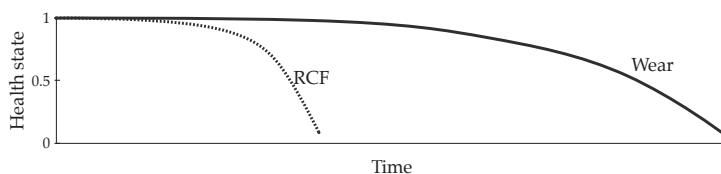


Figure 2.1: Example of different failure degradation for wagon wheels

## 2.2 RESEARCH GOAL

In general, if condition data from observations are combined with diagnostics and prognostics within a CBM strategy, maintenance can be planned effectively and executed efficiently.

The main purpose of this research is to develop an approach to and methodology for assessing the current state of railway wagon wheels and suggest a prognostic model for effective maintenance planning, leading to capacity assurance.

## 2.3 RESEARCH QUESTIONS

To fulfil these goals, the following research questions are asked:

1. How can CBM facilitate capacity assurance for rolling stock?
  - What are the challenges in collecting CM data for railway wheels?
  - How can the CM data be linked to DSS for maintenance?
2. How does information about state/health of the item affect the planning and execution of railway maintenance?

These research questions are answered in the five appended papers. Each paper makes a unique contribution to the research questions; see Table 2.1.

Table 2.1: Relationship between the appended papers and research questions

PAPER:	A	B	C	D	E
RQ 1	X				X
RQ 2		X	X	X	X

## 2.4 SCOPE AND LIMITATIONS

The scope of this research is limited to maintenance issues of rolling stock, focusing on maintenance management and the maintenance strategy of CBM.

Admittedly, the study has some limitations:

- Only heavy haul transport trains in northern Sweden are considered due to their load and the impact they have on the infrastructure. More specifically, the research confines itself to the iron ore wagons from LKAB.



- Only CBM and CM methodologies are considered; other maintenance strategies are outside the scope of this research.
- The measurement data in this study are from several different sources but the measurement systems are restricted to wayside stations, manual measurements, and maintenance data.
- Only data-driven models are considered in this thesis.



## RESEARCH METHODOLOGY

---

All research activities start with a problem that needs to be explained and understood. The term "research" has been defined in various ways, but Kumar [2008a] calls it an intensive and scientific activity undertaken to establish a fact, a theory, a principle or an application.

A research approach can be quantitative or qualitative or a combination of both. In simple terms, quantitative research uses numbers, counts and measures of things, whereas qualitative research adopts questioning and verbal analysis [Sullivan 2001]. Both qualitative and quantitative research methodologies have been applied in the research presented in this thesis.

### 3.1 RESEARCH STRATEGY

Depending on the purpose, research can take a number of different forms: experiment, survey, archival analysis, history and case study [Yin 2013]. The research described here opts for a case study approach. According to Yin [2013] case studies allow the researcher to focus on a holistic and real-world perspective. The environmental factors within the railway are very difficult to control, but materials, loads, and speeds can be controlled. Fig. 3.1 illustrates the main research strategy, also seen in Fig. 1.3 and 1.4. As the figures indicate, the data are collected by sensors using a measurement system and then processed into information. This, in turn, is processed in a model to consider either the current or future state.

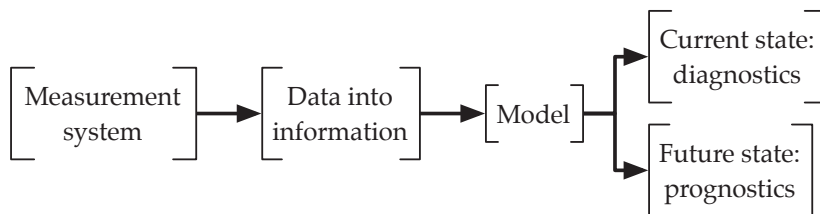


Figure 3.1: Research methodology

### 3.2 DATA COLLECTION AND ANALYSIS

Data can be defined as classifications of facts obtained by researchers from a studied environment [Cooper and Schindler 2006]. Data can also

be defined as the empirical evidence or information that scientists carefully collect according to rules or procedures to support or reject theories [Neuman 2003].

A survey of peer-reviewed journal papers, conference proceedings, articles, research and technical reports, and Licentiate and PhD theses was used to obtain the qualitative information used in this thesis. Specific keywords were used to search for information in well-known online databases, including Google Scholar, Elsevier, Science Direct and Emerald etc.

Quantitative information was obtained from measurements and the databases of the LKAB mining company, the research station (for more information see Chapter 4), wheel profile stations (for more info see Chap. 4), and DUROC Rail (wheel maintenance workshop). The data collection is described in more detail in Chapter 5.

## MONITORING AND DETERIORATION OF WHEELS

Manual inspections of railway vehicles vary in efficiency and effectiveness depending on the experience or the ability of the inspectors and environmental conditions [Schlake et al. 2011]. In recognition of these inefficiencies and the subjectivity of manual inspection, the railroad industry has developed systems to counteract them. One example is an eddy current or ultrasonic system which is used to find cracks that are not visible to the naked eye. There are several possible sensor setups as well; see Fig. 4.1. These sensors can be used for various monitoring techniques to detect faults and failures on the wheels, and all systems are used for non-destructive testing. Thermal sensors are used to detect bearing failures, but these are not strictly part of the wheel set.

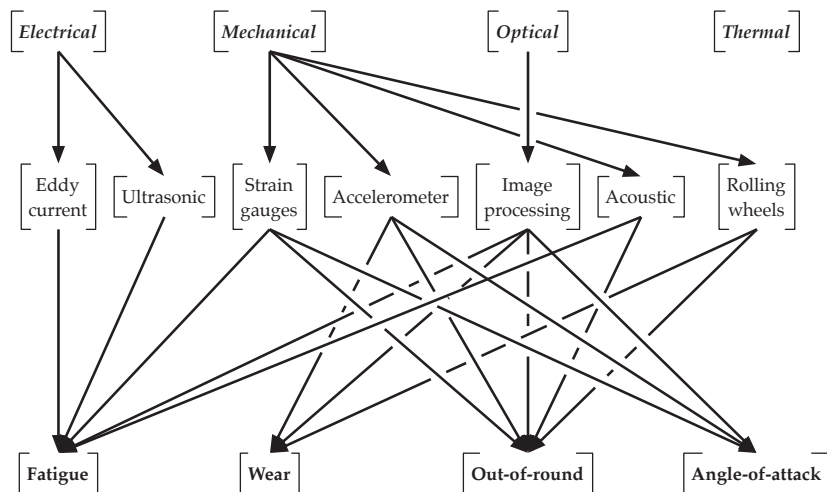


Figure 4.1: CM sensor types and wheel monitoring measures

These systems are at different maturity levels within the railway system; some are established methods of CM and are widely used while others are still under development [Lagnebäck 2007, Schlake et al. 2011].

On-board measuring can measure a chosen parameter along the whole route taken by the trains, while wayside systems placed along the track can measure several parameters for a whole train as it passes the measuring site [Matsumoto et al. 2008]. In most cases, it would not be economical to have sensors mounted on all vehicles in a fleet to monitor all possible conditions [Lagnebäck 2007]. Sensors mounted on in-service vehicles can, for example, be used to identify specific track defects during normal service [Ward et al. 2010].

Wayside detection systems provide a means of monitoring the condition of vehicles at track speed, ensuring that they are in a serviceable condition [Barke and Chiu 2005b]. Some of the sensors and measurement techniques shown in Fig. 4.1 can be used wayside and not mounted on the vehicles [Lagnebäck 2007]. For example, strain gauges, accelerometers, and image processing, acoustic, and temperature sensors are mature enough to be placed in wayside stations. Some can also be used for continuous monitoring mounted on the vehicle. Others are used for CM in the workshop.

#### 4.1 WAYSIDE CONDITION MONITORING

According to Zarembski et al. [2003] wayside detectors have been used in the railway industry for more than 60 years. In the beginning, wayside CM systems focused on bearing temperatures and dragging equipment and were used for alarm activation to prevent derailment due to equipment failure [Fröhling 2007, Fröhling and Hettasch 2010, Zarembski et al. 2003]. A new generation of wayside detectors was introduced in the early 1980s with the aim of finding vehicles with excessive loads that could potentially cause damage to track components [Zarembski et al. 2003].

At present, there are several monitoring systems that with the help of computer software can use trending and defined thresholds for failure detection. The forces or the profiles at the wheel-rail interface are parameters affect each other if there are any faults [Kartunen et al. 2013], for example out-of-round wheels or thin wheel flanges.

The importance of the accuracy and reliability of a specific measuring system is dependent on the degradation and/or failure mode of the parameter being monitored [Fröhling and Hettasch 2010]. Systems such as “vertical impact detectors”, which warn of imminent failures, need to be reliable. Some downtime and limited measurement misses can be tolerated in systems that monitor parameters that change slowly, for example, wheel profile wear.

##### 4.1.1 *Wheel-rail force measurements*

Force measurement detectors make it possible for vehicles with defective wheels likely to damage the permanent railway structures to be identified and removed from service immediately [Partington 1993]. Data on vertical impact loads between wheel and rail resulting from surface anomalies such as wheel flats have been used to create mathematical models of wheel-rail impact behaviour [Ahlbeck 1980]. Systems that solely measure the axle load of wheel flats are mostly placed on a tangent track with no gradient or a negligible gradient and where trains do not accelerate or brake [Larsson 2012].

Lateral forces are the result of poor steering bogies, train speeds outside the track's designed limits [Tunna et al. 2007], and longitudinal buff and draft forces transmitted by train action and coupler angularity [Bell and Roney 2011]. To prevent derailment accidents and abnormal wear, it is important to determine the actual state of the contact forces between wheel and rail [Matsumoto et al. 2008]. According to Matsumoto et al. [2008], lateral and vertical contact forces are especially important. The knowledge gained by measuring wheel-rail forces allows the stress state of the railway to be reduced [Anderson and McWilliams 2003].

Poor steering causes accelerated wheel flange wear, initiation of RCF, higher energy consumption, and accelerated deterioration of track components [Fröhling and Hettasch 2010]. Measurement of the lateral forces is best performed in narrow curves, as vehicles display their steering ability in curves. For an illustration of lateral and vertical forces, see Fig. 4.2(a), and for bogie/wheel placement in a curve, see Fig. 4.2(b).

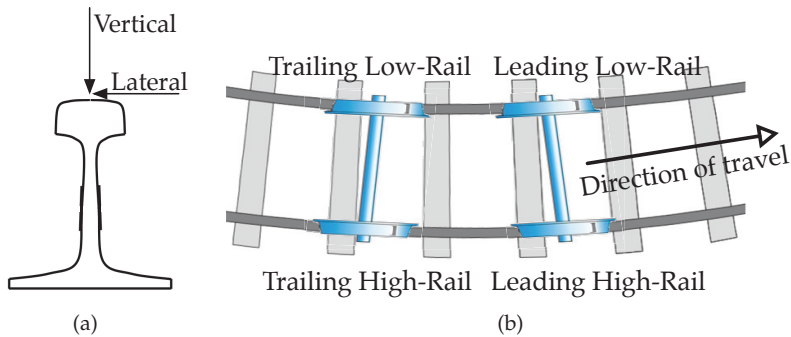
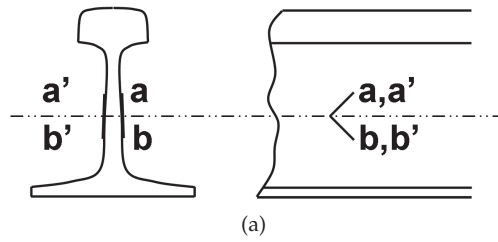


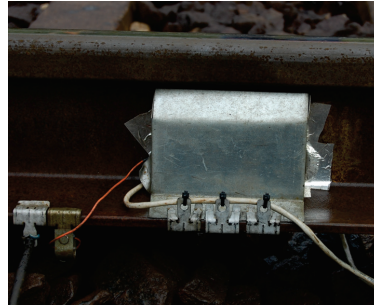
Figure 4.2: Force definition and wheel positions in a curve

**RESEARCH STATION** The research station outside the city of Luleå, for map see Fig. 6.1, is a modified version of a force-based truck performance detector (TPD), monitoring vertical and lateral forces in a single curve with a 484 m radius [Larsson 2012]. The measurement system consists of strain gauges attached to the web of the rail, as indicated in Fig. 4.3(a). Figs. 4.3(b) – (c) show the placement of the measurement equipment at the site; note that due to the harsh environment of railroads, a protective shield is placed on top of the strain gauges. For the most part, iron-ore trains with an axle load of 30 tonnes and a speed of 60 km/h are monitored [Larsson 2012]. For more information, see Paper B.

A TPD also determines the bogie performance by measuring vertical and lateral forces and  $A_{oA}$  [Anderson and McWilliams 2003, Coe et al. 2006, Larsson 2012]. The system can then calculate several corresponding parameters, as for example, lateral-over-vertical ratio, speed, and wagon weight.



(b)



(c)

Figure 4.3: Placement of sensors on the rail

#### 4.1.2 Wheel profile measurements

The wheel profile is critical to the railway vehicle's dynamic behaviour, stability and ride comfort; also important are the rate of wear and rolling resistance of the wheel and rail [Barke and Chiu 2005b, Jendel 2002]. The shape of the wheel profile has a relationship with derailment safety and the material strength of heavily worn wheels. CM of wheels enables scheduled maintenance of each ID-tagged vehicle.

A number of general wheel shape profile parameters are used to identify a good or bad profile [UIC - International Union of Railways 2004]; see Fig. 4.4. These are flange height ( $S_h$ ), flange thickness ( $S_d$ ), flange gradient ( $qR$ ), and tread hollow wear (TH). They are calculated using the back and top of the flange as reference points.  $S_h$  is calculated as the difference between a spot 70 mm from the back of the flange (running circle) and the top of the flange; see Fig. 4.4.  $S_d$  uses the width of the flange 10 mm above the running circle.  $qR$  is the distance between 2 mm below the flange top and the position of  $S_d$  calculation. Finally, TH calculates the height of a second flange on the field side of the profile; see Fig. 4.4.

Wheel profile measurements can be done manually, using a mechanical or laser unit, or automatically, using lasers and cameras.

**MANUAL** The MiniProf<sup>TM</sup> measurement system is used by many railroads to monitor wheel and rail profiles [Esveld and Gronskov 1996].



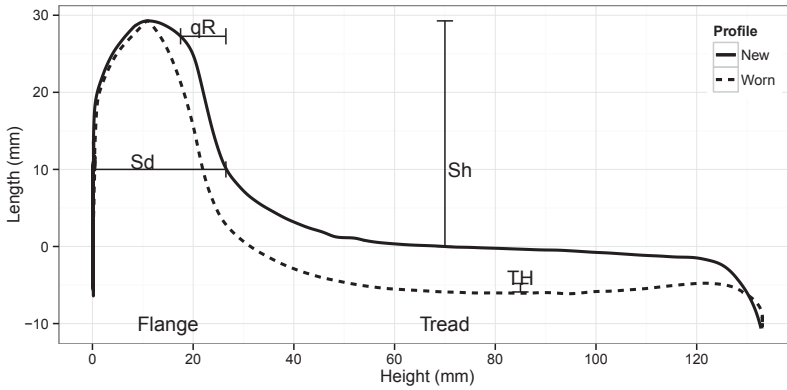


Figure 4.4: New and old profile and wheel profile parameters

This is one of the most reliable and accurate monitoring systems available. In fact, the results of other wheel profile monitoring systems or simulations are often compared to MiniProf to check their accuracy [Ansari and Hazrati Ashtiyani 2006].

MiniProf<sup>TM</sup> Wheel, see Fig. 4.5, has a sensing element consisting of a magnetic wheel which is 12 mm in diameter, attached to the end of two joint extensions. To measure the wheel profile, the MiniProf is magnetically attached to the wheel, as seen in Fig. 4.5. The back and top of the wheel are used as the horizontal and vertical references, respectively [Esveld and Gronskov 1996]. The system measures the profile with two degrees of freedom, and a computer calculates the profile in Cartesian coordinates. The resolution is in thousandths of a millimetre. During this calculation the  $S_d$ ,  $S_h$ ,  $qR$ ,  $TH$  are also retrieved (see Fig. 4.4).



Figure 4.5: Picture of MiniProf measurement equipment

**AUTOMATIC** Automatic wheel profile monitoring technology uses high speed cameras and lasers to capture the wheel tread profile of each rolling stock wheel as it passes [Braren et al. 2009, Wolstenholme 2008]. The equipment monitors wheel profiles against a maintenance standard for detection of worn wheels. The wheel profile measuring station installed outside Luleå can measure railway wheel profiles to speeds up to 120 km/h. It consists of four separate boxes, one on either side of each rail; see Fig. 4.6. The boxes contain a laser, a high-speed camera, and an electronic control system; more information can be found in Ref. [Asplund et al. shed] and Paper D.



Figure 4.6: Wheel profile measuring station

#### 4.2 WHEEL DETERIORATION

The profile change on wheels can also be large, especially in track sections with a high population of curves because the wheel flange is subject to large contact stress and creepage [Chang et al. 2010]. Damage mechanisms such as wear and plastic deformation are the main contributors to profile change. Plastic deformation in the wheel tread results from a combination of two different phenomena, RCF and thermal cracking [Vernersson et al. 2010]. RCF in operation can be either promoted or removed by wear; high levels of wear can partially or entirely remove surface cracks [Wu et al. 2011].

There are different degradation modes: electric equipment can, for instance, fail instantaneously, whereas assets that wear due to mechanical contact, such as the wheel/rail-contact, degrade gradually [Zoeteman 2001]. Generally speaking, how wheel profiles affect the performance of rail vehicles falls into two categories. The first category relates the safety of the system to the wheel profiles. The second category considers the

dynamic performance of the vehicle, for instance, vehicle dynamic stability, vehicle-track force levels and ride comfort [Jendel 2000].

The interaction between wheel and rail resulting in material deterioration is a complicated process, involving vehicle-track dynamics, contact mechanics, friction wear and lubrication [Charles et al. 2008]. The course of events called wear is similarly complicated, involving several modes of material deterioration and contact surface alteration [Enblom and Stichel 2011].

The wheel-rail contact is typically the size of a small coin,  $100 \text{ mm}^2$  [van Beek 2009]. The wheel/rail interface is a highly loaded contact. The forces that support, accelerate, brake, and guide the train are all transmitted through this small contact patch [Chaar 2004, Charles et al. 2008, Iwnicki 2009, Lagnebäck and Kumar 2005]. Rails and wheels are commonly made from plain carbon-manganese pearlitic steel. With the wheel set centred on straight track, if the left and right wheel rolling radii are equal, the wheel set can roll normally. The steering load contributes to increased wear and rolling contact fatigue, especially on curved tracks.

Frictional heating occurs when train cars reduce speed by using their brake pads against the running surface of the wheels. When the wheel surface layer is frictionally heated, and this is followed by the rapid cooling of the body of the wheel itself, there is an increased risk of forming martensite [Kalousek et al. 1996]. As martensite is much harder and more brittle than the surrounding material, it can break and initiate cracks. In addition, in-service freight car wheels may develop tread irregularities in the form of slid-flats, shells or spalls [Stone et al. 1992]. Any of these irregularities can cause high wheel impact forces [Nielsen and Johansson 2000, Stone et al. 1992, Stratman et al. 2007], with slid-flats, also called wheel flats, being the most common.

#### 4.2.1 *Wheel profile wear*

One definition of wear is the loss or displacement of material from contacting surfaces [Iwnicki 2006], and this is related to sliding, contact stresses, and material properties [Braghin et al. 2006, Chang et al. 2010]. The change in the shape of the wheel due to wear results in high wheel flanges, hollow worn wheels, and thin wheel flanges [Fröhling 2007]. Material loss may be in the form of debris. Material displacement may occur by transfer of material from one surface to another by adhesion [Tunna et al. 2007] or by local plastic deformation. In wheel-rail contact, both rolling and sliding occur in the contact zone.

The nature of the shape change in the wheel is a function of wear and material flow caused by various contact conditions between the two bodies [Tournay and Mulder 1996]. These contact conditions depend on track curvature, vehicle alignment, axle load, vehicle speed, vehicle type,

traction, and braking. See Fig. 4.4 for a visualisation of the parts of the wheel profile.

Most techniques to reduce the wheel profile change are based on limiting the wear, or material removal [Jendel 2000]. Wear is not generally a critical failure mode in rolling contact [Johnson 1989]. Wheels with uniform tread wear or hollow wear require little material removal, whereas wheels with flange wear require larger cuts to restore the profile [Fröhling and Hettasch 2010].

#### 4.2.2 *Wheel flats*

Wheel flats are formed when a wheel set is locked and skids along the rail [Ahlström and Karlsson 1999, Fröhling 2007, Nielsen and Johansson 2000] and is the most important source of vertical loads on the rail [Ahlbeck 1980]. Brakes may be poorly adjusted, frozen, or defective, or there may be high braking forces in relation to available adhesion [Barke and Chiu 2005a]. The friction between wheel and rail causes wear of the wheel surface to become flat instead of round [Stratman et al. 2007].

#### 4.2.3 *Out-of-round wheels*

Wheels with flats and tread damage or build-up are referred to as out-of-round (OOR) and it is generally accepted that these wheels cause large dynamic forces [Barke and Chiu 2005a]. Several different types of OOR may be present on a wheel [Johansson and Nielsen 2003, Nielsen and Johansson 2000].

#### 4.2.4 *Rolling contact fatigue*

RCF is a severe and growing problem for many heavy haul railways [Fröhling 2007]; it is the principal mode of failure of rolling surfaces and governs the safe life of components under a prescribed load [Johnson 1989]. Wheel damage occurs as fatigue cracks, initiated at or below the surface, result in material fall-out, such as shelling or spalling [Enblom 2009, Tunna et al. 2007].

**SPALLING** is the term used for the RCF phenomenon which occurs when surface cracks of thermal origin meet, resulting in part of the wheel coming away from the tread [Fröhling 2007, Nielsen and Johansson 2000]. It is associated with cracking induced by high transformation stress caused by surface martensite formation [Moyar and Stone 1991]. Cracks from spalling form both perpendicular and parallel to the wheel tread surface.

SHELLING is a term normally used for all types of subsurface-induced cracks [Fröhling 2007, Nielsen and Johansson 2000]. Wheel shelling is defined as the loss of relatively large (greater than 5 mm) pieces of metal from the wheel tread as the result of contact fatigue [Moyar and Stone 1991]. Typically, shelling cracks grow at an acute angle to the surface. Impact load can affect shelling in both crack initiation and crack propagation modes [Stone and Moyar 1989].



## DATA COLLECTION, PROCESSING AND ANALYSIS

This chapter describes the data sources used in the research, as well as the steps taken, from data collection to decision-support. Fig. 5.1 lists the data sources and depicts the analysis process. Data sources are described in Chapter 3, 4, and 6. The analysis process is shown in Figs. 1.3 and 1.4.

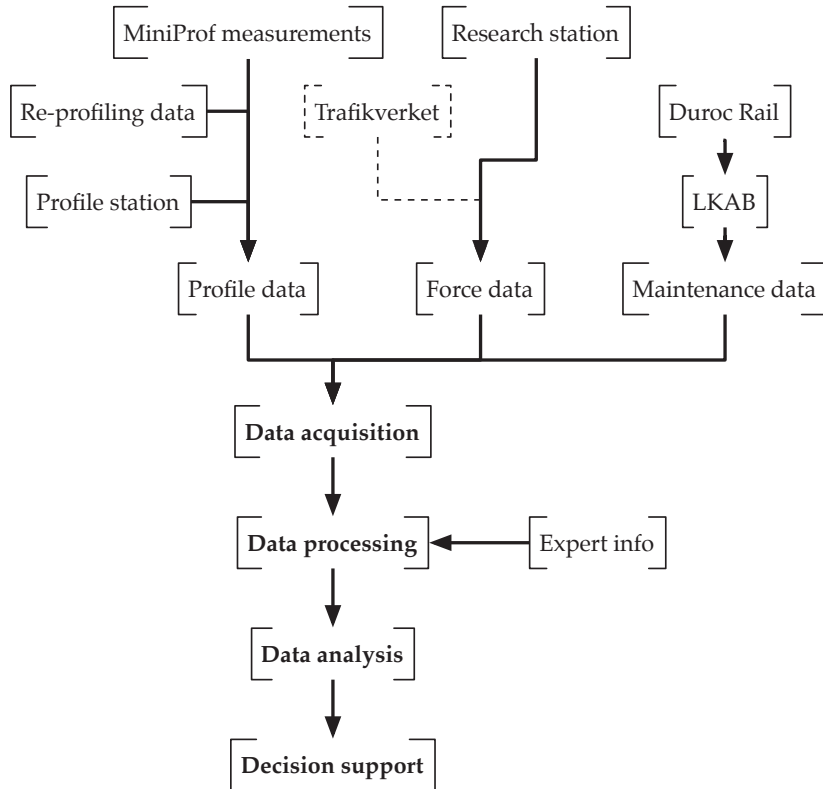


Figure 5.1: Data sources and analysis process

### 5.1 DATA ACQUISITION

The data collected in this research are from several different sources and databases. Some sources contain data for several usages; for example, the research stations collect data on both wheel/rail forces and weather.

### 5.1.1 *Profile data*

The wheel profile data were collected from three different sources. First, the manual profile measurements using MiniProf<sup>TM</sup> Wheel were done at the train yard in Luleå, the iron ore harbour in Luleå, and the train yard at the mine in Vitåfors. I did the measuring.

Second, the information on wheel re-profiling comes from the maintenance database of LKAB mining company. These data contain profile parameters and wheel diameters, both before and after re-profiling.

The third source of information is the automatic wheel profile measuring station outside Luleå. This station collects data for all wheels passing by its lasers. The data are processed into profile parameters and stored in a database. From this database it is possible to obtain data for a single vehicle or all vehicles with a specific operator.

### 5.1.2 *Force data*

The force data used in this research is collected from the research station outside Luleå. The measurements are performed in a narrow curve to record lateral and vertical forces. With this setup, longitudinal forces can also be measured. Vertical loads and transients can be used for failure detection on the wheel tread, while lateral loads are used to determine the steering ability of bogies and wheels.

The measurement system always measures the strain in the rail, but only records and stores the data in databases when a train passes the measurement points. Each train is logged separately; when the train has ID-tags, these are stored together with the data and a specific wheel set can be followed.

The Swedish railway network has several wheel impact load detectors, and these can also be used for data collection. These measurement systems are situated in tangent track and are used for vertical loads.

### 5.1.3 *Maintenance data*

The maintenance event data used in this research were gathered from the CMMS of LKAB mining company. The data contain maintenance work orders, wheel set data, placement history for specific wheels on specific wagons, and re-profiling data.

The data from DUROC only contain the number of wheel re-profiling, not the causes. Information is confined to either RCF or wheel wear. The data also indicate which part of the year or which train operator is linked to a particular failure mode.



## 5.2 DATA PROCESSING

Data processing always starts with data cleaning to remove incorrect or faulty data. Before cleaning, the data must be imported and transformed. The data come from different sources and have different formats, for example, ASCII-files, Microsoft Excel, and databases. In this research, the R statistical software<sup>1</sup> are used for data cleaning and processing.

Event data that are entered manually often contain errors, especially if the system is older and the instructions are not up-to-date. Errors in the data can also come from faulty or non-calibrated sensors or problems with data transfer.

The next step in data processing is exploratory analysis to check for additional (and strange) values in the data and to check the data's validity. Using visual tools is easier than reading several thousand lines of text.

### 5.2.1 *Information from experts*

In this thesis, research findings were discussed with experts to explain and validate the results, thus ensuring a high quality of analysis. The information obtained from these discussions is generally used to remove errors in the data.

## 5.3 DATA ANALYSIS

The data required for the analysis of diagnostics and prognostics of the LKAB trains in paper C and D are extracted from the database of the automatic measurement systems. The trains are sorted according to travel direction, since the rail forces are different when trains are loaded and unloaded. The analysis is performed for all trains measured.

The manual measurements are analysed for each wheel position in paper B.

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<sup>1</sup> More info on R: <http://www.r-project.org/>



## CASE STUDY

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Railway wheels deteriorate because of RCF or profile wear. These deterioration mechanisms can be monitored to find the faults before they turn into failures and the vehicle must be sent for corrective maintenance. Wheel profile degradation is easier to monitor and plan maintenance action by using wayside stations. RCF and OOR are monitored using vertical impact detectors.

### 6.1 IRON ORE TRANSPORT

The iron ore transport for the LKAB mining company in northern Sweden and Norway starts at the mines in Kiruna and Vitåfors near Gällivare and ends in the harbours of Narvik in Norway and Luleå in Sweden; see Fig. 6.1. This railway line has been in operation since 1903 and was originally designed for 14 metric tonnes in axle load [Asplund et al. shed]. In 2000, the axle load was increased from 25 to 30 metric tonnes [Arasteh khouy et al. 2013]. The loaded speed was also increased from 50 to 60 km/h.

The railway line between Narvik and Luleå primarily sees LKAB iron ore heavy-haul trains, but there are also passenger, freight, steel-slab and copper-ore trains on this line; see Fig. 6.2. The freight trains have lighter wagons up to 18 tonnes of axle load, the copper-ore trains have an axle-load of 22.5 tonnes, and the steel-slab trains have an axle-load of 25 tonnes. The iron ore trains consist of two IORE locomotive with 68 wagons, 750 metres long, with a total train weight of 8,520 tonnes.

Running heavy-haul railway traffic in a mountainous area north of the Arctic Circle is a challenging task [Nielsen and Stensson 1999], with many tight curves along the track experiencing high wear [Berghuvud and Stensson 1998]. The area along this line has varied geomorphology, topography, geology, and climate [Larsson-Kråik 2012]. The trains operate in harsh conditions, including snow in the winter and extreme temperatures ranging from  $-40^{\circ}\text{C}$  to  $+25^{\circ}\text{C}$  [Kumar et al. 2008].

At several places along Malmbanan various parameters of the passing trains are measured, including vertical and lateral forces in the wheel/rail interface, vertical impact, and wheel profile. This research uses data from two measurement stations outside Luleå. The first is a research station measuring wheel/rail forces in a curve of 484m radius. The second is a commercial automatic wheel profile station.



Figure 6.1: Map of northern Sweden and Norway

## 6.2 IRON ORE WAGON

In 2005, LKAB upgraded its wagon fleet from the existing UAD and UNO wagons to a new wagon, called Fanoo; see Fig. 6.3.

This wagon is the result of a design and manufacturing collaboration between LKAB and Kockums Industrier AB. The bucket is made by a company called Kiruna Wagon, the bogie is a three-piece Motion Control bogie from Amsted Rail Inc., and the wheels and axles are from Lucchini RS, Italy. Table 6.1 gives some technical specifications.

The Fanoo wagons travel in pairs (called Fammoorr) connected by a steel-rod (drawbar) at the A-end; see Fig. 6.4. The odd ID-labeled wagon is the master-wagon and contains the brake control system for the pair. A draw bar is preferable because its investment cost is less than the cost of a coupler. There are no moving parts that can malfunction; in addition, the longitudinal forces along the train are lower. In short, the overall maintenance cost can be lowered when the wagons are paired.

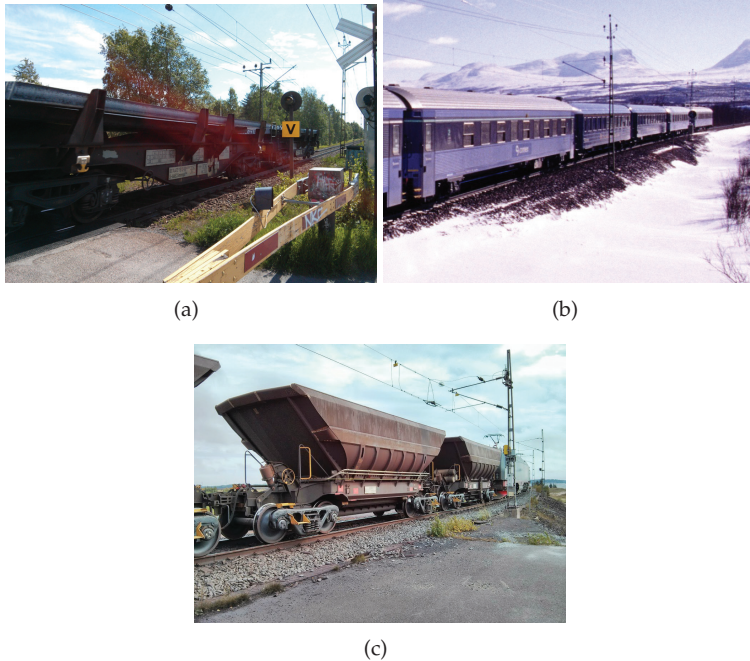


Figure 6.2: Trains trafficking the railroad between Luleå and Narvik

### 6.2.1 Wagon maintenance

At present, LKAB is performing its preventive maintenance based on travel distance, visual inspections by maintenance personnel and safety alarms from the infrastructure manager. Table 6.2 shows maintenance intervals and actions for specific components. Visual inspections are done in the yard before the wagons are loaded with iron ore, up to four times each day.

There are several methods to detect and monitor wheel wear and fatigue. One is visual inspection of the wheels at the railway yard; another is the use of wayside monitoring stations to detect faults or failures [Schlake et al. 2011]. A third opportunity occurs during general wagon maintenance in the workshop. Some advantages and disadvantages of these inspection methods are summarised in Table 6.3.

The wheel detection process is visualised in Fig. 6.5 and described in paper A. The risk/safety factor or cost shown in the figure refers to when a wheel has an undetected fault.

A number of failure parameters determine the proper maintenance action for the wagon and its wheels; see Fig. 6.6. When a faulty wheel is detected, a maintenance action is needed and a work-order is created. Fig. 6.6 looks specifically at wheels, illustrating what happens to a wheel at the beginning of the maintenance process.



Figure 6.3: The Fanoo iron ore wagon

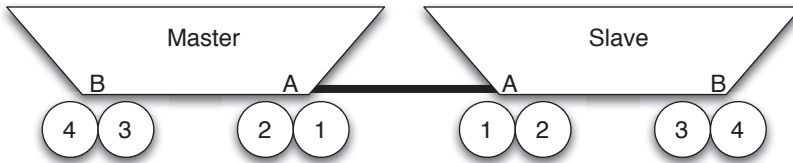


Figure 6.4: Designation of wagon, bogie, and axles

Table 6.1: Technical specification of the Fanoo wagon [LKAB 2006]

TECHNICAL SPECIFICATION	
Maximum speed (loaded)	60 km/h
Maximum speed (unloaded)	70 km/h
Wheel diameter (max)	915 mm
Wheel diameter (min)	857 mm
Bogie	Motion Control three-piece
Profile	WP4 (modified S1002 profile)
Wagon weight	21.6 metric tonnes
Cargo weight	102 metric tonnes
Maximum axle load	31 metric tonnes
Minimum curve radius	90 m
Brake system	Hanging, UIC type

Table 6.2: Maintenance intervals for different wagon components [LKAB 2010]

COMPONENT	MAINTENANCE ACTION	DISTANCE [KM]
Wagon	Inspection	80 000
Draw gear	Check	250 000
Frame	Check	500 000
Brake system	Revision	750 000
Draw gear	Revision	750 000
Axle box	Revision	800 000
Bogie	Revision	1 000 000
Brake system	Revision	1 000 000

Table 6.3: Advantage and disadvantages with different inspection methods

METHOD	ADVANTAGE	DISADVANTAGE
Visual	Quick and cheap	Not all faults can be detected
Wayside	Objective and repeatable measurements	CMMS and DSS are needed
Workshop	Early decisions	Expensive and time-consuming

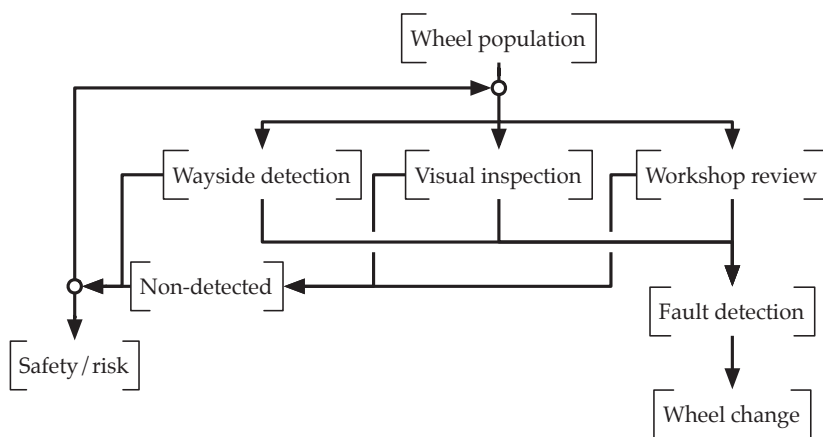


Figure 6.5: Wheel failure detection process

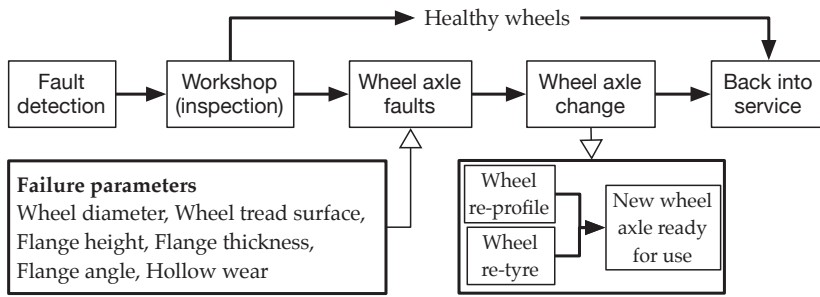


Figure 6.6: Wheel maintenance process [LKAB 2011]



## SUMMARY OF APPENDED PAPERS

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This chapter summarises the five appended papers. All papers study the same wagons and railway line.

**PAPER A** implements a framework for the continuous improvement of rolling stock maintenance, using the Plan, Do, Study, and Act process. In the first stage, the wheels are defined as the first area of improvement. The wheel detection process is suggested as a method to determine where risks are located. LCC-modelling is used to calculate risk and is a key performance indicator in the improvement process.

By using the CM tools for fault detection and combining these data with a life cycle cost model and continuous improvements, it is possible to lower the cost of wheel maintenance.

**PAPER B** presents the results of a study performed over 15 months on two LKAB iron-ore wagons. The purpose of the study was to improve the condition monitoring of the wheels on these wagons. The wheel/rail forces are determined by wheel position and vertical or lateral forces. The study also calculates the lateral over vertical (L/V) ratio to see how prone the wheels are to climb over the rail.

The wheel wear is greater at lower temperatures, especially below freezing. The lateral forces are generally larger for the leading axle; they also differ between the two wheels of that axle.

**PAPER C** presents CM techniques for railway vehicles and analyses measurement data from the research station outside Luleå Sweden. Two measurement systems are discussed: wheel impact load detectors and TPD. Data on vertical and lateral forces, speed, temperature and relative humidity were collected from March 2009 to May 2010.

The lateral forces for the four different wheel positions within the bogie have significantly different force signatures. The leading high-rail has high forces throughout the measurement period, while the three other positions increase with time and distance. This indicates that each position must be considered separately. The measurement system at the research station can be seen as a robust system because the forces from leading high-rail are within the limit of variation. Seasonal changes seem to have no influence. Changing the travel direction of the wagon shows distinctive differences, indicating differences in steering through left and right curves.

PAPER D uses CM data from wheel profile wear and wheel/rail forces for health assessment and decision support for wheel maintenance actions. The CM data are collected from two wayside measurement stations outside Luleå. From data on the wheel parameters only,  $S_h$  and TH show that several measured wheels are outside the safety limit. The two axles follow the wheel wear for  $S_h$  in that they follow a linear trend with time, which can be expected, while the lateral forces do not follow any apparent trend.

Using trending from the wheel profile station for maintenance decisions is a very good tool to predict when to remove a wagon from service for wheel maintenance. Such predictions must be integrated into the decision making process. Using the data for lateral forces is a good indicator of the steering ability of the wheel and bogie. A poorly steering vehicle increases wear and tear on both the vehicle and the infrastructure.

PAPER E presents a model for life cycle cost modelling of the wheels of the FANOO wagons. A number of wheel sets are selected to represent some part of the whole population. All data are from LKAB's CMMS and are filtered to remove faulty entries. Two different diameters are considered for the wheel; both RCF and wear are failure modes.

A natural wear of 3 mm for every 100 000 km is found to be the rate of degradation. By approximating this wheel wear and re-profiling, a total 1 200 000 km can be achieved. If trending of operational data, failure mode simulations, and optimised maintenance policies are used, at least this distance can be reached before re-wheeling is needed. Corrective and preventive maintenance have different limits for wheel removal, and there can be a difference in the amount of material removed by turning. With the help of wayside monitoring, material removal can become more streamlined.

## RESULTS AND DISCUSSIONS

This chapter presents CM data from the research station and profile measurement station outside the city of Luleå. It introduces a maintenance improvement idea and discusses the wheel profile assumption and results, along with the results given in the appended papers.

## 8.1 MAINTENANCE IMPROVEMENT

The iron ore wagon can be divided into several subsystems; the bogie is the critical subsystem with the largest maintenance cost. Bogies have several parts and components that wear differently; of these, the wheel and brake system are the most significant to maintenance. Fig. 8.1 shows these two parts and their influencing factors.

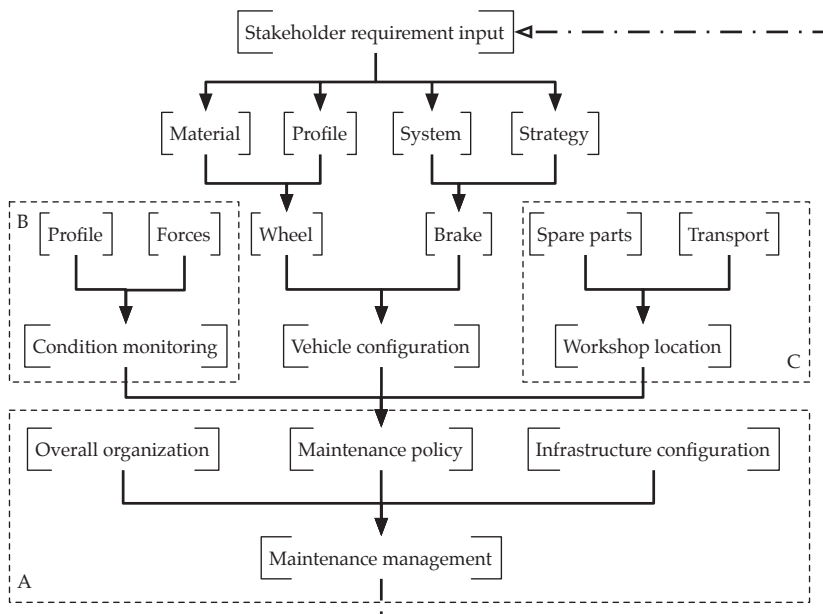


Figure 8.1: Maintenance management with influencing factors

Fig. 8.1 is connected to Fig. 1.3 in three blocks. Block A is maintenance management, B is maintenance preparation and assessment, and C is maintenance support planning. There is a loop linking maintenance management to stakeholder requirement input. Stakeholder requirements include the customers' decisions, as for example, the wheel material or profile.

One influencing factor shown in Fig. 8.1 that is hard to control in maintenance management is the configuration of the infrastructure system. These includes the rail profiles, track stiffness, track lubrication, number of curves, curve radiuses, sidings or double track, and the maintenance strategy, history, and status. All must be considered when managing the maintenance of a wagon. The organisation and maintenance strategy can be changed even if there may be difficulties, i.e., it is not a certainty.

An important part of the maintenance strategy in a CBM is CM, and for present purposes, the profile and wheel/rail forces, is the monitoring technique. The location of the workshops is key to considerations of the number of spares needed and how the transportation is to be handled. The configuration of the parts and components of the vehicle is also important; some parts of a vehicle are more prone to breaking than others, while others have wear as the failure mode.

The wheels on a freight wagon have several different failure modes, for example OOR, RCF, wheel flats, and profile wear. These failure modes and the maintenance strategy handling them must consider the influence of the material and profile of the wheel, as well as the brake system and braking strategy. Different profiles and materials can either introduce or remove cracks from the wheel surface. The brake system and braking strategy can introduce heat into the wheel, leading to possible material transformation and crack initiation.

### 8.1.1 *Life cycle modelling*

Paper A introduces a general LCC-model for maintenance improvement; see Eq. 8.1. The basis for this model is shown in Fig. 6.5 and 6.6, where  $C_A$  is the acquisition cost and  $C_I$  is the cost for inspections.  $C_{PM}$  and  $C_{CM}$  are the preventive and corrective maintenance costs, respectively, and  $C_R$  is the risk/safety cost.

$$LCC = C_A + C_I + C_{PM} + C_{CM} + C_R \quad (8.1)$$

In paper E the equation is altered slightly to accommodate the fact that the cost for re-profiling is the same regardless of whether re-profiling is done as corrective or preventive maintenance. The cost for downtime is added as a separate item.

Fig. 8.2 shows the life of several wheel sets. The diameter is calculated as 70 mm from the back of the flange; see Fig. 4.4. The natural wear from use is shown as angled lines; vertical lines show the material removed from the diameter by the turning machine at re-profiling. In the case studied, no measurement of the diameter was performed before re-wheeling, making the amount of natural wear for the last running period larger than expected.

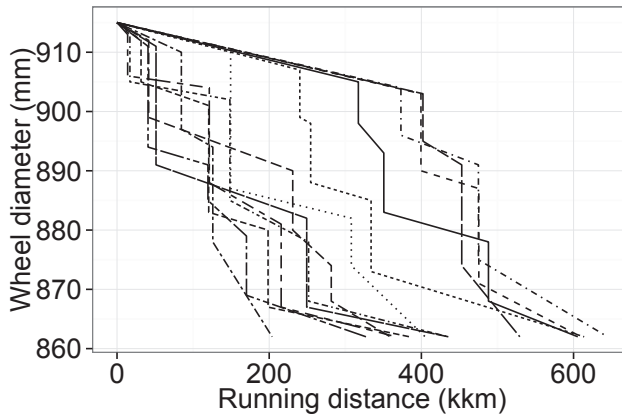


Figure 8.2: Material removal from diameter due to natural wear or re-profiling

The natural wear for the wheels in Fig. 8.2 is about 3 mm for every 100 000 km travelled. According to the data in the figure, a wheel set could travel 400 000 km before re-profiling is needed; at that point, about 8 mm of the diameter would be removed. Thus, the wheel set could travel for 10 years with today's yearly travel distance, with only two maintenance actions and reaching a total of 1 200 000 km.

Fig. 2.1 makes visible the difference in degradation rate between RCF and wear. Wheel wear from use is easier to see and measure, since cracks visible to the naked eye are usually 1 mm long. Today, visual inspections and workshop reviews, as shown in Fig. 6.5, are done manually, and maintenance personnel follow a subjective decision making process. Combining these inspections and reviews with CM data from wayside stations can help find faulty wheels and increase the running life of the wheels in traffic.

By analyzing the trending of collected condition monitoring data of the wheels, it is possible to predict the next maintenance actions. This, together with the use of LCC-model, can help maintenance management get the maximum distance from wheels before they need re-profiling. A wheel set that is almost at the safety limit can make a few more trips before the limit is reached and the wheel must be pulled out for safety reasons.

## 8.2 CONDITION MONITORING DATA

Fig. 8.1 illustrates the CM of the profile and forces. This research uses data from two wayside stations. The data are restricted to iron ore trains travelling loaded towards Luleå with data for the locomotives removed.

## 8.2.1 Profile data

The profile station captures the profile of all wheels on every train that passes. There can be problems calculating the profile from the captured image, resulting in missing data. The data collected and analysed here are for two 14-day periods, one in April and the other in August. The density function for the different wheel parameters,  $S_h$ ,  $S_d$ ,  $qR$ , and  $TH$ , is seen in Fig. 8.3. In April, about 44 000 wheels were captured, and in August 50 000; of these, a total of 46 000 wheels travel in the right direction. Of these, about 10 500 wheels are missing data.

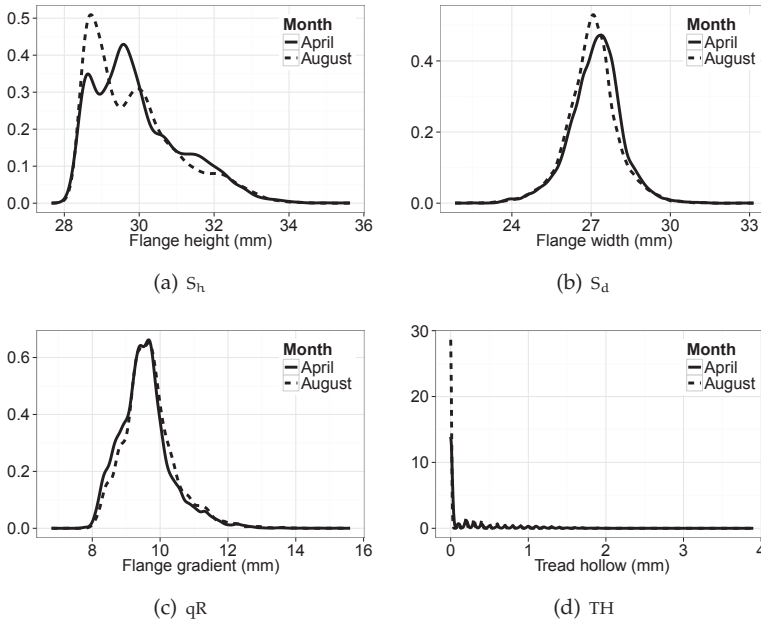


Figure 8.3: Density graphs for wheel profile parameters

There is a difference in peaks for August and April, as shown in Fig. 8.3(a). In August, the overall flange height of the wheels is less than in April: a newly turned wheel is a  $S_h$  close to 28 mm. This suggests that in August more wheels have been recently re-profiled, contradicting other studies, for example by Kalousek et al. [1996], where flange height wear is shown to be greater in winter. Another possible reason for the difference is the installation of a top-of-rail lubrication in June. Both months have the same number of wheels exceeding 32 mm, but none is above the safety limit of 36 mm.

For the flange thickness shown in Fig. 8.3(b) and the gradient in Fig. 8.3(c), the data seem to be normally distributed. If they reach a defined threshold, they trigger certain maintenance decisions.

For tread hollows, only a few wheels have values more than 1 mm; see Fig. 8.3(d). This indicates that the contact point between wheel and rail travels along the full width of the profile. A hollow worn wheel usually has a narrow running band where it is most heavily worn.

### 8.2.2 Wheel/rail force data

The research station collects wheel/rail force data for all passing vehicles. Each wheel is measured at three different points for about three metres. The measurements are done in micro strain and converted into kN. The data are collected for three 14-day periods in January, April, and August. January has about 51 000 rows of data, April has 82 000, and August has about 87 000. Each row of data represents one wheel axle and shows vertical and lateral forces for both wheels. In total, about 110 000 axles travel in the right direction.

Fig. 8.4 shows the vertical forces split according to the time of passing. The lateral forces are shown in Fig. 8.5.

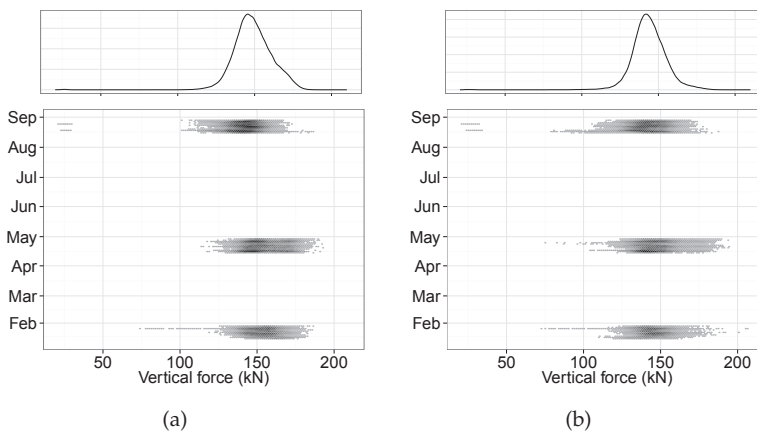


Figure 8.4: Vertical force frequency

There is some difference in the vertical load between the three time periods; see Fig. 8.4. The peak axle load is just under 300 kN; this is to be expected, as the allowed axle load for the train should average 30 metric tonnes.

The lateral forces for the outer/right wheel, Fig. 8.5(b), are around 0 kN with some differences between the time periods. The lower values for August are likely due to friction, since a top-of-rail friction modifier has been installed close to the measuring station.

The large differences in lateral forces for the inner/left wheel between the time periods, as shown in Fig. 8.5(a), are significant. The differences can be due to the friction modifier installed, but the lateral forces for

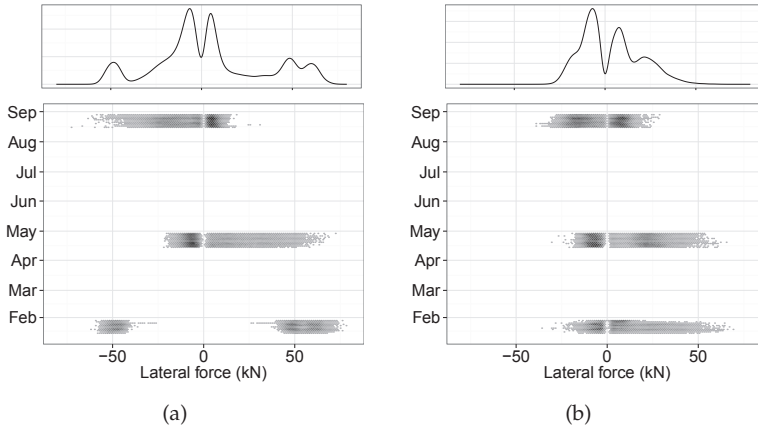


Figure 8.5: Lateral force frequency

February must be the result of something different. For example, the snow and ice build-up around the wheels and bogie may decrease the steering ability of the inner wheel and produce large lateral forces.

### 8.3 WHEEL PROFILE MEASUREMENT VERIFICATION

Most CM equipment only measures the profile at one point on the circumference of the wheel. Both the MiniProf and the automatic wheel profile station used in this thesis use this approach. In this section several measurements on one wheel are compared in order to verify the assumption that measuring one point is enough for the whole circumference of the wheel.

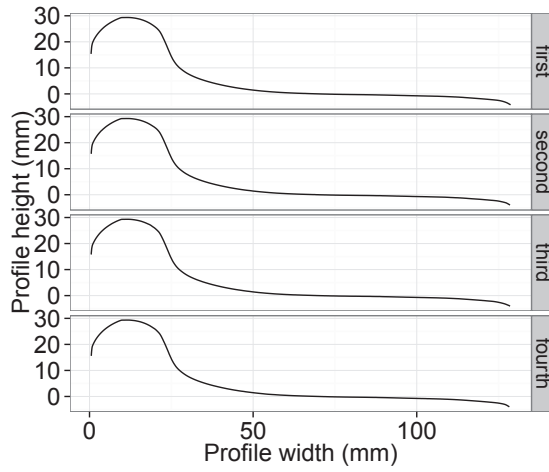
In Fig. 8.6 the profile is measured by a MiniProf at four different points along a third of the wheel circumference. The MiniProf calculates the wheel parameters, and these are presented in Table 8.1.

Table 8.1: Wheel parameters calculated by the MiniProf

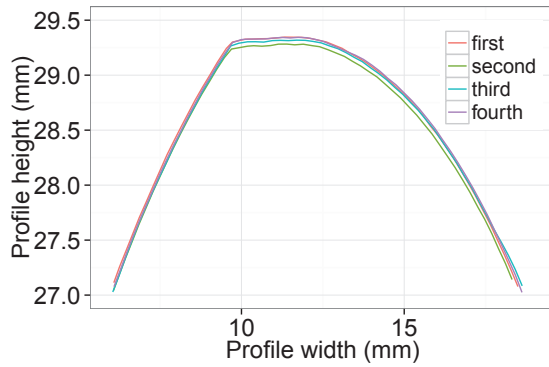
	$S_h$	$S_d$	qR
first	29.35	27.53	9.42
second	29.28	27.43	9.31
third	29.32	27.44	9.16
fourth	29.34	27.53	9.36

Fig. 8.6(a) shows that all four profile are similar, with approximately the same shape. When these four profiles are plotted with the running circle as reference, the difference between the profiles is only visible at





(a)



(b)

Figure 8.6: Wheel circumference assumption

the top of the flange; see Fig. 8.6(b). The difference is very small; this can also be seen from  $S_n$  in Table 8.1. According to these findings, the assumption that one measurement hold for the whole wheel is valid, since the wheel wear is gradual.



## CONCLUSIONS AND FUTURE RESEARCH

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This chapter presents the conclusions, discusses the contributions of the research and suggests directions for future research.

### 9.1 CONCLUSIONS

The thesis comes to the following conclusions:

*RQ1: How can CBM facilitate capacity assurance for rolling stock?*

Condition monitoring data supports effective maintenance planning, as well as assessments of the state of the items and to facilitate correct decision-making regarding maintenance actions. This assures the reliability and availability of the rolling stock.

Furthermore it is demonstrated that the LCC-model is a good engineering tool, but it must be continuously updated with new data either from simulations or by condition monitoring techniques.

In short, in CBM decisions are made based on real-time data from way-side CM stations which in combination with a LCC analysis, consisting of real and simulated data, facilitating selection of the best alternative maintenance actions leading to achievement of planned rolling stock capacity.

*RQ2: How does information about state/health of the item affect the planning and execution of railway maintenance?*

Railway operation in colder environmental conditions increases the natural wear rate of the wheels. Thus, the trending of the wheel performance data for different seasons should be considered when planning maintenance actions. There might be a need to change maintenance limits depending on the season.

The continuous monitoring of lateral forces on the vehicles can decrease the risk of derailment by continuous assessment of the physical state of the item. A large lateral force and insufficient friction could make a wheel continue to travel in tangent direction over the rail instead of following the curve, leading to abnormal wear (resulting in failure) or derailment. To decrease the risk of derailment, it is essential to understand the later forces generated in the wheel/rail contact and the state of the item measured through CM.

The data collected from CM and subsequently transformed into information will provide an improved RUL estimate for the item or system.

When the RUL is known and used in the decision-making process for maintenance actions, these decisions will lead to efficient and effective maintenance planning and execution of maintenance tasks which in turn will lead to rolling stock capacity assurance

## 9.2 CONTRIBUTION

The research makes the following contributions:

- It is demonstrated that the application of condition monitoring technologies and condition-based maintenance strategies for rolling stock enhances the effectiveness and efficiency of maintenance actions leading to elimination of failures and improvement in availability.
- An improved theoretical life cycle cost model considering acquisition, wheel turning cost, downtime due to wheel maintenance, inspection cost, and risk due to wheel failure or derailment is presented.

## 9.3 FUTURE RESEARCH

Based on the research conducted for the thesis, further research might consider the following:

- Combine the data-driven model with PoF-models to form a hybrid-model for use in future maintenance assessments.
- Develop dynamic DSS from the optimal strategy to use the existing CM tools to plan and assess the wagon maintenance.
  - Collect and clean data for the LCC to evaluate the current maintenance strategy. This can be a starting point for any further analysis of policy or strategy changes.
  - Collect data for simulations on wheel failure modes, running distances, and material removal at re-profiling to do a complete analysis of vehicle fleet wheel life.
  - Combine the simulated vehicle fleet data and the LCC model to perform simulations and evaluations of different maintenance strategies and performances to find the best possible maintenance strategy.

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Part II

APPENDED PAPERS



M. Palo, J. Ling, and P.-O. Larsson-Kräik,  
*“Maintenance performance improvement for rolling stock wheels,”*  
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# Maintenance Performance Improvement for Rolling Stock Wheels

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The service life of a railway wagon wheel can be significantly reduced through failure or damage, leading to excessive costs and accelerated deterioration. In order to monitor the performance of wheels on heavy haul wagons, this paper proposes implementing the Plan, Do, Study, and Act (PDSA) maintenance performance improvement process. As a case study, it looks at wheels on the heavy haul wagons of a Swedish company, considering all factors that may influence the need for maintenance. After investigating the PDSA process, it proposes the use of Key Performance Indicators (KPIs) for both risk and economic reasons. The paper concludes that the PDSA process and KPIs are useful tools to improve the maintenance performance of railway wheels.

## 1. Introduction

Railways capitalize on the low resistance between wheel and rail to create an energy efficient mode of transport. However, increasing emphasis on maintenance and life cycle costs (LCC) for rolling stock, such as wheels, and for infrastructure results in the need to predict wheel and rail wear (Enblom and Berg, 2005) to optimize maintenance decisions and estimations of remaining useful life. One of the most important elements in the dynamics of a railway vehicle is the interaction between the wheel and the rail (Charles et al., 2008). The wheel profile determines the stability of a vehicle (Barke and Chiu, 2005), and the rate of wheel surface wear determines the life length of a wheel (Braghin et al., 2006). Thus, effective maintenance will increase the wheel's life. But maintenance of rolling stock not only increases the life of the stock; it also reduces rail degradation (Kumar et al., 2008). As the wheels are in direct contact with the rails, degradation on the wheel surface and profile will cause rail degradation. Reduced wheel degradation through proper maintenance will therefore result in less rail degradation.

The most common wheel problem is flange wear (Larsson et al., 2003), a consequence of friction between wheel and rail (Reddy et al., 2004). To restore the flange, a substantial amount of metal is removed from the wheel tread. The four wheels of a bogie wear differently, depending on their position within the bogie, indicating differences in wheel/rail forces (Palo et al., 2012b).

To evaluate the condition of the wheels, condition monitoring equipment is placed along the track, using a technique called wayside detection. Either wheel/rail forces or wheel profiles can be measured to monitor the condition of wheels. Another method of monitoring is visual inspection of the wheels at the railway yard. Wheel monitoring is also performed in the wagon workshop when the wagon is there for repairs or regularly scheduled maintenance.

The life cycle cost (LCC) of a product can be considered a Key Performance Indicator (KPI) when determining the appropriate maintenance procedure for that product. LCC is made up of the costs to the manufacturer, user, and society (Asiedu and Gu, 1998). It is one of the most effective cost approaches when buying assets for the long term (Jun and Kim, 2007), as it helps engineers justify the selection of equipment based on the total cost over the life of the asset rather than just the initial purchase cost. Even though operating and support costs represent the most significant portion of the LCC, they are the most difficult to predict (Asiedu and Gu, 1998).

Given the number of stakeholders in the Swedish railway, such as contractors, transparent information systems are critical. The contractors have complete responsibility for all aspects of maintenance and maintenance support; they must guarantee performance and availability. A clear definition of maintenance, including objectives and responsibilities, is very important for cost effective maintenance and problem-free operation (Palo et al., 2012a). In practice, both on-site maintenance engineers and maintenance managers should know how maintenance is carried out and be aware of plans for future improvement (Lin et al., 2011).

This paper only considers wheels; for one thing, studying the whole wagon is very complex, and for another, the interface between wheel and rail has the greatest influence on maintenance costs for the train-track system. Finally, wheels constitute a large part of a railway's rolling stock maintenance cost and a there can be improvement made. The paper is organized as follows. The introductory section gives an overview of the wheel maintenance problem. Section 2 describes the research background and the maintenance process currently used. Section 3 suggests PDSA as a framework for improving maintenance. Section 4 posits LCC as a KPI for maintenance. Section 5 relates the topics under discussion to the case study, while Section 6 presents conclusions and suggests future work.

## 2. Background

### 2.1 Iron ore transport

The only existing heavy haul line in Europe, is the Iron Ore Line (Malmbanan); it stretches 500 km from Luleå in Sweden to Narvik in Norway, see Figure 1. The mixed traffic of the line includes both passenger and freight trains. The iron-ore freight trains consist of two IORE locomotives accompanied by 68 wagons with a maximum length of 750 metres and a total train weight of 8 500 metric tonnes, see Figure 1. The wagons are equipped with three-piece bogies, so called because each comprises one bolster and two side frames (Palo and Schunnesson, 2012). These pieces are connected using friction wedges and spring suspensions. The wagons are subject to a kilometre-based maintenance strategy.

In 2011, the LKAB mining company transported 25.7 MGT (million gross tonnes) from its mines in Kiruna and Malmberget; of these, 5.7 MGT were shipped from Luleå harbour. The trains operate in harsh conditions, including snow in the winter and extreme temperatures ranging from  $-40\text{ }^{\circ}\text{C}$  to  $+25\text{ }^{\circ}\text{C}$

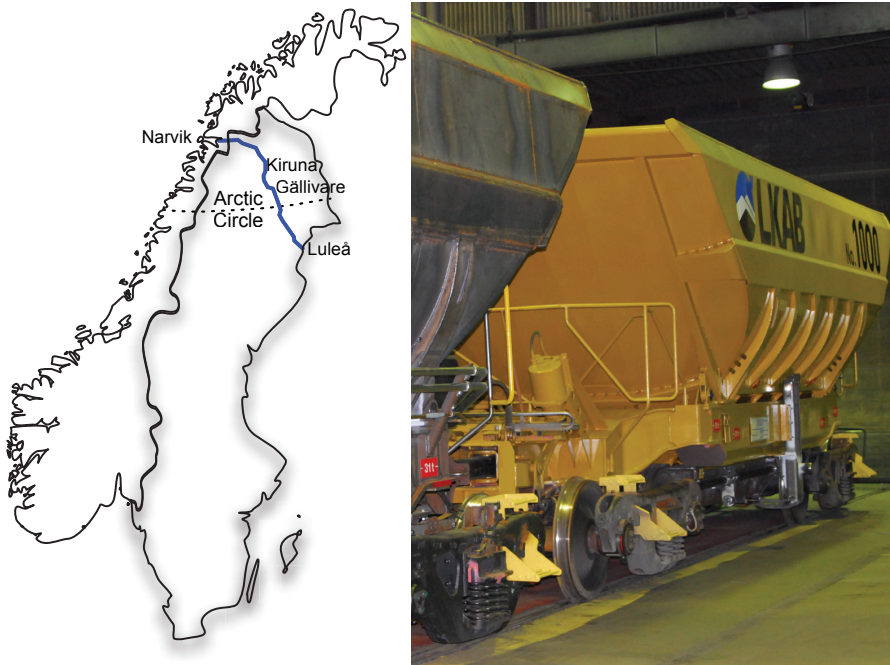


Figure 1: Geographical location in Northern Sweden and an iron ore train

## 2.2 Maintenance process

There are several methods to detect and monitor wheel wear and wheel fatigue. One is visual inspection of the wheels at the railway yard. Another is the use of wayside monitoring stations to detect faults or failures. A third option is during general wagon maintenance in the workshop. Wheel maintenance decision criteria are stricter and more rigid at the wagon workshop than at the railway yard. If a wagon with bad wheels is at the workshop, the wheels can be maintained before they reach their maintenance limit (opportunity based maintenance actions) (Palo et al., 2012a). There are a number of failure parameters that determine the proper maintenance action for the wheel before it is put back into service.

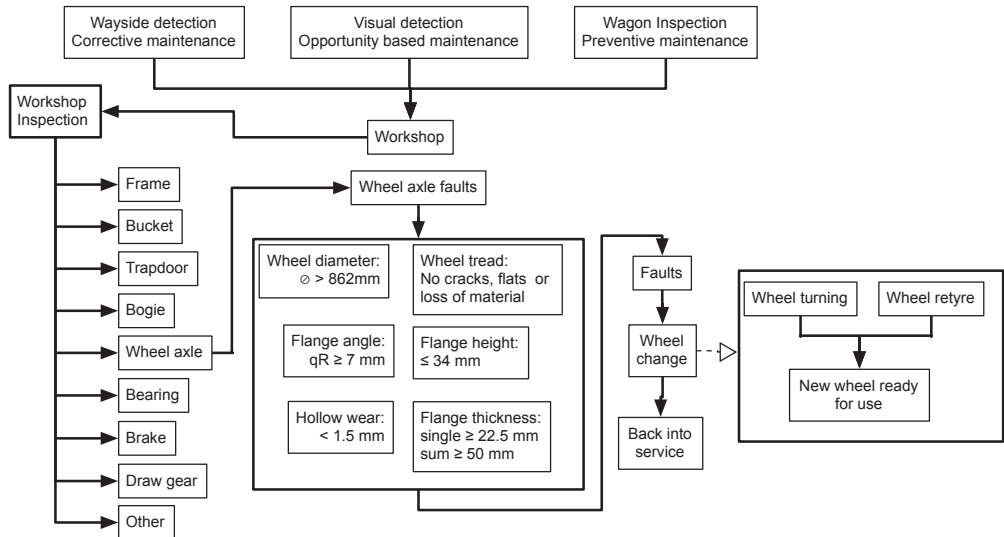


Figure 2: Inspection and maintenance process

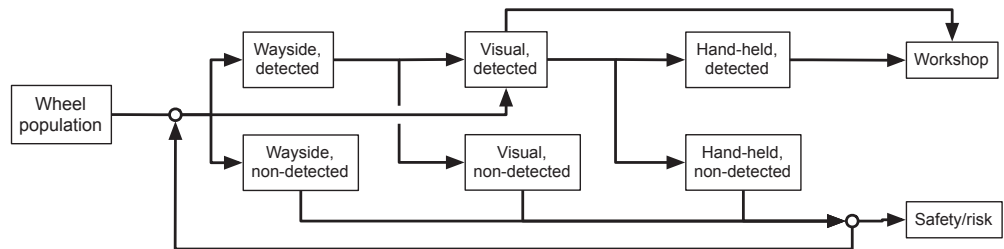


Figure 3: Wheel detection process

Figure 2 shows the overall maintenance process. The work order for a wagon to appear at the workshop can come from three different sources: safety alarms, visual inspections or predetermined running distance. Figure 3 looks specifically at wheels, illustrating what happens to a wheel with a damage or geometry failure at the beginning of the maintenance process. A faulty wheel is detected either visually using wayside detection systems, or manually using hand-held monitoring equipment. From here, a work order is generated and the wheel goes to the next stage. In either of these stages, the wheel can have a fault that is not detected. These non-detected faults represent a certain safety or risk cost.

The risk/safety factor or cost shown in Figure 3 refers to when a wheel has a fault that is not detected; in this case, the wheel will run to failure before it is caught in another detection cycle. The cost associated with these unplanned maintenance actions is treated as a risk cost in this paper. Risk management is a useful tool in decision making and strategy planning.

### 3. Maintenance performance improvement process

Dr. W.E. Deming developed a plan for continuous improvement, which he called the Shewhart Cycle for Learning and Improvement (Moen and Norman, 2010). The plan has four stages: Plan, Do, Study and Act. This process includes the following stages: plan a change aimed at improvement, carry out the change, examine the results and, finally, adopt the change or abandon it and run through the cycle again (Moen and Norman, 2010). In Figure 4 the maintenance process described in Figure 2 is set into a PDSA cycle.

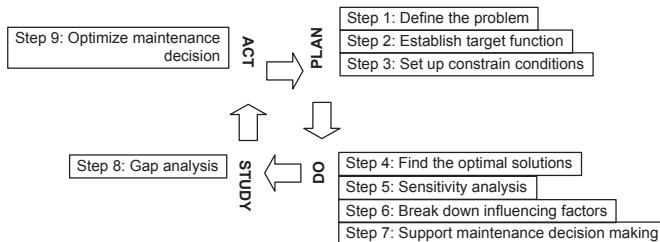


Figure 4: The different stages for continuous improvement

The different steps correspond to different actions taken during the improvement process. The four stages and nine steps are explained in more detail.

#### 3.1 Plan stage

Our aim in the plan stage is to define the problem and set up target functions and constraint conditions. First, we define our area of study, in this case, the maintenance of railway wagon wheels. In our second step, we define the life length of a wheel between re-tyres as 850,000 km of running distance. Next, we determine the number of wagons to be studied. We also determine the various costs: inspection cost, wheel turning (in house or outsourced), wheel re-tyre cost etc. In our final step, we must find and understand the influencing factors.

#### 3.2 Do stage

In the execution or do stage, our purpose is to analyze the defined problem. To this end, we first look for the optimal solution, using operations research, non-linear programming, dynamic programming and/or decision theory. Next, we perform a sensitivity analysis of the optimal solution. In the following step, we decide on the influencing factors priorities, for example, the condition monitoring parameters. Finally, we incorporate the influencing factors into the maintenance decision making.

#### 3.3 Study stage

In this stage, our aim is to perform gap analysis on a number of aspects to determine if the changes are leading to improvements. Interesting parameters to consider are the reliability of wheels, maintenance tasks and other key performance indicators (KPIs), as for example, LCC. When studying wheel reliability, we must consider the various failure modes a wheel can have, for example, wheel flats, rolling contact fatigue or profile wear. All these failure modes can have a considerable effect on the degradation of the infrastructure. It is of interest to determine whether there are any gaps between performed and expected maintenance tasks. It is also interesting to investigate whether the working process seen in Figure 2 is optimal. When calculating the LCC, we differentiate the costs associated with corrective and preventive maintenance and summarize the number of times each type of maintenance is performed.

#### 3.4 Act stage

Following the study stage, we review all actions to determine whether maintenance decisions have been optimal and should be continued. Usually, only condition monitoring and failure data are recorded. These data are seldom analyzed with a view to optimizing maintenance strategies, but they are actually very important in reducing unplanned work-orders and optimizing maintenance strategies. Nor should human factors be neglected, as they can have a large influence on the performed maintenance.

#### 3.5 Continuous improvement

As soon as the last stage is completed, the continuous improvement that PDSA is known for can only occur if the cycle is restarted. We must again define the problem and work our way through the whole PDSA cycle.

#### 4. Maintenance Life Cycle Cost Analysis

Reddy et al. (2004) shows how costs associated with rail maintenance are estimated separately for low rail, high rail and curve radius and added up to obtain the total cost of maintenance. The total cost of maintaining a segment of rail is equal to the sum of the following costs: preventive rail grinding cost, down time cost due to rail grinding, inspection cost, risk cost of rectification based on inspection, rail breaks and derailment, and replacement cost of worn-out unreliable rails.

Life cycle cost modeling is highly dependent on the scope and objectives of a model (Jun and Kim, 2007). Operational requirements and maintenance strategies should be developed before developing a life cycle cost model. Life cycle costing is an iterative way to find the most desirable alternatives. A baseline system, which is an initial design concept, may be improved throughout iterative LCC analysis. LCC analysis is a good tool to use as the economic parameter in the PDSA, since it accounts for all costs of a wheel between two re-tyres.

For a railway wagon wheel, the total cost for maintenance can be estimated by adding up the following; Acquisition cost  $C_A$ , Inspection cost  $C_I$ , Preventive maintenance cost  $C_{PM}$ , Corrective maintenance cost  $C_{CM}$ , and Risk/safety cost  $C_R$ . The LCC is then given by:

$$LCC = C_A + C_I + C_{PM} + C_{CM} + C_R \quad (1)$$

where  $C_A$  is the cost of purchasing and installation of two new wheel rims/discs on an axle. This is done either when taking a new axle into service or when the old axle is too worn. Inspection cost,  $C_I$ , is the cost associated with inspections and condition monitoring equipment in wayside stations, seen in Figure 3 or the start of the process in Figure 2. This is a fixed cost for each wheel, since it is difficult to predict how often a wheel is inspected or passes a monitoring station.  $C_{PM}$  is the cost associated with wheel axle faults, see parameters in Figure 2, detected at either wagon inspections in the workshop or visually when walking by the vehicle in the train yard.  $C_{CM}$  is a much larger cost than for preventive maintenance, since it constitutes the additional cost of changing an axle out on the line as well as transporting the vehicle back to a workshop or train yard.  $C_R$  is the risk/safety cost, as shown in Figure 3.

#### 5. Discussion

The railway makes extensive use of fault detection and condition monitoring tools. By using the data from these systems, an infrastructure manager or train operator can find failures among assets before they reach the point of becoming a fault. In the maintenance process used in our case, data from a number of sources can create a work-order in the workshop. If we refine the thresholds for these monitoring sources, we can optimise the overall maintenance cost.

This paper seeks to find a framework for this optimisation process, using PDSA as a tool. Within this, we have used LCC as the economic parameter, with the cost of risk/safety of wheel failure an important part of this parameter.

The condition monitoring tools available for predicting maintenance needs are not yet used to their full potential. However, accurate predictions can increase wheel reliability and life length and decrease the cost of maintenance.

#### 6. Conclusions

We think this paper offers a good framework to start the process of improving maintenance performance and decreasing the overall cost of wheel maintenance. This is, of course, only a beginning: the framework must be implemented and its performance evaluated before its full scale implementation. The authors are currently working on this; their results will be published in the near future.

#### Acknowledgement

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# Condition monitoring of wheel wear on iron ore cars

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## Abstract

Keeping wheel profiles in an acceptable condition is a major concern for both railway operators and infrastructure owners. The condition of the wheels influences both their wear and the required rail maintenance. Wheel wear affects the dynamic characteristics of vehicles and the dynamic force impact on the rail and, in a worst case scenario, can cause derailment.

This paper studies the correlation of wear rate and wheel force to temperature and seasonal differences, monitoring eight identical wheel axles of different ages for a full life cycle. The study notes differences in wheel wear and wheel/rail forces while operating with a 30 ton axle load and in temperatures ranging from  $-30^{\circ}\text{C}$  to  $+30^{\circ}\text{C}$ . It measures speed, vertical and lateral forces for every train passage and calculates the lateral-to-vertical force ratio at a research station near Luleå, Sweden.

The study concludes that wheel wear is significantly greater at lower temperatures. The magnitude and variation of lateral forces are strongly dependent on the bogie position, with the highest peak value recorded for the leading low rail. The L/V ratio is strongly seasonally dependent with large differences within a month due to changes in friction.

## Keywords

Condition Monitoring, Railway, MiniProf, Wheel Wear, L/V ratio, TPD

## 1 INTRODUCTION

Keeping wheel profiles in an acceptable condition is a major concern for both railway operators and infrastructure owners. For one thing, the dynamic behavior of the vehicle is highly dependent on the shape of the wheel profile. For another, wheel conditions are related to derailment safety. In addition, a significant percentage of vehicle maintenance cost is allocated to wheel maintenance.

The interaction between wheel and rail resulting in material deterioration is a complicated process, involving vehicle-track dynamics, contact mechanics, friction wear, and lubrication [1]. The course of events called wear is similarly complicated, involving several modes of material deterioration and contact surface alteration [2]. Rolling contact fatigue in railway wheels is increasingly important [3]. Even small failures or early cracks are costly, requiring maintenance and possibly causing delays.

To reduce cost and achieve a wheel's maximum life span, maintenance practices must be based on its condition. According to simulations performed by Braghin et al. [4], re-profiling wheels after 200 000km of service would nearly double their service life, thus minimizing life cycle costs. The ability to eliminate non-optimally performing equipment through the use of wayside detectors can translate directly into enhanced operations safety, improved asset life cycle costs, and increased operating efficiency through fewer unscheduled service disruptions [5]. Applying condition-based maintenance requires selecting a proper condition monitoring system, a database for collecting condition data, and an appropriate data analyzing process to make maintenance decisions from condition data.

One of the most difficult aspects of a condition-based maintenance strategy is making good maintenance decisions based on the available condition data. In this paper, we use the correlation of wear rate to temperature, wheel position within the bogie, and track force to pinpoint a cost-effective wheel maintenance interval.

### 1.1 Inspection and non-contact condition monitoring

An important goal of predictive monitoring is to prevent failure through the early, reliable, and cost-effective detection of faults in rolling stock [6], including the discovery of early cracks [3]. Traditional inspection techniques used in the railroad industry, such as drive-by inspections, are not as accurate and reliable as more rigorous and quantitative inspection methods [7]. For example, condition monitoring uses some level of knowledge of the system of interest to establish its current condition [8]. To this end, the railway industry uses wayside detection [9], a technique of detecting specific faults on rolling stock by interrogating sensors placed along the sides of tracks. This non-contact method can be used on trains travelling at track speed. It provides direct feedback to both operators and track owners on the condition of vehicles passing a wayside monitoring station. A survey mentioned by Stone et al. [10] notes that impact load detectors are effective tools for monitoring high impact load-producing wheels. There is also evidence that in-train inspections procedures are not as effective as shop inspections of the identified wheels.

There are several different methods of detecting dynamic force impact on the rail track. The two most commonly used are strain- and accelerometer-based systems. Accelerometer-based systems measure the motion of the rail resulting from the dynamic load of a passing wheel [9]. Strain-based systems measure the bending of the rail, as it is a direct measure of the applied load on the railhead. There are limitations to both methods. The registered acceleration method does not give a quantitative measure of the size of the impact load [11]. The strain-based system can have difficulty covering the combined circumference of all wheel diameters if not extended by sensors covering at least 3m of the track [12]. High-impact wheels have an impact force of 400 kN or greater; most often they have a flat spot on the tread surface [7]. Major defects in the tread surface can also cause high-impact force; these have a higher probability of leading to catastrophic failure.

## 2 CASE STUDY BACKGROUND

The iron ore line in northern Sweden starts in Luleå and ends in Narvik, Norway (see Figure 1). It is trafficked by both passenger and freight trains. The freight consists primarily of heavy haul trains with axle loads from 22.5 tons. The train operates in harsh climate conditions, including snow in winter and extreme temperatures ranging from  $-40^{\circ}\text{C}$  to  $+25^{\circ}\text{C}$  [13].

We studied two iron ore freight cars with a total of eight axles or wheel sets. These two cars are always connected by a steel rod when in use. Figure 2 shows their wheel and axle designations; the cars are connected at the A-end. Technical specifications appear in Table 1.

In order to calculate the wear trend, we made measurements with a MiniProf™ for a period of 15 months, from March 2009 to May 2010. We obtained the trends of track forces for the two cars from the research station at Luleå, Sweden, for the same period.

Table 1. Technical specifications for investigated iron ore cars

Maximum speed (loaded)	60 km/h
Wheel diameter (max)	915 mm
Wheel diameter (min)	857 mm
Axle load	30 ton
Bogie	AMSTED three-piece
Wheel profile	UNO wp4

The cars in the case study use three-piece bogies, so called because each comprises one bolster and two side frames. The bogie suspension system has non-linear frictional characteristics. Efficient track twist performance without losing vertical wheel load is an advantage of this structure [14]. At the present time, bogie maintenance is based on travelled distance [12]. A computerized maintenance planning system uses RFID on the cars and wayside antennas on the route to make these calculations. Based on its determination of total mileage, the system can generate lists of cars ready for overhaul. Daily manual inspection at the rail yard complements the system by identifying cars not able to operate until the next service based on mileage.



Figure 1. The iron ore line from Luleå to Narvik

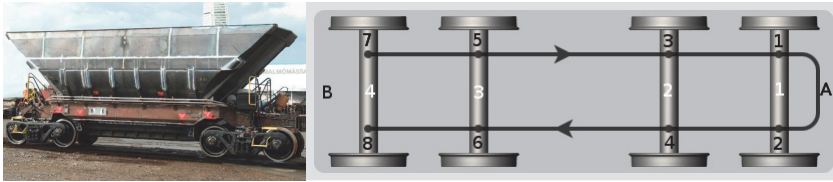


Figure 2. Iron ore train car and designation of wheels and axles

### 3 MEASUREMENT SYSTEMS

#### 3.1 MiniProf™

The measurement system MiniProf™ is used by many railroads to monitor wheel and rail profiles [15]. MiniProf™ is one of the most reliable and accurate monitoring systems. In fact, the results of other wheel profile monitoring systems are often compared to MiniProf™ to check their accuracy.

The MiniProf™ Wheel (see Figure 4a) has a sensing element consisting of a magnetic wheel of 12 mm attached to the end of two joint extensions. It measures the profile with two degree of freedom, and a computer calculates the profile in Cartesian coordinates. The resolution is in thousands of millimeters. During this

calculation it also retrieves the flange thickness (Sd), flange height (Sh), and flange gradient (qR) (see Figure 4b).

To measure the wheel profile, the MiniProf™ is magnetically attached to the wheel. The back and top of the wheel are used as horizontal and vertical references respectively [15]. Even given the high accuracy of the instrument itself, there can be inaccuracies in measurement procedures, such as dirt or physical inaccuracies at the back of the wheel. Therefore, a calibration must be done to compare measurements at different times. We used a two-point calibration, beginning with a vertical adjustment to the top point of the flange, followed by a horizontal adjustment based on the inclined part of the backside of the flange. Figure 3 shows the procedure.

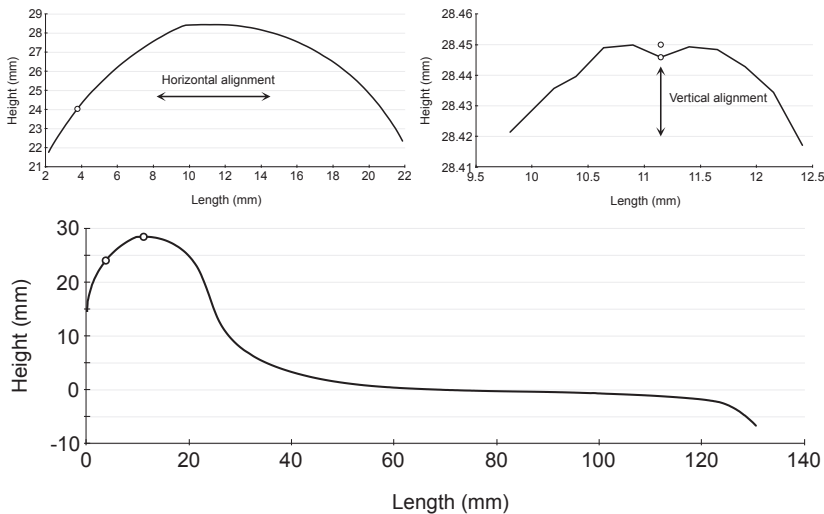


Figure 3. Alignment of profiles between different measurements

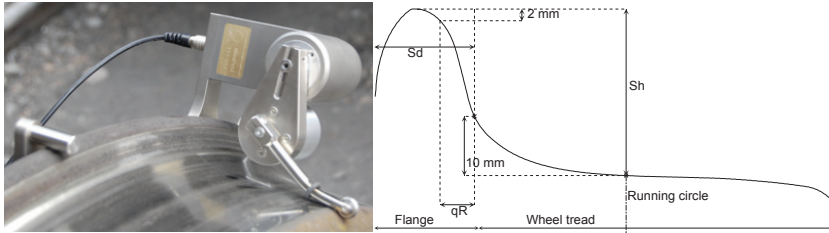


Figure 4. Picture of MiniProf™ Wheel measurement system and an explanation of  $Sh$ ,  $Sd$  and  $qR$  calculation

### 3.2 Research station at Luleå

The optimal Truck Performance Detector (TPD) layout allows a thorough evaluation of the bogie’s “dynamic” curving performance by checking left and right rotation as well as the bogie’s ability to return to a neutral tracking position in the tangent section [5]. The TPD measures wheel/rail forces *via* strain gauge sensors on the rails in selected reverse curves, with a modified version installed in a single-curve load station [16]. The system measures the lateral and vertical forces produced by each wheel set as it negotiates the curve where the detector is located [17]. A TPD can indicate poor bogie performance *via* measured forces, angle of attack, and corresponding derived values as lateral-to-vertical (L/V) force ratios [16]. The strain gauges quantify the force applied to the rail through a mathematical relationship between the applied load and the strain on the rail web or rail foot.

The research station is a modified TPD station, monitoring forces for all passing trains situated on a curve with a radius of 484m. The measurement system consists of strain gauges attached to the web of the rail as indicated in Figure 5. Figures 5a-b show how the system is attached to the rail.

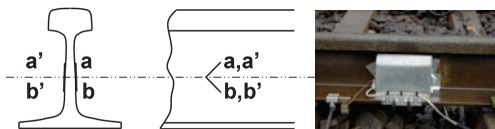


Figure 5. Picture of measurement system placement at the research station

## 4 RESULT

To monitor wheel wear for a full life cycle, we selected eight identical wheel axles of varying

ages. However, during the project period, two axles had to be changed for newly turned wheels due to the detection of high-impact loads. Figure 6 shows the age of the eight wheel axles and their progression throughout the study. As seen in the figure, we included a service life from 0 to almost 350000 km in the project

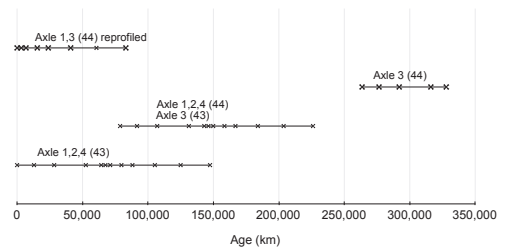


Figure 6. Age distribution of studied wheels

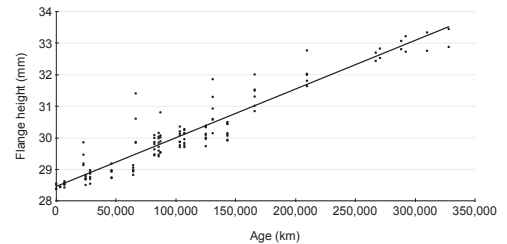


Figure 7. Flange height versus age

The profile statuses of the wheel are characterized by flange and tread wear and are quantified by the flange thickness and flange height [18]. The flange height is calculated as the difference between the running circle and flange top. Figure 7 shows the flange height changes with age for all wheel axles. The wear rate in the same figure shows a clear linear trend with increasing service life. While this agrees with the findings of Wilson et al. [19], their results [19] showed a lower slope. This could be due to differences in the vehicle/track system and/or the climate.

#### 4.1 Wheel wear and temperature

The yearly average temperature for Luleå is +2°C. In Figure 8, a monthly average is calculated for the period 2000 to 2010 and appears as the long curved line. Each time the cars pass the research station outside Luleå the temperature is measured. In Figure 8, this is shown as a maximum, minimum, and mean for each month. As shown in the figure, the temperatures are below zero for a long time each year; on some days, they fall below -30°C. It should be noted that in December 2009 and January 2010, the cars were standing still for maintenance.

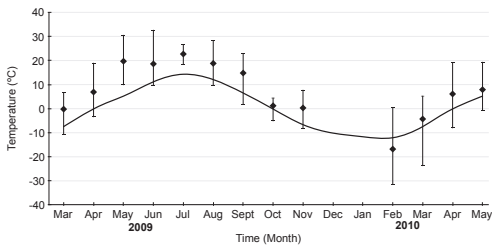


Figure 8. 10-year monthly average and temperatures for each passing of research station

In its depiction of wheel/rail dynamics, the linear trend for flange height in Figure 7 shows some of the complexity of railway systems. In this study, another dimension was also important: namely, the climate differences between summer and winter. According to a study by Kalsousek et al. [20], between 1982 and 1994 there was a two- to five-fold variation in wheels removed, with a large increase in winter wheel removals due to high wheel flanges. This indicates that tread wear rates must be many times higher in winter than in summer. In Figure 9, wheel wear is plotted against the average temperature between two profile measurements. The calculated wheel wear is in mm per 100 000 km travelled distance.

As Figure 9 makes apparent, there is increased tread wear during the colder periods of the year. Most years, snow is present from November to April on large sections of the investigated track. Snow crystals on the wheel tread melt during braking, ensuring that a water-oxide slurry is present on the wheel surface for a prolonged

time [20]. In wet conditions, the slurry will contribute to increased wheel tread wear.

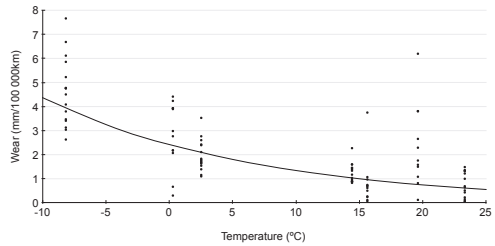


Figure 9. Wear at running circle in mm/100 000 km compared to temperature

#### 4.2 Wheel/rail forces

The research station outside Luleå measures the vertical and lateral forces of all passing trains, as well as their angle-of-attack and speed. Because of the high axle loads, train speed for a loaded iron ore train is restricted to 60 km/h with an allowed 9 km/h extra until the system engages the brakes. Each axle is permitted a 30 ton average vertical load for the whole train. As seen in Figure 10, the trains are within their allowed 9 km/h, and the vertical loads are centered at the targeted 30 ton.

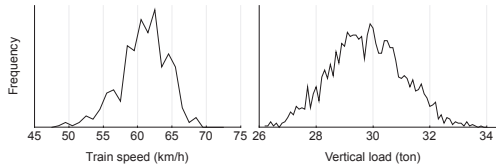


Figure 10. Frequency of speed and vertical load for loaded trains

The lateral force on the wheel set includes the gravitational force created because the plane of contact is not parallel to the track level [21]. The wheel set vertical load thus applies a lateral component of force to the rail, and this is picked up by the wheel set. The lateral forces measured are defined as positive towards the curve center. Figure 11 contains the frequency graph for the lateral force of each wheel position in the bogie.

As seen in Figure 11, the lateral forces for the leading axle are larger than those for the trailing axle. Studies by Wu and Robeda [22] and Elkins and Eickhoff [23] show a difference in lateral forces between leading and trailing axles as well

as between the high and low rail. The leading axle in Figure 11 shows a clear difference between the high and low rail. Also visible is the fact that the trailing axle creates lower lateral forces, possibly because it runs closer to the radial position [24].

In Figure 11, the leading high rail has forces up to 100 kN. That is expected since as Barbosa notes [25], this is the first wheel into the curve. That the leading low rail has forces from -10 to 130 kN is unexpected, but according to Elkins [26], it can be caused by large angles-of-attack.

### 4.3 L/V force ratio

Flange climb derailment is the result of combined lateral and vertical wheel/rail interaction forces [27]. Nadal's formula [28] is often used to determine the limit of the L/V ratio and is based on a simple force balance to calculate the ratio before a derailment occurs. If the friction coefficient between wheel and rail is  $\mu$  and the wheel flange angle is  $\alpha$ , as shown in Figure 12, changes in wheel and rail wear will influence  $\alpha$ . The L/V ratio is given by the following formula:

$$\frac{L}{V} = \frac{\tan \alpha - \mu}{1 + \mu \tan \alpha} \quad (1)$$

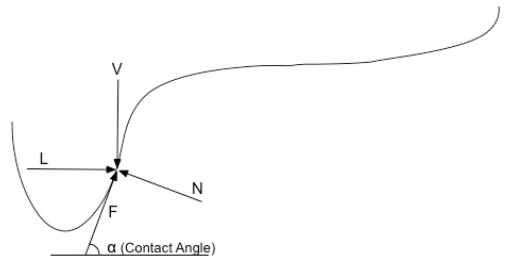


Figure 12. Flange forces at wheel climb

Tests conducted on rail vehicles as well as roller rig laboratory tests have frequently shown L/V ratios in excess of Nadal's limit without derailment [27]. The ratio for the lead outer wheel is indicative of the likelihood of derailment [16, 29], and there is a large curve radius dependency. According to Coe et al. [16], high-rail L/V ratios in the range of 0.3 to 0.4 are indicative of a poorly steering vehicle with a hard flange contact. In a study by Magel et al. [21], high L/V ratios of 0.7 to 0.8 appeared in one to two points per thousand.

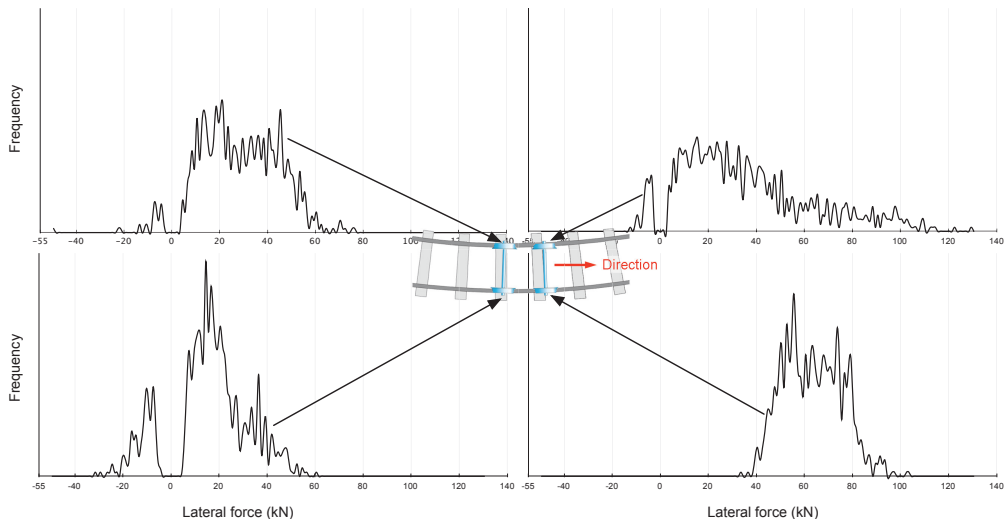


Figure 11. Frequency of lateral forces from different positions within bogie



The vertical forces of the iron ore cars considered in this study are normally distributed with a mean of about 30 ton (see Figure 10). The lateral forces, however, differ significantly between the different wheel positions (see Figure 11). The investigated train cars operate in an area with large temperature variations over the year (see Figure 8). Figure 13 presents the L/V ratios for a year for one wheel when it is on a leading high rail. The figure clearly shows seasonal differences that may affect the wheel's wear conditions.

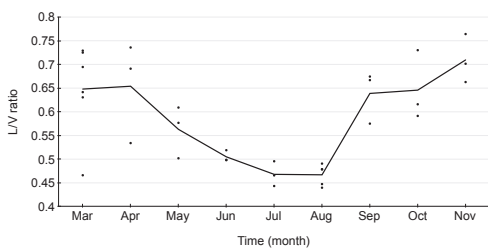


Figure 13. L/V ratio on leading high rail

Changes in the L/V ratio are related to changes in friction between wheel and rail (see formula 1). The friction conditions may vary from adequate adhesion with dry and clean steel-on-steel surface to low adhesion due to contamination, humidity, and applied friction modifiers [18]. Rail lubrication can significantly affect lateral forces when curving [22]. The decreasing trend seen from April to July takes place during a period of mostly dry weather and increasing temperatures. During the warm season, wayside wheel/rail curve lubricators are used. The driver can also use sand if the friction is too low. From August, the temperature starts to drop and the weather changes; hence, the increasing trend.

## 5 CONCLUSION

From the preceding measurements, we conclude the following:

Wheel wear is greater at lower temperatures, and there is an evident trend. At  $-10^{\circ}\text{C}$  there is five times more wear than at  $+25^{\circ}\text{C}$ . Even for temperatures around  $0^{\circ}\text{C}$ , there is evidence of large differences in wear between different wheels. This makes the issue of wheel wear and temperature extremely intriguing. Further

investigation calls for at least a full year of continuous measurement and a larger population of wheels.

The leading axle in a bogie has larger lateral forces than trailing axles, as mentioned by Wu and Robeda [22], and Elkins and Eickhoff [23]. It is also evident that lateral forces on the high rail are generally higher and have narrower spectra than those on the low rail. The most alarming issue amongst the data is that lateral forces on the leading low-rail can exceed 130 kN. This corresponds to an L/V of 0.9, indicating very poor steering and the possibility of derailment.

The L/V ratio is clearly seasonally dependent. According to Nadal's formula, the L/V is dependent on both  $\mu$  and  $\alpha$ . Since friction changes for each passage, this is an indicator of trend changes and of large differences within a month. Wheel and rail wear change over time, but neither occurs quickly. This issue needs further study on a larger population of wheels.

## 6 ACKNOWLEDGEMENT

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Monitoring and Machine Failure Prevention Technologies



# Rolling stock condition monitoring using wheel/rail forces

M Palo, H Schunnesson, U Kumar, P-O Larsson-Kräik and D Galar

Paper presented at CM 2012 & MFPT 2012, The Ninth International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, London, UK, June 2012

*Railway vehicles are efficient because of the low resistance in the contact zone between wheel and rail. In order to remain efficient, train operators and infrastructure owners need to keep rails, wheels and vehicles in an acceptable condition. Wheel wear affects the dynamic characteristics of vehicles and the dynamic force impact on the rail.*

*The shape of the wheel profile affects the performance of railway vehicles in different ways. Wheel condition has historically been managed by identifying and removing wheels from service when they exceed an impact threshold. Condition monitoring of railway vehicles is mainly performed using wheel impact load detectors and truck performance detectors. These systems use either forces or stress on the rail to interpret the condition.*

*This paper will show measurements taken at the research station outside Luleå in northern Sweden. The station measures the wheel/rail forces, both lateral and vertical, at the point of contact in a curve with a 484 m radius at speeds of up to 100 km/h. Data are analysed to show differences for various wheel positions and to determine the robustness of the system.*

## 1. Introduction

Railways use the low resistance of movement between wheel and rail to create an energy efficient mode of transport. The most important element in the dynamics of a railway vehicle is the interaction between the wheel and the rail<sup>[1]</sup>. Keeping wheels and vehicles in an acceptable condition is therefore a major concern for both railway operators and infrastructure owners. Wheel impacts on a railroad track can cause extensive damage, the ultimate form of which is rail breakage. Apart from affecting the actual rail, dynamic impacts can also degrade and cause premature damage to the track's sub-grade. Depending on the track curvature and the type of bogie design, each wheel/rail system may exhibit significant differences in steering and dynamic stability<sup>[2]</sup>.

To evaluate the loads generated by wheel/rail interaction, North American railways have adopted the use of detection and condition monitoring technologies<sup>[3]</sup>. The technique of placing condition monitoring equipment along the track is referred to as wayside detection<sup>[4]</sup>. Wayside detectors are mostly used for exception reporting; for example, determining large wheel impact forces from a wheel flat, which is the simplest use of these detectors<sup>[5]</sup>. A more sophisticated use of wayside detector data is to monitor the changes in forces over time, which in combination with temperatures and wheel position can be used to predict when a threshold condition will be reached.

In a study performed on a metro line, only a few real-time alarms caused by traditional track force threshold limits were registered<sup>[6]</sup>. In this case, structured condition monitoring was used in combination with structured maintenance planning. There are also issues with differences in track structure and climate to consider when trying to compare data or information from different track systems or geographical locations. In this paper, an analysis of the different wheel/rail force data collected from the research station is carried out and the robustness of field measurements shown.

## 2. Condition monitoring of railway vehicles

Condition monitoring aims to record the current (real-time) condition of a system<sup>[1]</sup>. Traditional inspection techniques used in the railroad industry, such as drive-by inspection, are not as accurate and reliable as more rigorous and quantitative inspection methods<sup>[7]</sup>. Wayside detection systems provide a means of monitoring the condition of vehicles, ensuring that they are in a serviceable condition<sup>[4]</sup>. How track-friendly a vehicle is depends not only on its design, speed and axle load, but also on its maintenance condition<sup>[8]</sup>. It is not uncommon for wheels on both sides of a wheel axle to degrade differently, despite having the same axle load and initiating tread defect<sup>[6]</sup>. Wheel condition has historically been managed by identifying and removing wheels from service when they exceed a vertical impact load threshold<sup>[9]</sup>. These thresholds are typically based on when a wheel/rail impact is presumed to cause sufficient stresses to the track structure.

Force measurement detectors make it possible for vehicles with defective wheels, which are likely to cause damage to the permanent railway structures, to be identified and removed from service immediately<sup>[9]</sup>. Vertical impact loads between wheel and rail resulting from surface anomalies such as wheel flats have been used to create mathematical models of wheel-rail impact behaviour<sup>[10]</sup>. Systems that solely measure the axle load of wheel flats are mostly placed on a tangent track with no gradient, or a negligible gradient, where trains do not accelerate or brake<sup>[11]</sup>. When measuring the lateral forces, it is an advantage to perform measurements in narrow curves in which the vehicles can show their steering ability. Lateral forces are the result of a poorly-steering bogie and trains moving at speeds different from the optimal curve speed, but they are also the result of longitudinal buff and draft forces transmitted through train action and coupler angularity<sup>[12]</sup>.

### 2.1 Wheel impact load detector

Increasing concern about damage to track components arising from high-impact loads generated by damaged wheels led to the installation in 1985 of the first wheel impact load detector (WILD) by British Rail<sup>[9]</sup>. The WILD system was originally installed to monitor damaging track forces; obvious benefits are obtained from the early detection of rolling-stock wheel defects.

The installation of WILDs requires no radical modification of

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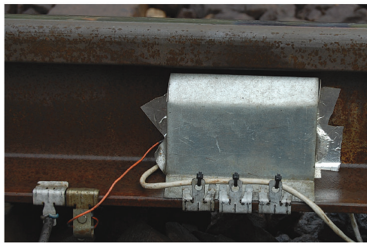
Mikael Palo, Håkan Schunnesson, Uday Kumar, Per-Olof Larsson-Kräik and Diego Galar are with Luleå University of Technology, Luleå, SWE-971 87, Sweden. Email: mikael.palo@ltu.se

the existing track structure<sup>17</sup>. WILD sites consist of strain gauges arranged along a 30-foot stretch of track, and the strain gauges are welded to the web of the rail<sup>13</sup>. WILDs have been depended on to identify wheels with shells, spall and out-of-rounds since the early 1990s, and have continued to protect railroads from damaging loads and derailments due to broken rails<sup>5</sup>. The impact load detecting system also offers the opportunity to define criteria for the removal of railway wheels, based not only on a visual inspection of wheel tread defects but also on the impact loads measured by the detectors<sup>14</sup>.

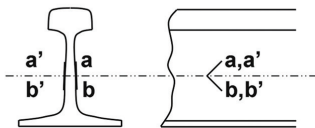
### 2.2 Truck performance detector

Truck performance detectors (TPD) measure both vertical and lateral forces/stresses when a vehicle passes. TPDs can evaluate bogie performance, vehicle lubrication conditions, prevent derailment and increase the safety and efficiency of the railway as a whole<sup>3</sup>. Proper curving of vehicle bogies (trucks) is essential to insure proper system performance<sup>15</sup>. Conventional visual bogie inspection methodology cannot detect all bogie defects that cause poor curving performance.

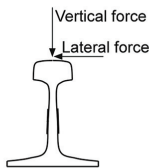
A typical force-based TPD site designed for the evaluation of a three-piece freight wagon bogie consists of an ‘S’ curve arrangement where two narrow curves arc in opposite directions<sup>16</sup>. These curves should have a radius of between 291 and 436 m. The array consists of eight measurement zones (cribs) of gauge, three in each curve and two in the tangent section<sup>13</sup>. The TPD layout allows a thorough evaluation of the bogie’s ‘dynamic’ curving performance by checking left and right rotation as well as its ability to return to a neutral tracking position in the tangent section<sup>17</sup>.



(a)



(b)



(c)

**Figure 1. Measurement equipment, sensor placement and force definition: (a) measurement system placed on the rail; (b) measurement sensor placement; (c) definition of wheel/rail forces**

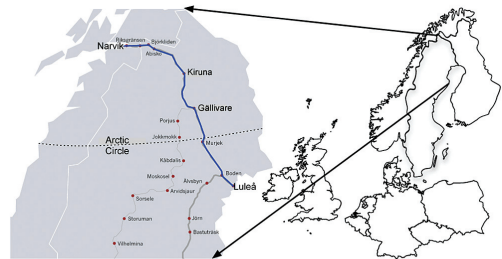
### 2.2.1 Research station outside Luleå, Sweden

In a research station outside Luleå, the wheel/rail forces are measured, both lateral and vertical, in a curve with a 484 m radius for speeds of up to 100 km/h<sup>11,18</sup>. The research station is a simplified version of a TPD, consisting of only one measurement zone. Due to the hostile environment of railroads, there is a weatherproofing shield on top of the strain gauges, see Figure 1(a).

The measurement system consists of several strain gauge sensors micro-welded to the web of the rail, as indicated in Figure 1(b). The measured forces are vertical and lateral, see Figure 1(c), with the positive lateral force outwards in the curve. Lateral forces are the result of a poorly steering bogie and trains moving at speeds different from the optimal curve speed, but they are also the result of longitudinal buff and draft forces transmitted through train action and coupler angularity<sup>17</sup>.

## 3. Case study description

The only existing heavy haul line in Europe, called the Iron Ore Line (Malmbanan), stretches 500 km from Luleå in Sweden to Narvik in Norway, see Figure 2(a). On the line, there is mixed traffic consisting of both passenger and freight trains. The iron ore freight trains consist of two IORE locomotives accompanied by 68 wagons with a maximum length of 750 m and a total train weight of 8,500 tonnes, see Figure 2(b). In 2010, LKAB mining company transported 26 MGT (million gross tonne) from their two mines in Kiruna and Malmberget; of these, 6 MGT were shipped from Luleå harbour. The trains operate in harsh climate conditions, including snow in the winter and extreme temperatures ranging from  $-40^{\circ}\text{C}$  to  $+25^{\circ}\text{C}$ <sup>19</sup>.



(a)



(b)

**Figure 2. Malmbanan and trafficking iron ore train: (a) Northern Sweden with Malmbanan; (b) photo of an iron ore train**

The results presented in this paper are recorded from two iron ore freight wagons with the Amsted three-piece bogie, designated 43 and 44. The wagons were followed for a period of 15 months, from March 2009 to May 2010. These wagons travel with an average axle load of 30 tonnes and a loaded top speed of 60 km/h from Malmberget towards Luleå. During the period, the wagons have random positions in the train, from right behind the

locomotive to being the last two wagons. The iron ore trains are closely monitored; all vehicles have RFID tags for identification and are connected to the measurement system.

Figure 3(a) shows the set-up of a wagon with wheel, axle and bogie designation; as shown, the two wagons are always connected at the A-end with a steel rod. This means that our two wagons travel as a pair with one wagon having its B-end first and the other its A-end. If they travel in the other direction, this is reversed. This presents two different scenarios when passing the research station, as either 43 or 44 is travelling first. Figure 3(b) shows the designation for the wheels of a bogie when passing the research station.

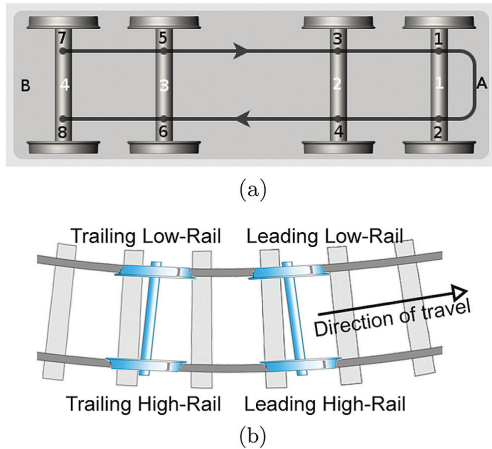


Figure 3. Wagon set-up and wheel position when passing the research station: (a) set-up of a wagon with A and B end as well as wheel and axle numbering; (b) wheel positions for a bogie in a curve

During the project time, both speed and vertical load varied. This variation can be seen in Figures 4(a) and (b). As is shown, train speeds are allowed up to 9 km/h over the set limit of 60 km/h. The restriction of 30 tonnes on the vertical load is an average for the whole train set.

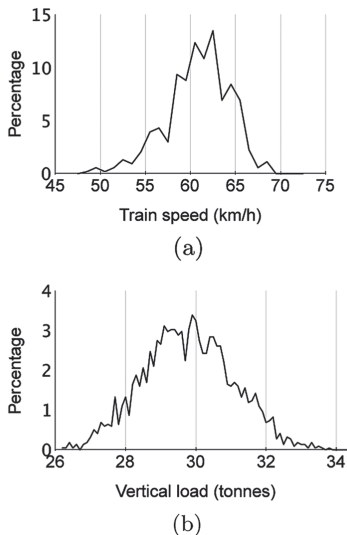


Figure 4. Speed and vertical load: (a) speed for loaded trains; (b) vertical load for loaded trains

For the test, the wheel axles on the two investigated wagons were put together as a mix of new and old, see Figure 5(b). This was done to collect data for a full wheel life cycle, between wheel turnings (re-profiling). During the project, two axles had to be exchanged for new ones due to wheel damage. In Figure 5(a), the monthly average temperature for Gällivare and the average, maximum and minimum temperatures from the research station are shown.

During two periods the wagons were stationary in the maintenance workshop, at 64,000 km or day 193 and 80,000 km or day 259, see Figure 5(b). The first stationary period was caused by wheel damage and the second was caused by bogie revision and inspection. During the revision, draft sills were measured and centre bowl liners in the bogie were inspected.

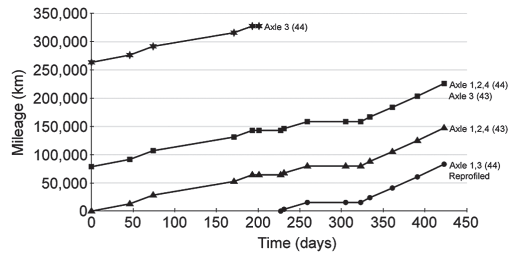


Figure 5. Mileage of wheel versus time of the project

Between 80 and 100,000 km there are fewer force measurements due to a malfunction in the RFID-tag reading between the wagons and the research station. This was during February and March 2010.

## 4. Results and discussion

### 4.1 Lateral forces for different positions in bogie

The four different wheel positions of the bogie (see Figure 3(b)) show differences in the signature of the lateral forces. The leading axle is the first of the two to negotiate the curve and therefore usually has a larger lateral force. The trailing axle follows and thus has a lower lateral force. Figure 6 shows data from one bogie (43A) travelling loaded towards Luleå when it is the leading bogie of the wagon. The x-axis shows the distance the wheel has run since new, almost 150,000 km.

The leading high-rail consistently shows large lateral forces. This is expected since it is the first wheel of the bogie and wagon to steer through the curve. Table 1 gives the average values of each wheel in Figure 6. The wheels on the high-rail (Figures 6(c) and (d)) have the largest average values on the bogie. This is expected as they steer the wagon. Both wheels of the leading axle (Figures 6(b) and (d)) have larger average values than the trailing axle (Figures 6(a) and (c)).

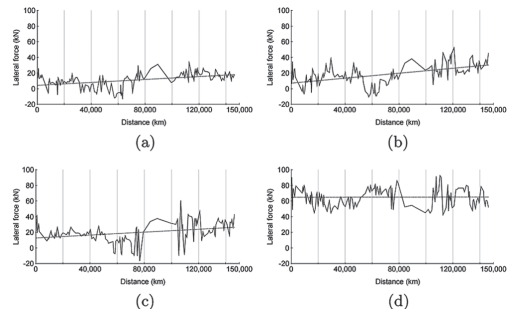


Figure 6. Lateral forces from all wheel positions in a bogie for 150,000 km of travel distance: (a) trailing low-rail; (b) leading low-rail; (c) trailing high-rail; (d) leading high-rail

**Table 1. Average for graphs in Figure 6 in kN**

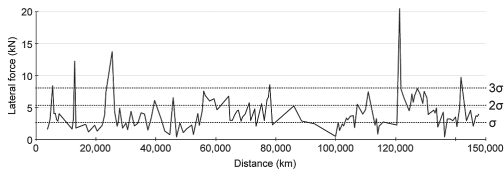
Figure 6	(a)	(b)	(c)	(d)
$\bar{x}$	10.9	18.2	19.3	65.1

Another interesting parameter is the trend line in Figure 6. In Figure 6, (a)-(c) show increasing trends while (d) remains steady or decreases. This indicates a possible relationship between running distance and lateral forces for all wheel positions except the leading high-rail. This clearly indicates that to evaluate lateral forces instead of the running distance, the position in the bogie has to be known.

**4.2 Robustness of field measurements**

Looking at the measurements in Figure 6, there is a question about the lateral forces that the passing wheels generate from time to time, even if the wear of these wheels is approximately the same. There are several possible reasons for these variations, including placement in the train, friction coefficient, temperature, humidity and bogie configuration. However, in the project, all these factors were monitored and offer no explanation of the variation in lateral forces. To more accurately determine how the lateral forces compare between measurements, the leading high-rail wheels for all four studied bogies were collected while travelling loaded towards Luleå, always with the same wheel positions (wagon 43 first). In Figure 7, the data from these four wheels are plotted for the average of the wheels for each passage.

Figure 7 shows how these four wheels follow each other, even when two axles of one wagon had to be changed for new re-profiled wheels at 64,000 km, C and D from Table 2. The pattern of the peak forces on these wheels is very similar for each passage, and the patterns seen well duplicated between passages. However, the wheels are not consistently either the largest or smallest. The small variations might be from the dynamic force additive, friction coefficient, bogie condition and configuration or from speed changes. Some parameters that might change the friction coefficient are water, surface roughness, vertical load, dust or metal particles.



**Figure 7. Standard deviation plot for lateral forces on leading high-rail**

In Table 2, the average, maximum and minimum forces for the graphs in Figure 7 have been calculated to distinguish any differences or similarities. The variations for these four wheels and all measurements are  $\sigma = 2.7$  kN. From the graphs in Figure 7 and Table 2, we see that these four wheels follow each other's forces well, even if D in Table 2 has a slightly lower average. One explanation for this behaviour is that this wheel was changed for a new one during the study. From Figure 7 and Table 2, it is apparent that the forces are not much different for these wheels, even if they have different running distances. A new wheel has forces similar to those of a wheel that has run 140,000 km. The data for these four wheels are consistently similar over 15 months for each time of measurement, even if they differ greatly between one measurement and the next. This indicates that the measurement system is ideal for repeated use on prolonged series of measurements.

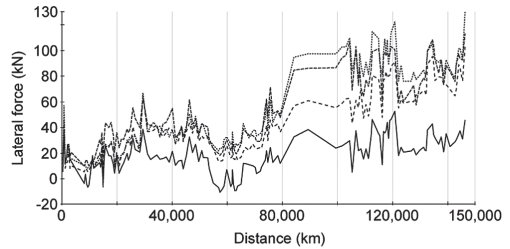
The main question is: what kind of data are most useful for condition monitoring of wheels and bogie?

**Table 2. Max, min and average forces in kN and wheel starting km for Figure 7**

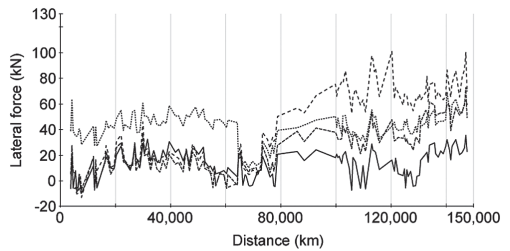
Figure 7	A	B	C	D
$\bar{x}$	63.5	62.4	63.3	60.8
Max	93.6	91.5	93.0	93.6
Min	40.3	39.3	39.6	38.7
Starting km	0	0	78,700	263,580

**4.3 Changes in lateral forces due to direction of travel**

From the data, the leading low-rail seems the most promising for condition monitoring. In Figures 8(a) and 8(b), the leading low-rail has been plotted for the two scenarios described earlier, for travel of loaded trains towards Luleå. In the first scenario in Figure 8(a), wagon 44 travels first; it travels second in the second scenario in Figure 8(b).



(a)



(b)

**Figure 8. Lateral forces for leading low-rail: (a) Wagon 44 travelling first, scenario 1; (b) Wagon 43 travelling first, scenario 2**

There are very different behaviours between the scenarios in Figures 8(a) and 8(b). From these Figures we may assume that the lateral forces of a single bogie or wagon may differ according to its direction of travel. This indicates a need to measure in two reverse curves (both left and right) to be able to collect data on both wheels of an axle as leading low-rail, depending on whether the bogie is leading or trailing. Such data should permit a better understanding of the condition of the wheels and bogie.

From the data collected for 15 months, there is no clear indication that weather or seasonal changes influence the lateral force for this wheel position. If they had an effect, there should be a similar magnitude of forces at the beginning and the end of the study.

**5. Conclusions**

The four different wheel positions in a bogie show significantly different force signatures. The leading high-rail has high forces that remain unaffected by the change in running distance, while the three others increase over the distance.



The measurement system at the research station is shown to be robust. During the 15 months of measuring, most collected data point to the leading high-rail, for the scenario whereby wagon 43 travels first and is within  $3\sigma$ , the limit of variation. The mix of wheels, some starting at 0 km others at 78,700 km, seems to have no or very little influence on the lateral forces acting on the leading high-rail.

Directional changes of the wagon, for example turning around at loading or unloading, show distinctive differences in lateral forces for the leading low-rail with running distance. This might be because the dynamics of the wagon differ little from wear when turning left or right. In order to collect all possible data in one run, there is a need for a second measurement point in a reverse curve with the same radius.

### Acknowledgements

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## The evolution from e(lectronic) Maintenance to i(ntelligent) Maintenance

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# Condition Monitoring at Wheel/Rail Interface for Decision-making Support

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## Abstract

Many railway assets, such as wheel sets, suffer from increasing wear and tear during operation. Good condition monitoring based on good decision-making techniques can lead to accurate assessment of the current health of the wheels. This, in turn, will improve safety, facilitate maintenance planning and scheduling, and reduce maintenance costs and down-time.

In this paper, wheel/rail forces are selected as a parameter (feature) for the condition monitoring of wheel health. Once wheels are properly thresholded, determining their condition can help operators to define maintenance limits for their rolling stock. In addition, if rail forces are used as condition indicators of wheel wear, it is possible to use measurement stations that cost less than ordinary profile stations. These stations are located on ordinary tracks and can provide the condition of wheel sets without causing shutdowns or slowdowns of the railway system and without interfering with railway traffic.

The paper uses the iron ore transport line in northern Sweden as a test scenario to validate the use of wheel/rail forces as indicators of wagon and wheel health. The iron ore transport line has several monitoring systems, but in this paper only two of these systems will be used. Wheel/rail force measurements are performed on curves to see how the vehicle negotiates the curve, and wheel profile measurements are done on tangent tracks not far away. The vehicles investigated are iron ore

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wagons with an axle load of 30 tonnes and a loaded top speed of 60 km/h. The measurements are non-intrusive, since trains are moving and assets are not damaged during the testing process.

Keywords

Condition monitoring, wheel/rail interface, decision-making, wayside monitoring

## 1. Introduction

The importance of the maintenance function and, therefore, of maintenance management has grown in recent years (1). Today's railways face increasing pressure from customers and owners to improve safety, capacity, and reliability – while controlling expenses and tightening the budget (2). In Sweden, the railway system is deregulated (3) and has many stakeholders (4), see Fig. 1. As the figure shows, each layer in the system can comprise several companies, and any company can be on a number of layers.

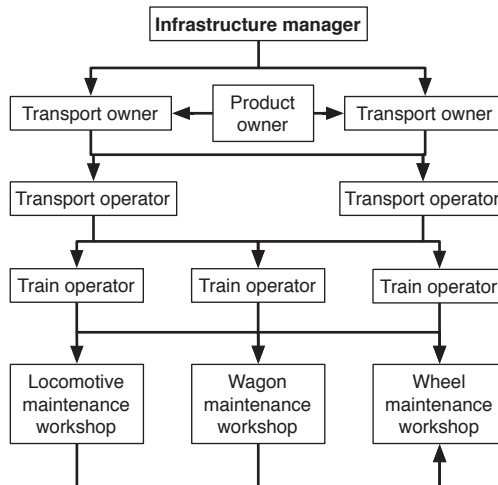


Fig. 1. Stakeholders within the deregulated Swedish railway system

Railways capitalise on the low resistance between wheel and rail to create an energy efficient mode of transport. However, increasing emphasis on maintenance and life cycle costs (LCC) for rolling stock and for infrastructure results in the need to predict wheel and rail wear (5) to optimise maintenance decisions and estimations of remaining useful life.

A railway vehicle is a complex electromechanical vehicle comprised of several complex systems. Each system is built from components which, over time, may fail. When a component does fail, it is difficult to identify the failed component because the effects or problems that the failure has on the system are often neither obvious in terms of their source nor unique. The ability to automatically diagnose problems that have occurred or will occur in the rolling stock systems has a positive impact on minimising the downtime.

Previous attempts to diagnose problems occurring in locomotive and wagons have been performed by experienced personnel with in-depth individual training and experience working with these systems. Typically, these experienced individuals use available information recorded in a log. Looking through the log, the experienced individuals use their accumulated experience and training to map incidents in locomotives or wagon systems in an effort to pinpoint the problems that may be causing the incidents. If the incident-problem scenario is simple, the approach works fairly well.

However, if the incident-problem scenario is complex, it becomes difficult to diagnose and correct failures associated with the incidents.

Computer-based systems are currently used to automatically diagnose problems in a locomotive in an attempt to overcome some of the disadvantages associated with relying on experienced personnel. Typically, a computer-based system utilises a mapping between the observed symptoms of the failures and the equipment problems using techniques such as table look ups, symptom-problem matrices, and production rules. These techniques work well for simplified systems with simple mappings between symptoms and problems. However, complex equipment and process diagnostics seldom have such simple correspondences. In addition, not all symptoms are necessarily present if a problem has occurred, thus making other approaches more cumbersome.

The above mentioned approaches either take a considerable amount of time before failures are diagnosed, or provide less than reliable results, or are unable to work well in complex systems. There is a need to be able to quickly and efficiently determine the cause of any failures occurring in the system, while minimising the need for human intervention.

A data-driven model may be a feasible solution in scenarios where many data are collected and relations can be established in a contextual way. In fact, data-driven models rely on relationships derived from training data gathered from the system. Condition monitoring systems typically use thresholds for features in time series data, spectral band thresholds (usually from vibration signals), temperatures, lubricant analyses, and other observable condition indicators, under the assumption of steady-state operating conditions. Rail forces seem to be another feature which can provide useful information once they are properly thresholded.

Data-driven models are not new in the railway sector. Many methods used in railway condition monitoring rely on data-driven techniques. In fact, with feature extraction to obtain track quality factors or the degradation stage of the bearings in the vehicles, the health of both track side and rolling stock can be assessed using mathematical tools based on the experience and variability of condition indicators. This is especially relevant in complex systems like railways and has been successfully applied in the aircraft industry as well.

In summary, the paper proposes an approach for railway vehicle health assessment based on the fault identification of wheels. It uses a data driven model that establishes a maintenance threshold based on the fusion of wheel profiles and rail forces. The system is useful for identifying wagon problems and proposing remedial measures to repair or correct the problems without requiring the permanent supervision of humans. In addition, the fusion of the variables does not require additional tests or inspections since measurements can be performed using track side techniques which are non-intrusive by nature, thus minimising shutdowns and slowdowns. This is important because stoppages are costly and highly inconvenient, including those for maintenance purposes; they dramatically reduce the capacity of the infrastructure and the availability of vehicles.

## **2. Wayside condition monitoring**

Condition monitoring aims to record the current (real-time) condition of a system (6). The technique of detecting specific faults on rolling stock by interrogation sensors placed along the sides of tracks is called wayside detection (7). Wayside detection sites are able to send reports on all passing vehicles, not only those exceeding the safety limits. These systems provide a means of monitoring the condition of vehicles, ensuring that they are in a serviceable condition (7). How track-friendly a vehicle is depends not only on its design, speed and axle load, but also on its maintenance condition (8).

Traditional inspection techniques used in the railway industry, such as drive-by inspections, are not as accurate and reliable as more rigorous and quantitative inspection methods (9). The most important element in the dynamics of a railway vehicle is the interaction between the wheel and the rail (6). The repetitive high impact forces involved cause a rapid deterioration of both rolling and fixed railway structures. A wheel impacting on a railroad track can cause extensive damage, the ultimate form of which is rail break. Keeping wheels and vehicles in an acceptable condition is, therefore,

a major concern for both railway operators and infrastructure owners. The measurement of wheel profiles and wheel/rail forces through wayside condition monitoring helps the railway meet customer expectations without compromising system safety (10).

Rail traffic operators in Sweden have to face considerable wheel re-profiling costs within their freight vehicle fleet (11). Reasons for re-profiling include rolling contact fatigue (RCF), wheel flats, out of roundness, and uniform wear. Both wear and rolling contact fatigue are deterioration phenomena (12) and affect the lifetime of the wheels. Imperfections on the wheel tread can have a detrimental influence on both track and vehicle components (13). Several different types of out-of-roundness may appear in railway wheels (14). Examples of these wheel tread imperfections include wheel flats or tread material loss due to rolling contact fatigue cracks. In fact, wheel flats are amongst the most common local surface defects of railway wheels (15). Finally, the wear at the wheel/rail interface is an important problem for railways. The evolution of the profile shape as a result of wear has a strong effect on the vehicle's dynamics and its running stability, leading to performance variations in negotiating both curves and straight tracks (16). Wheel condition has historically been managed by identifying and removing wheels from service when they exceed a vertical impact load threshold (17). These thresholds are typically based on when wheel/rail impact is presumed to cause sufficient stress on the track structure.

### 2.1. Wheel profile measurements

Wheel profile is critical to the railway vehicle's dynamic behaviour, stability and ride comfort; also important are the rate of wear and rolling resistance of the wheel and rail (7; 18). The shape of the profile is related to the prevention of derailment and the material properties of heavily worn wheels. Fig. 2 shows various wheel parameters: flange height (Sh), flange thickness (Sd), flange angle (qR) and hollow wear (TH). Sh is calculated as the difference between a spot 70 mm from the back of the flange (running circle) and the top of the flange. Sd uses the width of the flange 10 mm above the running circle. qR is the distance between 2 mm below the flange top and the position of Sd calculation. TH calculates the height of a second flange on the field side of the profile. It is not uncommon for wheels on both sides of a wheel axle to degrade differently despite having the same axle load and initiating tread defect (17).

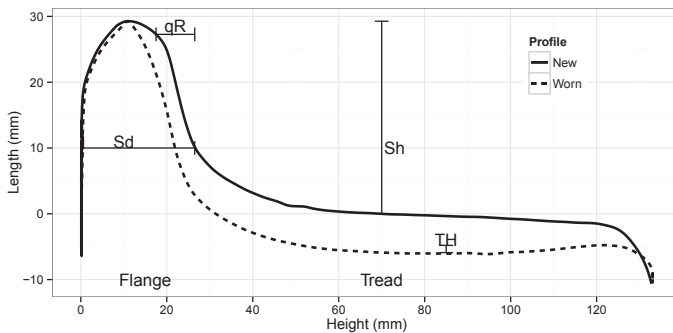


Fig. 2. Wheel profile, with wheel parameters

Automatic wheel profile monitoring technology uses high speed cameras and lasers to capture the wheel tread profile of each rolling stock wheel as it passes (19). The equipment monitors wheel profiles against a maintenance standard to detect worn wheels.



## 2.2. Wheel/rail force measurements

Force measurement detectors make it possible for vehicles with defective wheels, which are likely to cause damage to the permanent railway structures, to be identified and removed from service immediately (20). Out-of-round wheels can be detected using a wheel impact monitor (21). These wayside detection systems are available commercially and report impact as either a force at the wheel/rail interface or a relative measure of the defect.

Vertical impact loads between wheel and rail resulting from surface anomalies such as wheel flats have been used to create mathematical models of wheel-rail impact behaviour (22). Systems that solely measure the axle load of wheel flats are mostly placed on a tangent track with no gradient or a negligible gradient where trains do not accelerate or brake (23).

When measuring the lateral forces, it is best to perform measurements in narrow curves. This is where the vehicles show their steering ability and, thus, lateral forces become apparent. For an illustration of lateral and vertical forces, see Fig. 2.2. Lateral forces are the result of poor steering in bogies, with train speeds outside the track design, and of longitudinal buff and draft forces transmitted through train action and coupler angularity (24).

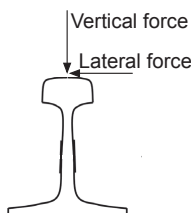


Fig. 3. Definition of wheel/rail force in a curve

## 2.3. Maintenance decision support

Two basic risks in a railway system are shutdowns and slowdowns. These risks materialise in economical losses; the only way to prevent the loss is to perform proper maintenance. To plan maintenance, the development of faults can be modeled in three ways: using symbols, using mathematical formulations based on physical principles, and using data.

*Symbolic models* A symbolic model uses empirical relationships described in words (sometimes numbers as well) rather than as mathematical or statistical relationships. For example, a certain semantic description may be a rule for determining whether a fault exists under a given set of conditions. Work orders and maintenance reports, handwritten by maintenance crews, provide good general descriptions of causal relationships but do not give adequately detailed descriptions of complicated dependencies and time varying behaviour. This is usually off-line information, often recorded in the Computerised Maintenance Management Systems (25); it gives important hints on the context or scenario where the fault is developing so that the real fault can be distinguished from false alarms. The integration of work orders from both rolling stock and infrastructure is essential to reproduce the exact scenarios where a shutdown might occur, allowing maintenance staff to predict shutdowns and take preventive action.

*Physics of failure models* A model based on the physics of failure allows prediction of system behaviour using either an analytical formulation of system processes (including damage mechanisms) based on first principles or an empirically derived relationship. Many investigations into damage mechanisms have been conducted, producing important empirical damage models that are valid in a fairly narrow range of conditions, such as wear, fatigue cracking, corrosion, and fouling. Specific damage mechanisms are generally studied and characterised under standard test conditions. Physics-based models

are very useful for describing the dynamics of time-varying systems, including different operating modes, transients, and variability in environmental stressors, but a great deal of effort is required to develop and validate the model.

*Data-driven models* A data-driven model relies on relationships derived from training data gathered from the system. Condition monitoring systems typically use thresholds for features in time series data, spectral band thresholds (usually from vibration signals), temperatures, lubricant analyses, and other observable condition indicators, under the assumption of steady-state operating conditions. A data-driven approach considers a condition indicator signal to be a set of random variables in a stochastic process represented by probability distributions. Many methods have been developed for monitoring and diagnosing faults in equipment components and process equipment, using a combination of process measurements and indirect measurements related to faults (such as vibrations and lubricant analysis features), extracting and ranking features with a variety of classification techniques. Sensor fusion has been used for fault diagnosis by combining different data sources to improve accuracy (26). Almost all successful data-driven FDI models are for systems that can be considered time invariant, i.e., the dynamics of the system and the damage accumulation rate do not vary with time.

Many methods used in railway condition monitoring rely on data-driven techniques. In fact, feature extraction to obtain track quality factors or to determine the degradation stage of wheels in the vehicles are instances when the health of both track side and rolling stock can be assessed using mathematical tools without a deep physical knowledge, based simply on the experience and variability of condition indicators. This is especially relevant in complex systems like railways and has been successfully applied in the aircraft industry as well (27).

To mitigate the risk of failure, condition monitoring, which performs incipient fault detection, is routinely applied to railway assets. The general aim is to move from reactive/routine based maintenance to a condition-based or even predictive maintenance regime. This has been achieved in the railway industry; see Fig. 4 for an example. However, the identification of proper measurements is a challenge, as not all failure modes are detectable using condition monitoring systems. Therefore, wheel condition monitoring using lateral forces, as a data-driven approach for maintenance decision support, to detect an impending wheel fault/failure seems feasible.

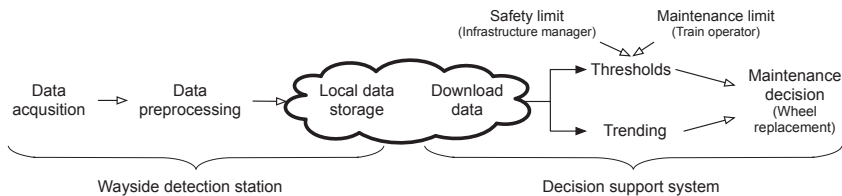


Fig. 4. The process from data collection to maintenance decision

Once the main physical parameter (feature) to be monitored has been identified, a second challenge arises, namely, integrating data from multiple heterogeneous information systems. This integration will provide an enterprise class foundation for the analysis tool set and greatly reduces the efforts and risks involved in the development of analysis tools. This is an area of considerable interest for large scale systems such as railways. The integration and interoperability of systems enables decision makers, such as maintainers, to make informed decisions based on the status of the assets. In particular, in situations where the deteriorating status of an asset is detected and a failure occurs due to wear, replacement of the asset, the wheels in this case, can be scheduled in an accurate way to maximise the dependability of the rolling stock.

### 3. Case description

The only existing heavy haul transport in Europe is in northern Sweden and Norway. It stretches 500 km from Luleå in Sweden to Narvik in Norway, see Fig. 5(a). The line's mixed traffic includes both passenger and freight trains. The iron-ore

freight trains consist of two IORE locomotives accompanied by 68 Fanoo wagons with a maximum length of 750 meters and a total train weight of 8 500 metric tonnes; see Fig. 5(b).

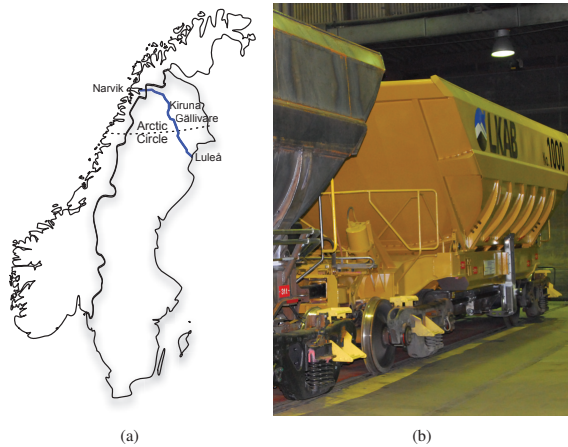


Fig. 5. Iron ore transport line in northern Sweden and a Fanoo iron-ore wagon

In 2012, the LKAB mining company transported 26.3 MGT (million gross tonnes) from its mines in Kiruna and Malmberget; of these, about 20 % were shipped from Luleå harbour. The trains operate in harsh climate conditions, including snow and ice in the winter and temperatures regularly ranging from -40°C to +25°C.

Fig. 6 shows the set-up of a wagon with wheel axle, bogie and wagon designation; as shown, the two wagons are always connected at the A-end with a steel rod (draw bar). This means that the two wagons travel as a pair with one wagon having its B-end first and the other its A-end. The odd numbered wagon is the master-wagon and this one contains the brake control system for the pair. The wagon pair are always connected and receive the same maintenance for all components except the wheel axles which are changed when they need maintenance.

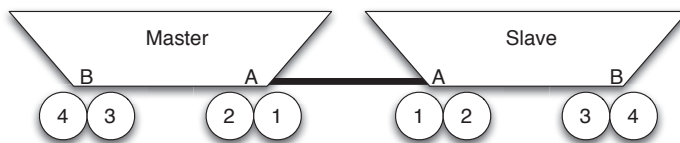


Fig. 6. Designation of wagons and the names for bogie and axles

### 3.1. Wheel profile measurement station

Outside Luleå a profile measuring station was installed in October 2011 and configured for data collection and transfer during the winter and spring of 2012. From the data, this study collected wheel profiles of all passing vehicles to see if they could be used by infrastructure managers and train operators.

The measurement system consists of four separate boxes, one on either side of each rail; see Fig. 7. The boxes contain a laser, a high-speed camera, and an electronic control system. When a train passes the boxes, the first wheel triggers a sensor 200 meters before the box; the protection cover opens and the laser beam starts to shine. When the next wheel passes, the

camera takes a picture of the laser beam projected onto the surface of the wheel. Heating elements have been installed to make measurements possible during the cold and snow of winter.



Fig. 7. Picture of rail and profile measurement system

### 3.2. Wheel/rail force measurement station

In a research station outside Luleå, lateral and vertical wheel/rail forces are measured in a curve with 484 m radius for speeds up to 100 km/h (23; 28). Mainly iron-ore trains with an axle load of 30 metric tonnes and a loaded speed of 60 km/h are monitored (23).

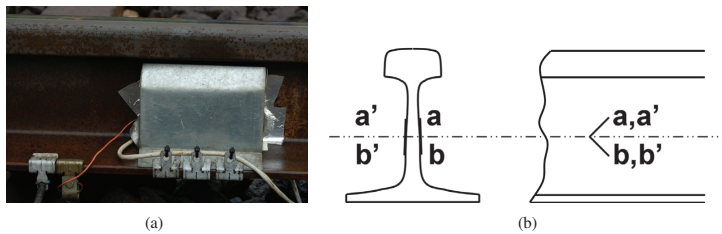


Fig. 8. Measurement system and sensor placement on the rail

The measurement system consists of several strain gauges sensors micro-welded to the web of the rail, as indicated in Fig. 8(b). There are three measurement positions on each rail, covering three meters in length, which corresponds to the circumferences of most wheels. The measured forces are vertical and lateral, see Fig. 2.2, with the positive lateral force outwards in the curve. Due to the hostile environment of railroads, there is a weather proofing shield on top of the strain gauges, see Fig. 8(a).

### 3.3. Maintenance decisions

The intended life length of a iron ore wagon wheel between re-wheeling is at least 800 000 km of running distance, with a yearly travel distance for the wagons of about 160 000 km. Re-profiling for wheel profile wear is done between 200 and 300 000 km. The wheels are visually inspected up to four times each day as they are loaded with iron ore. The wagons that travel from Gällivare to Luleå pass the condition monitoring sites up to three times each day.

The wheel profile is manually measured each time the wagon is at the workshop for maintenance, usually two or three times per year. The wheels might be pulled out early due to wheel damage, detected either by monitoring systems or visual inspections; see Fig. 9 for the maintenance process. At the moment, the wheel tread surface can only be checked by visual inspection, but there are indications that condition monitoring can help detect faults in the future.

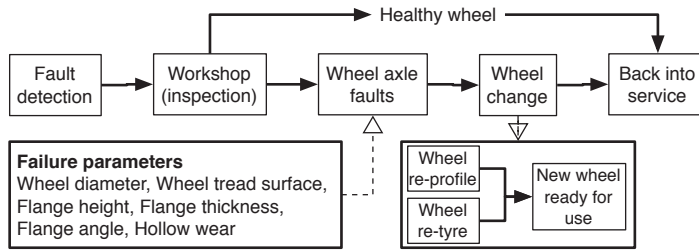


Fig. 9. Process for wagon and wheel maintenance action

### 4. Results and discussions

This paper shows results and discusses the data collected from the wheel profile and force measurement station outside Luleå. The profile station measures the whole profile of the wheel and then calculates specific parameters; see Fig. 2. The maintenance limits set by the operator and safety limits from the infrastructure manager appear in Table 1.

Table 1. Safety and maintenance limits for wheel parameters

	Maintenance limit	Safety limit
Flange height	34 mm	36 mm
Flange thickness	22.5 mm	22 mm
Flange angle	7 mm	6.5 mm
Hollow wear	1.5 mm	2 mm

Fig. 10 shows the wheel parameters from Table 1 plotted for each wheel of all iron ore trains measured between February and May of 2013. The horizontal dashed line represents the safety limit set by the infrastructure manager. One laser was down between the end of February and beginning of April; therefore, only measurements from one side are available during this time.

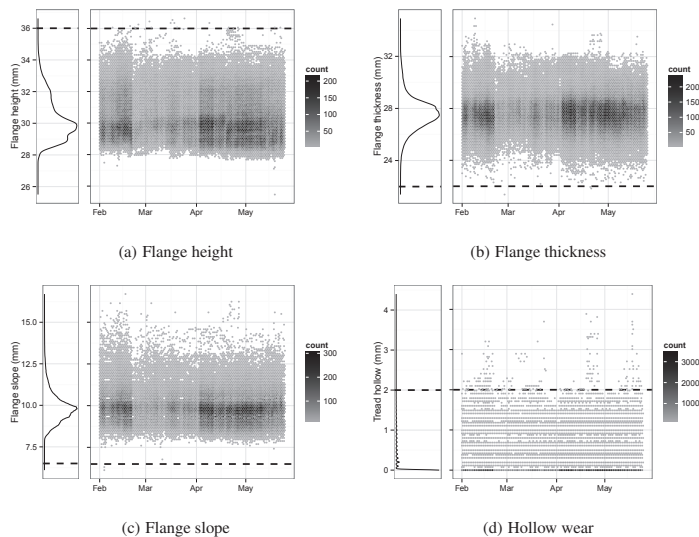
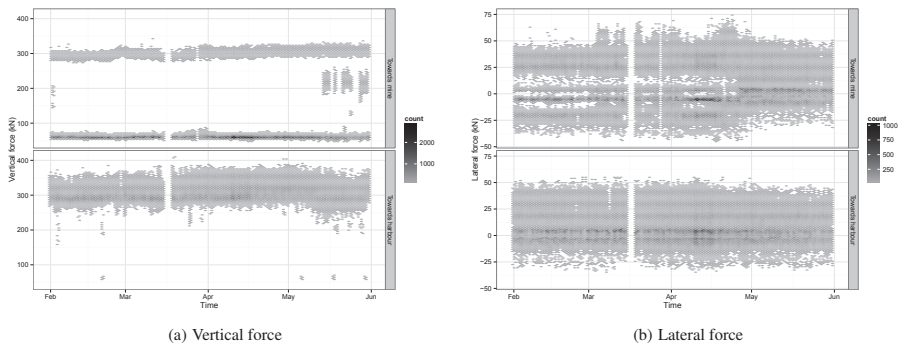


Fig. 10. Distribution for each train and total density of wheel profile parameters

The research station measure the vertical and lateral strain in the rail and calculate the corresponding forces through conversion factors. The conversion factor in vertical direction uses a running average for the last 10 iron ore locomotives for calibration, since the locomotives have a known axle load and the environmental factors can than be neglected. The calibration in lateral direction uses a calibration tool. Fig. 11 show a representation of vertical and lateral forces for all measured iron ore trains. Within the graphs the trains are separated on direction either they travel towards the harbour or back to the mine. In Fig. 11(a) are the vertical forces are distinctly different based on travel direction. When travelling towards the harbour all axles have forces around 300 kN which is the allowed limit. When travelling back to the mine the wagons have a much lower axle load under 100 kN while the locomotive have the same load. In Fig. 11(b) the difference between travelling direction is not as significant, there is still some difference with travel toward the harbour having slightly larger values. This is probably from the fact that a loaded wagon will have a bit more difficult change direction of the body mass.



**Fig. 11.** Wheel/rail force distribution for each train

This study follows two wagons (4703 and 4704) travelling from the mine in Gällivare to the harbour in Luleå from the middle of March to the end of May 2013. A round trip from the mine to the harbour and back is a distance of 428 km or 29 960 tonnes-km. The data presented are flange height from the profile measurement station and lateral forces from the wheel/rail force measurement station. Data for these wagons are gathered only when they travel toward Luleå. The axles selected are axle 1 from 4703 and axle 4 from 4704; see Fig. 6 for an explanation. The data are for when wagon 4704 is travelling first. The left profile measurement corresponds to the left wheel from the force measurements, and the right profile measurement corresponds to the right one

Wheel data collected and shown are for the flange height of the wheel; this corresponds well to the profile wear of the wheel found in an earlier study on the same fleet of vehicle; see Ref. (28; 29). The earlier study concluded that the leading axle was the best source of data for condition monitoring using wheel/rail forces.

#### 4.1. Wheel profile wear data

Data from the profile measurement station were collected as the wagon passed the station. Fig. 12 shows the flange height for the two wheels from the leading axle of the leading bogie. A severe wear regime is assumed due to the linearity of the measured wear, neither wheel is new and no rapid run-in behaviour is seen. There is a small difference in flange height between each measurement. This is due to that the measurements are not made on the same spot of the wheel, but the whole wheel circumference is assumed to have the measured profile.

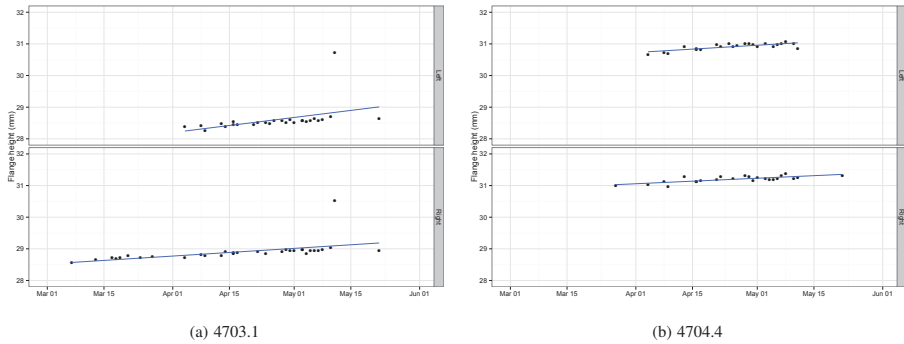


Fig. 12. Flange height data for the selected wheel axles

In both graphs in Fig. 12, the wear rate is approximately the same and the wear for the right wheel is slightly greater. The wear pattern is as expected between the beginning and end of the period. There is one outlier on each wheel of 4703; this could reflect a data identification mismatch but cannot be disregarded or removed at this point.

#### 4.2. Wheel/rail force data

Data from the force measurement station are processed and analysed as vehicles pass. In Fig. 13 all collected passings of the same axles are as shown in Fig. 12. As seen in earlier studies on the same vehicle fleet (28; 29), the lateral forces need to be separated on a position within the bogie. The lines in the graphs are LOESS regression lines, and the gray area is the standard error, showing the trend for that wheel. The top graphs in Fig. 13 are for the left wheel and the bottom two are the right wheel.

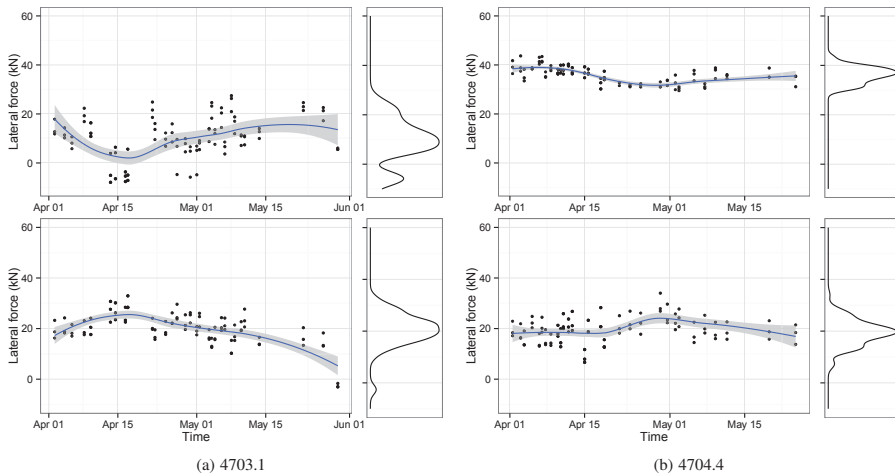


Fig. 13. Lateral wheel/rail force data for the selected wheel axles

The wheels from 4704, Fig. 13(b), are more worn than those of 4703, Fig. 13(a). This is one possible reason for the larger forces from 4704 compared to 4703. Other influencing factors are the other axle of the bogie, steering forces in the

bogie, or the closest coupled wagon and bogie. Earlier findings show that the left leading wheel can be a good indicator for a more worn or poorly steering wheel and bogie. The right wheels of both axles are similar in how the forces are distributed even if there is a larger spread in Fig. 13(a). The left wheel from 4703 shows large differences in forces between measurements; the reason for this is not known and should be investigated.

Both wheel axles in Fig. 13 experience the same conditions when passing the research station, since they are always connected. The difference in forces for each passing show the difficulty involved in comparing data from different axles and positions with one another. Difference in friction, from for example moisture and lubrication, on the track poses a problem when we are trying to compare different measurements, since lateral forces on a dry day can drop up to 50% if it starts to rain.

## 5. Conclusions

From the preceding measurements and data, we reach the following conclusions.

The trending possibilities for the wheel profile are excellent and should be developed. In this study, the wheels only traveled a small portion of what they would normally do in a year, namely, about 160 000 km. While our measurement period is short and in the middle of the lifetime, however, it shows the linearity of the wheel wear that is assumed in the severe wear regime. By extending the study to follow several wheels from new until re-profiling. We will then be able to see when the wear changes from mild to severe and then to catastrophic. This information will be useful for maintenance planning and decision making.

Using the wheel/rail force data for decision-making support is difficult. One problem is that the data have not been collected for a long enough period, not all seasons are accounted for. According to earlier findings (28; 29), the condition data collected at this interface say little about how the wheel profile looks, but they do indicate on the steering ability of the wheel and the bogie. This data is very useful for the maintenance manager in planning for maintenance on the wagon, a poorly steering wagon increase the wear and tear on both vehicle and infrastructure. The maintenance manager and personnel need to keep in mind that there are different lateral force signatures for the different wheel positions within the bogie.

With a linear wear pattern and lateral forces, it would be very easy for maintainers to make decisions on when to pull out wheels and wagons for maintenance. In this case, we assume linear wear for the flange height, but the lateral forces can change significantly between two passings. Using flange height as a parameter for a maintenance limit can be very useful in maintenance planning with today's maintenance and safety limits. Using maintenance limits for the iron ore wagon can prevent wheels from exceeding the safety limits. A better use of wayside condition monitoring systems will help to reduce the number of worn wheels in traffic. At this point, there is no maintenance or safety limit on lateral wheel/rail forces. Using tools for combining different types of wayside monitoring can help to determine possible maintenance/safety limits.

## 6. Future work

Future work should combine from the wayside stations with simulated data for the same wagons and track configurations to create a hybrid model. Such a model would provide more complete information by combining some or all three model types (symbolic, data-driven, and phenomenological). This, in turn, would allow more accurate recognition of wheel health. While most models incorporate some prior knowledge, little work has been done on explicitly using hybrid models for fault diagnostics and maintenance decision-making. This particular hybrid model could be used to determine if existing maintenance and safety limits should be changed or complemented by the consideration of other parameters.



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# Life cycle cost model for rolling stock freight wheels

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## Abstract

All businesses need equipment to deliver services or manufacture goods, and that equipment must be kept in good working order. In the railway industry, the service life of a railway wagon wheel can be significantly reduced through failure or damage, leading to excessive costs and accelerated deterioration. Its degradation can be controlled and failed equipment restored to operational status by proper maintenance procedures. Life cycle costing (LCC) is an iterative way to find the most desirable alternative between several maintenance options.

This paper uses maintenance data for heavy haul freight vehicles to create a life cycle cost model for wheel sets. The proposed model uses trending operating data and failure mode simulations to suggest an optimised maintenance policy. It determines that a travel distance of at least 1 200 000 km can be reached by a wheel set between re-wheeling. Wayside condition monitoring can find wheels requiring immediate maintenance, and the analysis of the trending of wear and running distance increase the understanding of when to remove a vehicle for wheel and wagon maintenance.

## 1 Introduction

All businesses, for example, mining, manufacturing, and transport, need equipment to deliver services or manufacture goods [15]. But all equipment is subject to failure, especially as it ages. The degradation of the equipment can be controlled and failed equipment restored to operational status through the use of proper maintenance procedures [15]. However, maintenance can represent a major operating cost [11].

Many industries, including the railway industry, are searching for ways to improve the performance of systems and subsystems to ensure safe and reliable service [20]. Life cycle cost (LCC) is an iterative way to find the most desirable maintenance alternatives [12]. The LCC of a product can be considered a key performance indicator when determining the appropriate maintenance procedure for that product. LCC is made up of the costs to the manufacturer, user, and society [2]. It is one of the most effective cost approaches when buying assets for the long term [12], as it helps engineers justify the selection of equipment based on the total cost over the life of the asset rather than just the initial purchase cost.

Even though operating and support costs represent the most significant portion of LCC, they are the most difficult to predict [2]. For railroad transportation, the operation and maintenance cost is a large part of the total cost. The low resistance of movement between wheel and rail and the effective guidance by the rail is an energy efficient and reliable mode of transport for freight and passengers. But the railway's emphasis on maintenance and LCC for infrastructure and for rolling stock, such as wheels, results in the need to predict wheel and rail wear [10] to optimise maintenance decisions and accurately estimate remaining useful life.

One of the most important elements in the dynamics of a railway vehicle is the interaction between the wheel and the rail [9]. The wheel profile determines the stability of a vehicle [5], and the rate of wheel surface wear determines the life length of a wheel [8]. Thus, effective maintenance will increase the wheel's life. Wheel maintenance also reduces rail degradation [13]. As the wheels are in direct contact

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with the rails, degradation of the wheel surface and profile will cause rail degradation. Reducing wheel degradation through proper maintenance will result in less rail degradation.

The most common wheel problem is flange wear [14], a consequence of friction between wheel and rail [19]. To restore the flange, a substantial amount of metal is removed from the wheel tread. The four wheels of a bogie wear differently, depending on their position within the bogie, indicating differences in wheel/rail forces [18]. To evaluate the condition of the wheels, condition monitoring equipment is placed along the track, using a technique called wayside detection.

This paper uses maintenance data for heavy haul freight vehicles to create a life cycle cost model. Only the wheel sets are considered, as studying the whole wagon is very complex. In addition, the interface between wheel and rail has the greatest influence on maintenance costs for the train-track system. Finally, as wheels constitute a large part of a railway's rolling stock maintenance cost, their analysis presents an opportunity for improvement.

## 2 Life cycle assessment

Life cycle costing and assessment can be used to create a general model containing: Acquisition cost  $C_A$ , Inspection cost  $C_I$ , Preventive maintenance cost  $C_{PM}$ , Corrective maintenance cost  $C_{CM}$ , and Risk/safety cost  $C_R$ .

$$LCC = C_A + C_I + C_{PM} + C_{CM} + C_R \quad (1)$$

In the specific context of rolling stock wheel sets,  $C_A$  is the cost of purchasing wheel discs, and  $C_I$  is the cost associated with manual inspections and reviews and/or condition monitoring equipment in wayside stations.  $C_{PM}$  is the cost associated with faults detected at wagon inspections in the workshop, as seen in Figures 1.  $C_{CM}$  is the maintenance cost for wheels found in visual inspections at the train yard.  $C_R$  is the risk/safety cost, as shown in Figure 1. The cost of or revenue from decommissioning or scrapping a wheel set is not part of this model but should be considered.

### 2.1 Life cycle cost model

In this paper, failures are modelled as a point process with an intensity function  $\Lambda(m)$  where  $m$  represents the number of kilometres travelled by a wheel set and  $\Lambda(m)$  is an increasing function of  $m$  indicating that the number of failures in a statistical sense increases with the travelled distance of the wheel set. As a result,  $N(M_{i+1}, M_i)$ , the number of failures over  $M_i$  and  $M_{i+1}$ , is a function of kilometres travelled,  $m$ , and is a random variable.

Let the kilometres travelled of wheel sets,  $m$ , be known, and let  $F_n(m)$  denote the cumulative wheel failure distribution modelled as a Weibull distribution given by:

$$F_n(m) = 1 - \exp^{-(\lambda m)^\beta} \quad (2)$$

$\Lambda(m)$  is given by:

$$\Lambda(m) = \frac{f_n(m)}{1 - F_n(m)} = \frac{\lambda\beta(\lambda m)^{\beta-1}\exp^{-(\lambda m)^\beta}}{1 - (1 - \exp^{-(\lambda m)^\beta})} = \lambda\beta(\lambda m)^{\beta-1} \quad (3)$$

with the parameters  $\beta > 1$  and  $\lambda > 0$ . With condition on  $N(M_{i+1}, M_i) = n$ , the probability is given by:

$$P\{N(M_{i+1}; M_i) = n\} = \frac{\left\{ \int_{M_i}^{M_{i+1}} \Lambda(m) dm \right\}^n \exp^{-\int_{M_i}^{M_{i+1}} \Lambda(m) dm}}{n!} \quad (4)$$

This type of characterisation is appropriate because the failed wheel set is made operational through repair or replacement, and no action is taken with regards to the remaining wheel sets in operation. Since the number of failed wheel sets replaced at each failure is very small relative to the whole wheel set population, the rectification action can be viewed as having negligible impact on the failure rate of the wheel set population as a whole; see Barlow and Hunter [6].

The expected number of failures over period  $i$  and  $(i + 1)$  is given by:

$$E [N(M_{i+1}; M_i)] = \lambda^\beta ((M_{i+1})^\beta - (M_i)^\beta) \quad (5)$$

where the total accumulated kilometres travelled by a wheel set,  $M_i$ , is given by:

$$M_i = \sum_{j=0}^i m_j \quad (6)$$

### 2.1.1 Modelling wheel set degradation

Data on wheel set degradation have also been collected from LKAB's CMMS database. These data are obtained from the wheel turning machine, before and after turning. The machine has a measurement error of  $\pm 0.01$  mm; diameter, flange height, and flange thickness are all presented as integers.

From the wheel profile measurement data, we create a stochastic wheel diameter model, using the effect of wear from operation and turning; see Fig. 5(a). The wheel diameter ( $D_{70}$ ) after  $i^{\text{th}}$  period can be modelled as:

$$D_{w_i} = D_0 - \sum_{j=0}^i D_{NW_j} + D_{TW_j} \quad [D_{w_i} \leq D_c] \quad (7)$$

where  $D_{NW_j}$  is the wheel diameter loss due to operational traffic wear and  $D_{TW_j}$  is the wheel diameter loss due to wheel turning in period  $j$ .

The safety wear limit  $D_c$  for the wheel profile (P04) used for the iron ore transport is given by Eq. 8. The diameter of the wheels is calculated as 70 mm from the back of the flange,  $D_{70}$ ; see Fig. 5(a). This diameter often corresponds well with flange height measurements and is a good measure of material removal at wheel turning. Several other diameters can also be used for condition monitoring, i.e., determining how much of the wheel will be removed. In this paper, the second diameter,  $D_{25}$ , is calculated as 25 mm from the back of the flange. Earlier studies [22] on the same wagons verify this measurement. Therefore,  $D_c$  can be obtained by:

$$D_c = \begin{cases} 857 \leq D_{70} & \text{or} \\ 877 \leq D_{25} \end{cases} \quad (8)$$

where  $D_c$  is the critical wheel diameter for wheel replacement based on safety recommendations. In this paper, UIC regulation 510-2 [23] is considered by both operators and infrastructure managers.

The % worn out level, remaining useful wheel life of a wheel set after  $i^{\text{th}}$  period is given by:

$$RUL_i = 100 \times \frac{D_i - D_c}{D_0 - D_c} \quad (9)$$

### 2.1.2 Modelling wheel turning cost

Let  $t$  be the cost of turning the wheel per maintenance workshop visit of the wheel set and  $n_{L_i}$  be the number of turning events for  $i^{\text{th}}$  wheel of all wheels under consideration;  $N$  is the total number of turning periods up to the safety wear limit for renewal, and  $r$  is the discounting rate. Then, the wheel turning cost/year is given by:

$$c_t = \left\{ \sum_{i=1}^{N-1} \frac{t \times n_{L_i}}{(1+r)^i} \right\} \times \frac{r}{1 - \frac{1}{(1+r)^N}} \quad (10)$$

### 2.1.3 Modelling downtime cost due to wheel maintenance (loss of operation)

Let  $h_{DT}$  be the expected downtime due to each turning of the wheel,  $n_{L_i}$  be the number of turning events for  $i^{\text{th}}$  wheel of all wheels under consideration, and  $d$  be the expected cost of downtime per hour. Then, downtime cost due to loss of traffic is given by:

$$c_d = \left\{ \sum_{i=1}^{N-1} \frac{n_{L_i} \times h_{DT} \times d}{(1+r)^i} \right\} \times \frac{r}{1 - \frac{1}{(1+r)^N}} \quad (11)$$

### 2.1.4 Modelling inspection cost

Let  $I_f$  be the inspection per wheel-set and  $i_c$  be the cost of each inspection. Annual inspection cost over the wheel's life is given by:

$$c_i = c_{i_Y} + c_{i_W} \quad (12)$$

where

$$c_{i_Y} = \left\{ \sum_{i=1}^{N_{I_Y}} \frac{i_c}{(1+r)^i} \right\} \times \frac{r}{1 - \frac{1}{(1+r)^N}}; c_{i_W} = \left\{ \sum_{i=1}^{N_{I_W}} \frac{i_c}{(1+r_j)^i} \right\} \times \frac{r}{1 - \frac{1}{(1+r)^N}} \quad (13)$$

where

$$N_{I_Y} = \text{Integer} \left[ \frac{M_N}{I_{f_Y}} \right]; N_{I_W} = \text{Integer} \left[ \frac{M_N}{I_{f_W}} \right] \quad (14)$$

and  $r_j$  is the discounting rate associated with the interval of inspection.

### 2.1.5 Modelling risk cost of wheel failure and derailment

Let  $C_r$  be the cost per rectification of wheels on an emergency basis, modelled by  $G(c)$  and given by

$$G(c) = P[C_r \leq c] \quad (15)$$

For an example, if  $G(c)$  follows an exponential distribution, it is given by

$$G(c) = 1 - \exp^{-\rho c} \quad (16)$$

where the expected cost of each wheel failure repair on an emergency basis is given by:

$$\bar{c} = \frac{1}{\rho} \quad (17)$$

Let  $k$  be the expected cost of repairing potential wheel failures based on planned manual inspections and  $a$  be the expected cost per derailment. In this case,  $k$  and  $a$  can be modelled in similar manner.

The risk cost associated with wheel failures and derailment is based on the probability of manual inspection detecting potential wheel failure vs. wheel failure not detected by manual inspections, derailments and associated costs.

Let  $P_i(B)$  be the probability of detecting potential wheel failures using manual inspection,  $P_i(A)$  be the probability of undetected potential wheel failures leading to derailments,  $n_{NDT_i}$  be the number of detected potential wheel failures using manual inspections,  $n_{RB_i}$  be the number of wheel failures between two manual inspections, and  $n_{A_i}$  be the number of accidents in period  $i$ . Then, the risk cost is given by:

$$c_r = \left\{ \frac{\sum_{i=0}^N E[N(M_{i+1}, M_i)] \times [P_i(B) \times k + (1 - P_i(B) \times P_i(A)) \times a + (1 - P_i(A)) \times \bar{c}]}{(1+r)^i} \right\} \times \frac{r}{1 - \frac{1}{(1+r)^N}} \quad (18)$$

where  $P_i(B)$  and  $P_i(A)$  can be estimated based on  $n_{NDT_i}$ , the number of manual inspections detecting potential wheel failures,  $n_{RB_i}$ , the number of wheel failures between two manual inspections  $n_{A_i}$ , and the number of accidents between two manual inspections in period  $i$ .

### 2.1.6 Modelling replacement costs of worn-out wheels

Let  $c_{re}$  be the expected cost of replacement for wheels; this cost consists of labour, material, equipment, and the consumable and downtime costs of wheel replacement. The downtime for wheel replacement is much longer than for wheel re-profiling. Let  $I$  be the cost of current investment in new wheels. In this paper, the cost of replacement is assumed to occur at the beginning of each year and is simplified as the annual cost of investment in new wheels. Then,  $c_{re}$  is given by:

$$c_{re} = I \times \frac{r}{1 - \frac{1}{(1+r)^N}} \quad (19)$$



### 2.1.7 Modelling total cost of wheel maintenance

Costs associated with wheel maintenance are estimated as a total cost of maintaining a set of wheels, summing up the costs for Preventive wheel turning, Downtime due to wheel turning (loss of operation), Inspections (manual), Rectifications based on manual inspections, Repair of wheel sets, Derailments, and Replacement of worn-out and unreliable wheels. This total cost is given by:

$$C_{tot} = c_t + c_d + c_i + c_r + c_{re} \quad (20)$$

The cost parameters used in the total cost calculations appear in Table 1.

Table 1: Cost parameters

Parameter	Cost
$i_{c_Y}$	1 SEK
$i_{c_W}$	50 SEK
$d$	700 SEK
$t$	2 000 SEK
$r$	35 000 SEK
$k$	100 000 SEK

## 3 Wheel condition monitoring

Condition monitoring (CM) can provide information on the current state of a system, using both diagnostic variables and environmental conditions that can affect the system's future life [4]. This information can be used for prediction, prognostics, and maintenance activity planning. Monitoring can be executed with different levels of automation, from relying entirely on human senses to assess the condition to using fully automated and integrated monitoring systems to measure and analyse, e.g., vibrations, temperatures, pressures etc. [7].

There are several methods to detect and monitor wheel wear and wheel fatigue; see Fig. 1. One is visual inspection of the wheels at the railway yard. Another is the use of wayside monitoring stations to detect faults or failures [21]. A third opportunity occurs during general wagon maintenance in the workshop. In any of these scenarios, the wheel can have a fault that is not detected. The risk/safety factor or cost shown in the figure refers to when a wheel has an undetected fault that becomes a failure before the next loop.

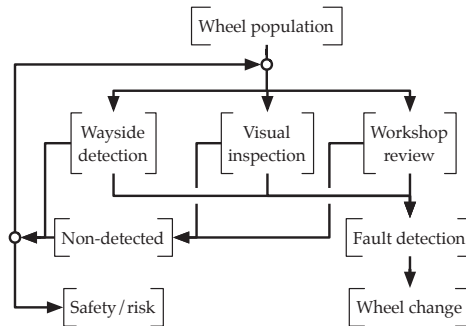


Figure 1: Wheel detection process

Wheel maintenance decision criteria are stricter and more rigid in the wagon workshop than at the railway yard. If a wagon with bad wheels is at the workshop, the wheels can be maintained before they reach their maintenance limit (opportunity based maintenance actions) [16].

## 4 Case description

The railway line between Narvik and Luleå, Fig. 2 primarily sees iron ore heavy-haul trains from LKAB mining company, but passenger, freight, steel-slab and copper-ore trains use this line as well. The iron ore transport for LKAB in northern Sweden and Norway starts at the mines in Kiruna and

Vitåfors near Gällivare and ends in the harbours of Narvik in Norway and Luleå in Sweden. This railway line has been in operation since 1903 and was originally designed for 14 metric tonnes of axle load [3]. In 2000, the axle load was increased from 25 to 30 metric tonnes [1]. The loaded speed was also increased from 50 to 60 km/h.

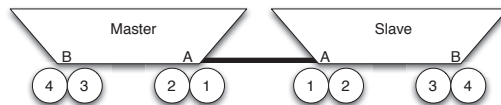


Figure 2: Iron ore transport line in northern Sweden and Norway

The iron ore trains consist of two IORE locomotives with 68 FANOO wagons, 750 metres long, and a total train weight of 8.520 tonnes; see Fig. 3(a). The wagons are equipped with three-piece bogies, each comprising one bolster and two side frames [17]. These pieces are connected by friction wedges and spring suspensions. The wagons are subject to a kilometre-based maintenance strategy.



(a)



(b)

Figure 3: An iron ore train; Designation of wagon, bogie and axles

Fig. 3(b) shows the set-up of a wagon with wheel axle, bogie and wagon designation; as shown, the two wagons are always connected at the A-end by a steel rod (drawbar). This means that they travel as a pair with one wagon having its B-end first and the other its A-end. The odd ID-labelled wagon is the master-wagon; it contains the brake control system for the pair. The wagon pair are always connected; they receive the same maintenance for all components except the wheel axles which are changed when they need maintenance. The wheels have a diameter of 915 mm as new and are not allowed to be used in traffic below 857 mm; the maintenance limit is set at 862 mm.

The intended life length of a iron ore wagon wheel between re-wheeling is at least 800 000 km of running distance, with a yearly travel distance for the wagons at between 120 000 and 140 000 km. Re-profiling for wheel profile wear is currently done between 200 000 and 300 000 km. The wheels are

visually inspected up to four times each day as they are loaded with iron ore, and a workshop review is performed every 80 000 km. The wagons that travel from Gällivare to Luleå pass two wayside condition monitoring sites up to three times each day. These sites measure the wheel profile and wheel/rail forces.

In 2012, LKAB transported 26.3 MGT (million gross tonnes) from its mines in Kiruna and Malmberget; of these, about 20% was shipped from Luleå harbour. It is predicted that by 2015, 37 MGT finished products will be transported from the mines.

## 5 Case study

The data have been collected from LKAB's computerised maintenance management system (CMMS). The data include wagon wheel work orders with detailed information on re-profiling, movement of wheel axles to and from wagons, and wheel failure modes. There are two main types of failure mode for railway wheels: rolling contact fatigue (RCF) and wear. Wear evolves slowly, while RCF has a more rapid rate of deterioration; see Fig. 4. In 2012, 366 wheel sets were sent for re-profiling or re-wheeling for high flanges. Almost double that number, 722 wheel sets, had RCF failure.

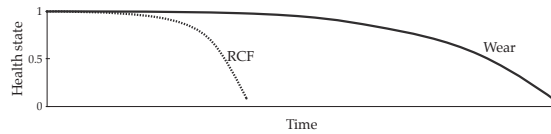


Figure 4: Wheel degradation for RCF and wear

Fig. 5(a) visualises the difference between a new and a worn profile. The diameter is measured at a point 70 mm from the back of the flange. This point is also called the running circle. When a wheel axle is re-profiled, the different failure modes represent different depths of material that must be removed to create a new clean profile. In Fig. 5(b), several wheels have been chosen to show natural wear and material removal at re-profiling. Due to the operating conditions, the average material removed from the diameter at re-profiling for a worn wheel is 10 mm, and for RCF, 30 mm.

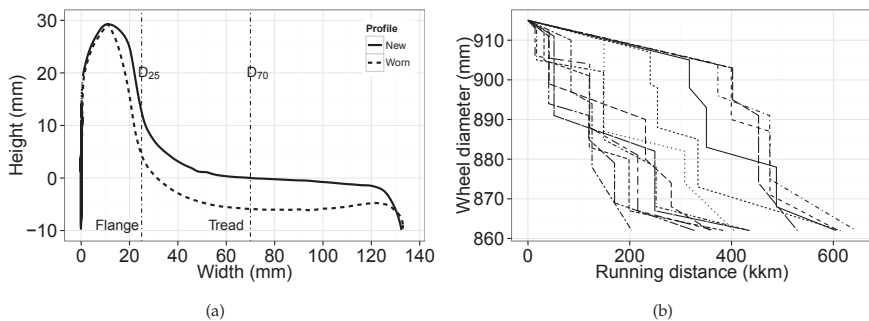


Figure 5: Difference between new and worn profile; Material removal from natural wear and from re-profiling

The lines in Fig. 5(b) represent different wheel axles between two re-wheelings. The data for these axles are from 2007 to 2012. The changes in the vertical direction indicate the diameter loss from re-profiling the wheels back to the original profile, while changes in the horizontal direction show the running distance. No measurement of diameter was performed before re-wheeling, making the amount of natural wear for the last running period larger than expected. Fig. 6 shows the density function for the natural wear in mm per 1000 km and for diameter loss at wheel turning.

## 6 Discussions and conclusions

In a CMMS system, there is almost always missing data or data have been entered incorrectly. This must be considered in the analysis and can be very problematic in creating models based on the CMMS operating data. The models in this paper use the data that are available after faulty data entries are

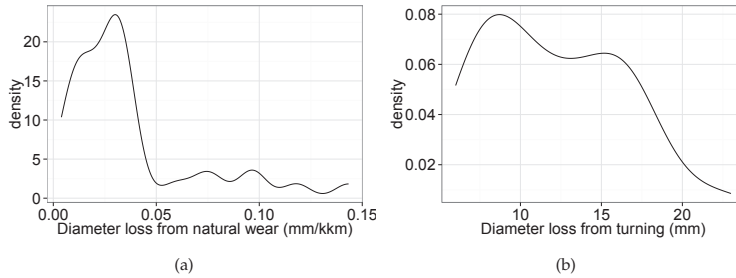


Figure 6: Density graphs for diameter loss from natural wear and wheel turning

removed. The models must be updated continuously to include recent actions and changes. With an updated model, it is possible to isolate a small portion of the data and predict changes in costs.

The natural wear for the wheels is about 3 mm on the diameter ( $D_{70}$ ) for every 100 000 km of distance travelled. According to this estimation, a wheel would be able to travel over 1 900 000 km before requiring re-wheeling. This is not physically possible given current safety limits. However, this paper suggests if trending of operational data, failure mode simulations, and optimised maintenance policies are used, greater distances can be achieved. For example, a wheel travelling 400 000 km between two re-profiling, with 8 mm removed at turning, and with high flange as the failure mode could travel for approximately 10 years at today's yearly travel distance, with only 2 re-profiling maintenance actions before the next re-wheeling, for a total of 1 200 000 km.

The proposed life cycle cost model considers the maintenance actions resulting from inspection and review as corrective maintenance, as the cost for re-profiling a wheel set is the same, but maintenance managers differ as to whether inspections comprise corrective maintenance while reviews are preventive. In any event, inspection limits reflect the safety limits set by the infrastructure manager and are designed for safety and risk purposes, while review limits require a wheel to be removed earlier with possibly less loss of material. Both inspection and review can be improved with the use of wayside profile monitoring stations. This type of monitoring can find wheels requiring immediate maintenance, and the analysis of the trending of wear and running distance can increase the understanding of when to remove a vehicle for wheel and wagon maintenance.

## 7 Future work

Future work should combine trending found in the operating data and simulations of failure modes with the LCC model to evaluate possible changes in the policies/strategies for operation and maintenance. When an optimal policy is determined, it can be field-tested on a small group of vehicles or even a whole fleet. The LCC-model will then be updated with new operating data, creating a continuous improvement loop.

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