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Condition monitoring at the wheel/rail interface for decision-making support

Mikael Palo[1], Diego Galar[1], Thomas Nordmark[2], Matthias Asplund[3] and Dan Larsson[4]

Abstract

Many railway assets, such as wheels, suffer from increasing deterioration 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 wheelsets 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 track not far away. The vehicles investigated are iron-ore 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

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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 Figure 1. As the figure shows, each layer in the system can comprise several companies, and any company can be on a number of layers.

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 comprising 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 the 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

[1]Luleå Railway Research Center, Luleå University of Technology, Luleå, Sweden
[2]LKAB, Kiruna, Sweden
[3]Swedish Transport Administration, Luleå, Sweden, Luleå Railway Research Center, Luleå University of Technology, Luleå, Sweden
[4]Damill AB, Luleå, Sweden

Corresponding author:
Mikael Palo, Luleå Railway Research Center, Luleå University of Technology, Luleå 97187, Sweden.
Email: mikael.palo@ltu.se

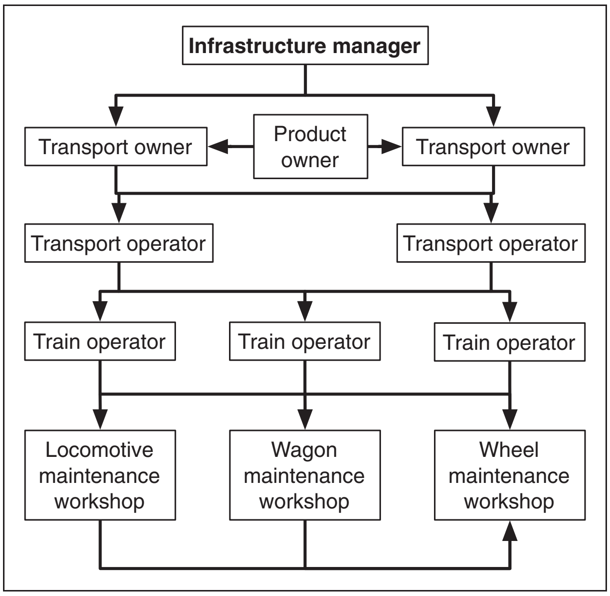

Figure 1. Stakeholders within the deregulated Swedish railway system.

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 such as 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.

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.

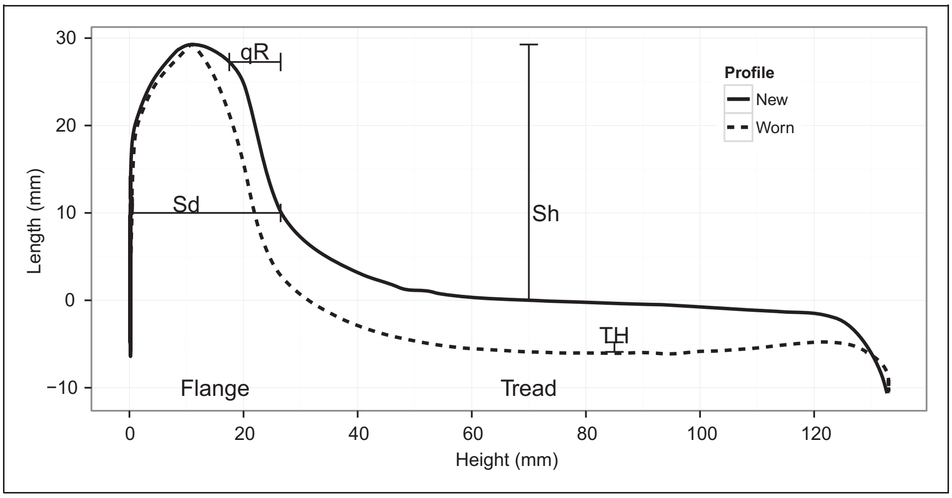

Figure 2. Wheel profile, with wheel parameters.

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.

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. Figure 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]

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.

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]

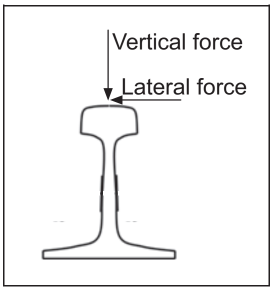

Figure 3. Definition of wheel/rail force in a curve.

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 Figure 3. 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]

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 modelled 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 fault detection and isolation (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 such as 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 Figure 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

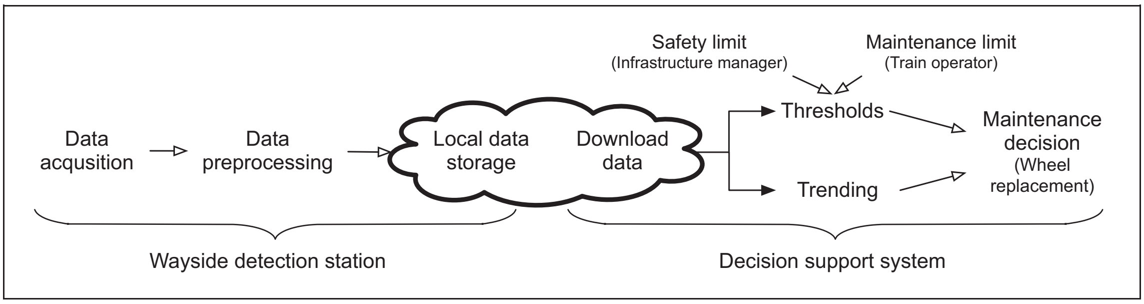

Figure 4. The process from data collection to maintenance decision.

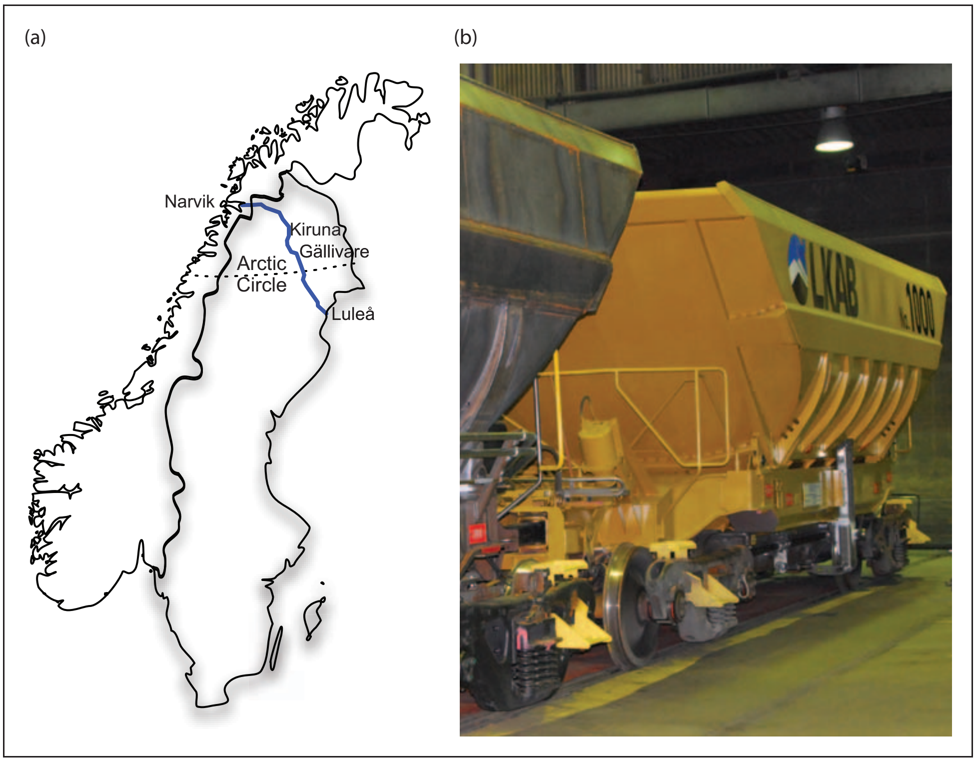

Figure 5. Iron-ore transport line in northern Sweden and a Fanoo iron-ore wagon.

for maintenance decision support, to detect an impending wheel fault/failure seems feasible.

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.

Case description

The only existing heavy haul transport in Europe is in northern Sweden and Norway. It stretches 550 km from Luleå in Sweden to Narvik in Norway, see Figure 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 8500 metric tonnes; see Figure 5(b).

In 2012, the LKAB mining company transported 26.3 MGT (million gross tonnes of iron-ore) from its mines in Kiruna and Malmberget; of these, about

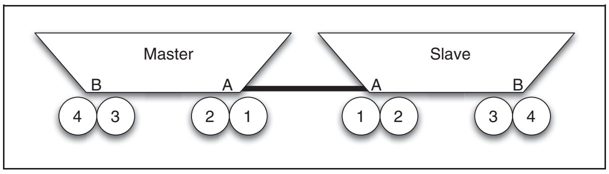

Figure 6. Designation of wagons and the names for the bogie and axles.

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.

Figure 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.

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 Figure 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.

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]

The measurement system consists of several strain gauges sensors micro-welded to the web of the rail, as indicated in Figure 8(b). There are three measurement positions on each rail, covering 3 meters in length, which corresponds to the circumferences of most wheels. The measured forces are vertical and lateral, see Figure 3, with the positive lateral force outwards

Figure 7. Picture of the rail and profile measurement system.

in the curve. Owing to the hostile environment of railroads, there is a weather proofing shield on top of the strain gauges, see Figure 8(a).

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 130,000 km. Re-profiling for wheel profile wear is 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. 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 Figure 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.

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 Figure 2. The maintenance limits set by the operator and safety limits from the infrastructure manager appear in Table 1.

Figure 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.

The research station measures the vertical and lateral strain in the rail and calculate the corresponding forces through conversion factors. The conversion

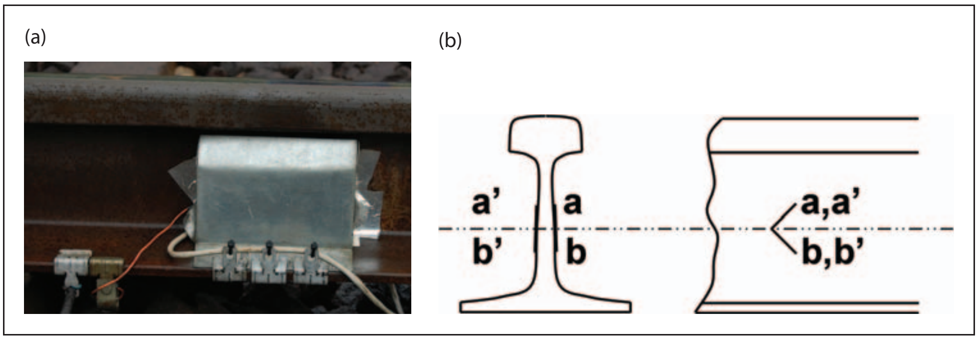

Figure 8. Measurement system and sensor placement on the rail.

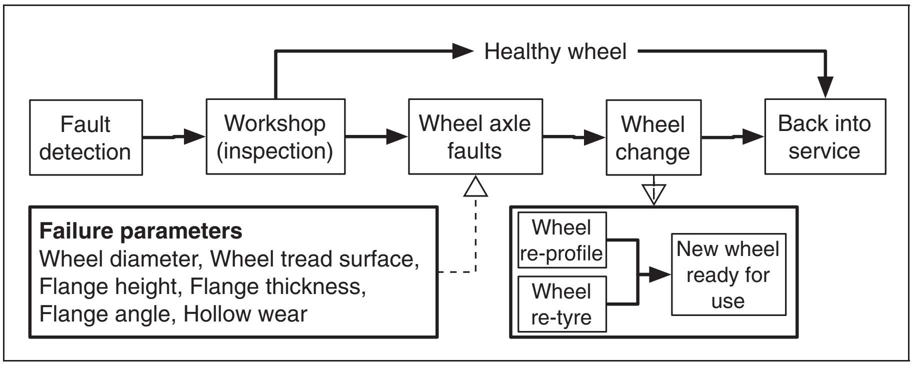

Figure 9. Process for wagon and wheel maintenance action.

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

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. Figure 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 Figure 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 Figure 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.

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 Figure 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.[28,29] The earlier study concluded that the leading axle was the best source of data for condition monitoring using wheel/rail forces.

Wheel profile wear data

Data from the profile measurement station were collected as the wagon passed the station. Figure 12

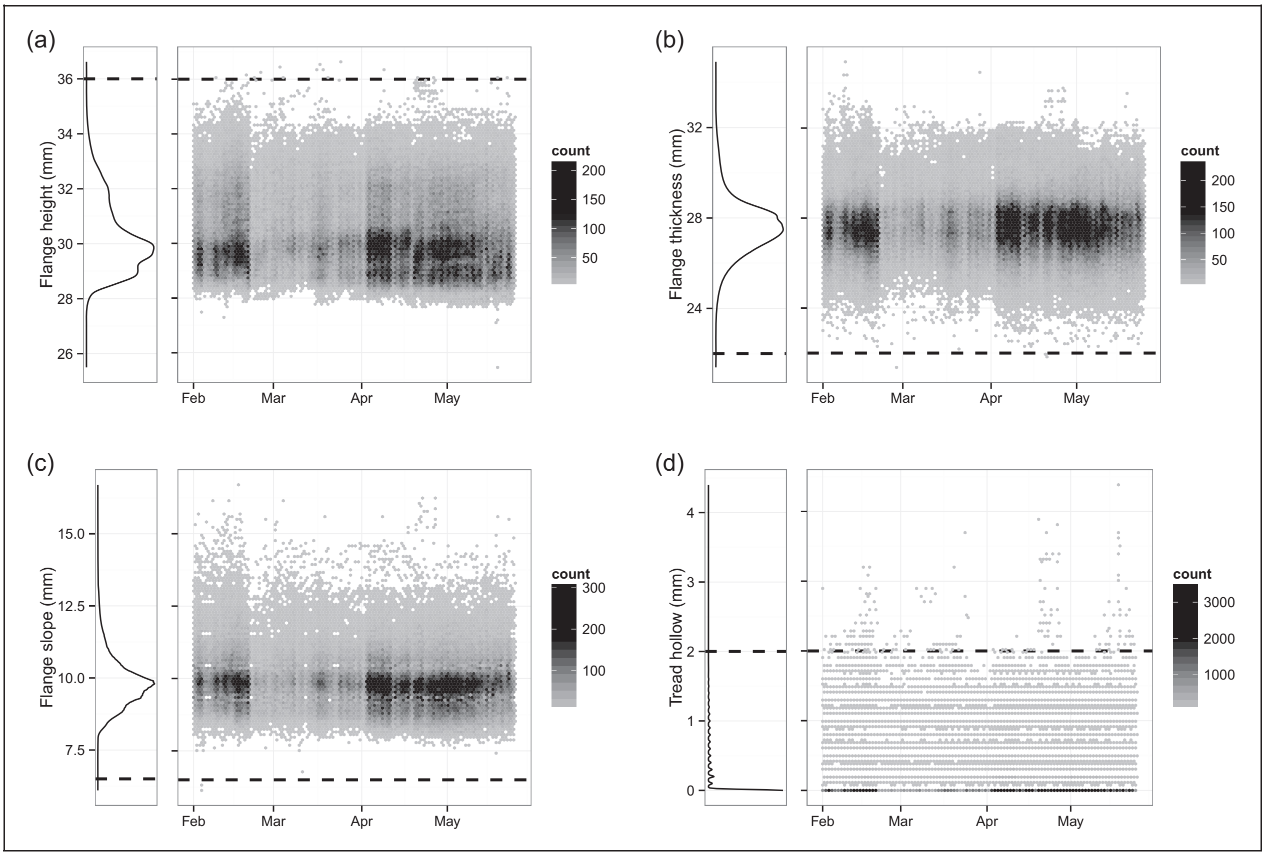

Figure 10. Distribution for each train and total density of wheel profile parameters: (a) flange height; (b) flange thickness; (c) flange slope; (d) hollow wear.

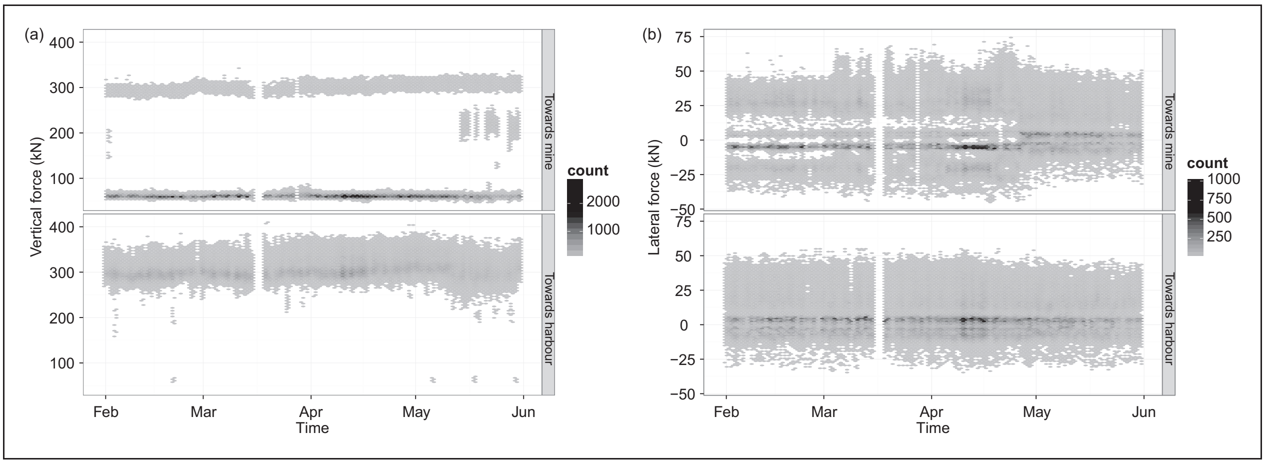

Figure 11. Wheel/rail force distribution for each train: (a) vertical force; (b) lateral force.

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.

In both graphs in Figure 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;

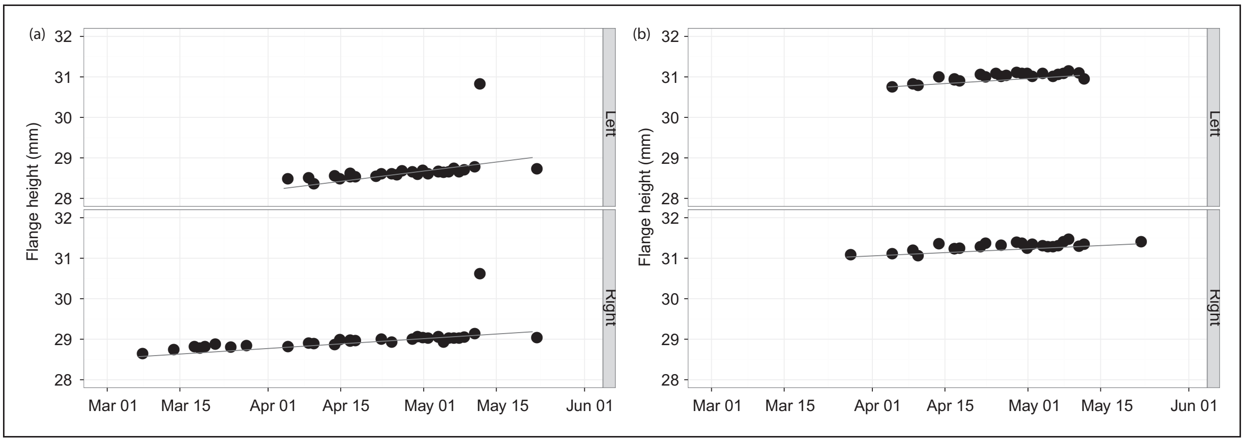

Figure 12. Flange height data for the selected wheel axles: (a) 4703.1; (b) 4704.4.

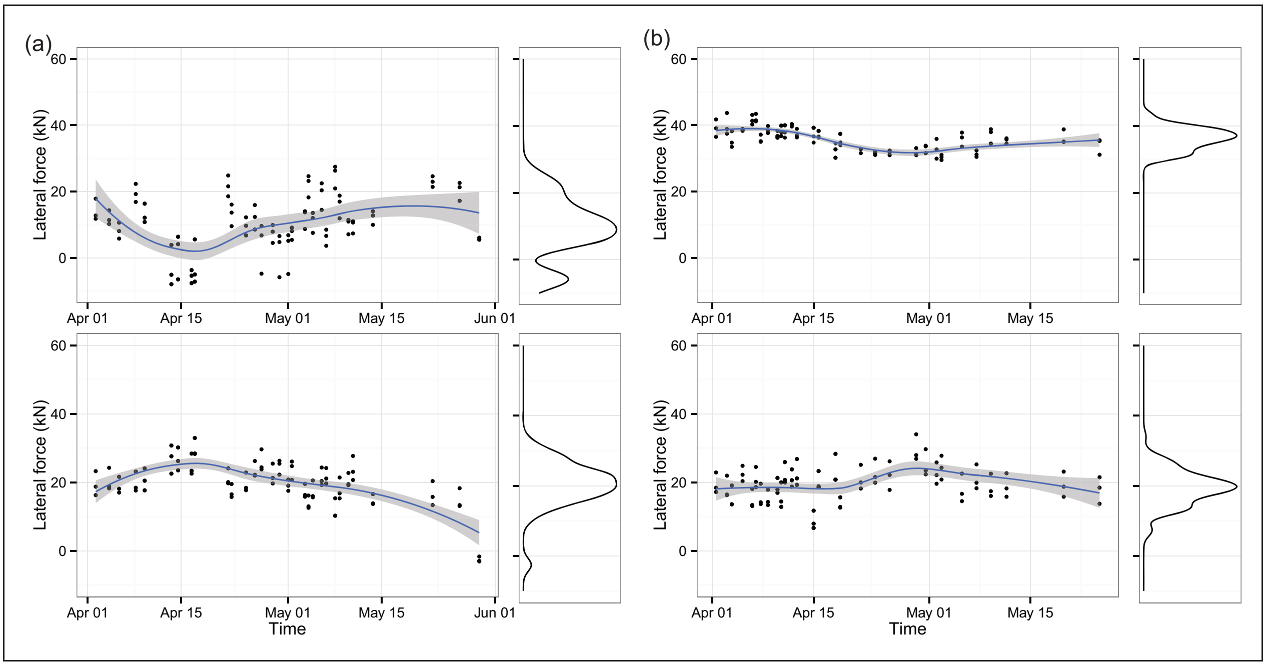

Figure 13. Lateral wheel/rail force data for the selected wheel axles: (a) 4703.1; (b) 4704.4.

this could reflect a data identification mismatch but cannot be disregarded or removed at this point.

Wheel/rail force data

Data from the force measurement station are processed and analysed as vehicles pass. In Figure 13 all collected passings of the same axles are as shown in Figure 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 grey area is the standard error, showing the trend for that wheel. The top graphs in Figure 13 are for the left wheel and the bottom two are the right wheel. The lateral forces from a wheel set can differ between two measurements due to factors from the vehicle and the environment. For example, the friction coefficient can change during the day from dew in the morning to drying up later in the day, and this can change the lateral force by up to 50%.

The wheels from 4704 (Figure 13(b)) are more worn than those of 4703 (Figure 13(a)). This is one possible reason for the larger forces from 4704 compared with 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 Figure 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 Figure 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. Differences in friction, from for example moisture and lubrication, on the track pose a problem when we are trying to compare different measurements, since lateral forces on a dry day can drop by up to 50% if it starts to rain.

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 130,000 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. Combining trending of the lateral forces together with weather data will be very useful for the maintenance manager in planning for maintenance on the wagon, a poorly steering wagon increases 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.

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 whether existing maintenance and safety limits should be changed or complemented by the consideration of other parameters.

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