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# Novel Detection And Prediction Tool For Bearing Damages On Heavy Haul Vehicles Using Way-Side Detectors

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# NOVEL DETECTION AND PREDICTION TOOL FOR BEARING DAMAGES ON HEAVY HAUL VEHICLES USING WAY-SIDE DETECTORS

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## ABSTRACT

Incipient bearing damages on heavy haul vehicles can lead to detrimental disruptions in heavy haul operation and even to derailment of trains. The consequences are damage of the railway infrastructure, loss of freight and equity, and an interruption of traffic. This paper presents a novel method to detect and predict the onset of bearing damages using a combination of multiple way-side detectors. The method is based on a statistical normalization of detector information and subsequent generation of a bearing damage score time series reflecting the abnormal condition of a specific bearing on a rail car. The method is implemented in a cloud-based service solution which reflects each bearing as a digital twin and tracks the condition throughout the operation of a railcar. The solution is applied to a heavy haul operation in Scandinavia to quantify performance of the analytics in terms of true and false positives is currently ongoing.

## INTRODUCTION

Bearing damages on heavy haul operation do not only jeopardize the transport of a specific good to reach its destination, but also the infrastructure that the train operates on. Consequently, there are both regulations and practices in place which should both protect the infrastructure and the rolling stock. The current state of the art in the area is well summarized by Corni et.al. (2017) in their introduction, and as can be seen from there that the focus of research and development for bearing damage detection has been targeting on-board solutions.

In this study data fusion from multiple way-side detector stations where wheel impact forces, acoustic emissions and bearing temperatures are measured are used to detect and predict bearing damages. While this is in line with Tsukahara et. al. (2013), there are numerous challenges that need to be considered, which are described. First, the multi way-side detector approach has not be targeted thus far which requires not only a local data integration and fusion, but also spatially distributed integration of data and correctly associating them with the bearing assets. Second, usually one sensing principle has been used to observe emerging damages, making the approach sensitive to shortcoming in the sensing approach. But combining different sensing principles, increases the complexity in the design and tuning of the analytics scheme tremendously.

In previous research, it has been shown that bearing damages can be related to an increase in vibrations (Corni et.al., 2015, Su and Sheen, 1993, SKF, 2012), an increase in the bearing temperature (Jin et.al., 2013), and acoustic emissions (Tsukahara et.al., 2013). Typically, research monitors one of those aspects and draws conclusions on the bearing condition, but it is still unclear how bearing damages progress in their severity from initiation to failure according to Nagatomo and Toth (2006). As a result, an estimation of the remaining useful life is hard to establish.

The approach taken by this study makes use of the current trend of digitalization of the railway infrastructure enabling the tracking of individual rail cars and locomotives and associate them with the way-side detector measurements. A platform enabling the data integration from multiple stakeholders has been suggested in Karim et.al. (2015) and has now been in operation in Scandinavia for decision making in operation and maintenance since 2016. An advantage of properly integrating, associating and managing the data from from spatially distributed and multiple stakeholders is the possibility to reduce the need for the installation of dedicated on-board solutions for each individual rail car, and instead investing in high performing way-side equipment. The challenge though lies in the need for a more centralized and complex data infrastructure. The experience from using such a platform for monitoring and prescribing maintenance actions in the context of wheel damages is reported in Birk et.al. (2019). The proposed approach will use the same digital platform to realize a bearing damage detection and prediction.

The paper is organized as follows. First bearing damages and their relation to wheel-track interaction forces, bearing temperatures and acoustic emission is discussed. Then the analytics approach that is proposed is summarized followed by a description of a decision support based on the analytics. Thereafter, the validation principles are presented and discussed complemented by observations surrounding the validation efforts. The paper ends with some conclusions and an outlook to future work.

### Bearing Damages and Relation to Secondary Data

Bearings are crucial components in railway operation in general and heavy haul specifically. Due to its vitality, the process of condition monitoring and underlying technology enabling this is well developed for this application. Common parameters to monitor regarding bearing fault detection consists of vibrations and temperatures. Both parameters are well-known to indicate defect bearings but depending on root cause and how far the damage has progressed the signification of these parameters may vary.

Generally, there are two common approaches for condition monitoring of railway vehicles, wayside monitoring and on-board monitoring. Wayside monitoring is performed via stationary detectors installed along the track, measuring passing vehicles. Whereas on-board monitoring is performed by sensors mounted on the vehicle or even the specific component in focus. Both has their advantages and disadvantages but for this paper only wayside detector information has been available and thereby considered.

Hot-box detectors are one type of wayside detector used to monitor the condition of the bearings. The hot-box detectors measure the temperature of the bearings on the passing vehicles via an infrared sensor. Normally these measurements are then compared against a threshold value and triggers an alarm if the temperatures exceed this threshold.

Acoustic bearing detectors is another type of wayside detector which can be used to monitor bearing conditions. Utilizing the frequency of the sound and various signal processing techniques these detectors can identify individual bearings and their sound signal on passing trains. The processing can also identify which component within the bearing that are producing the noise and, in some cases, even classify the cause. This information is usually provided as an alarm indicating component, severity of noise level and bearing position on vehicle.

Besides parameters such as vibration and temperature, having a more direct relation to the status of the bearing, operating and environmental factors are important to consider.

In cases with vehicles travelling over long distances with varying axle loads and weather conditions, monitoring the operational and environmental contexts allows for an understanding on what the bearings are exposed to and are expected to handle. Weather is not only important as a parameter affecting the life length of the bearing, but also as a parameter having impact on the behavior on the wayside detector. The location at which the detector is installed along the track, and the operational context of the detector is of importance to understand under which conditions the measurements are carried out. Depending on the context, surroundings and type of detector the results might not be directly comparable against each other.

The wheel condition is another factor which can be related to the condition of the bearing. At least information considering damages or extensive wear of the wheel. Depending on the type of wear or damage and severity, the changed vehicle dynamics and increased rail forces could impact the bearing negatively or even initiate bearing damages. For this reason, data from wayside detectors focusing on wheel condition such as wheel profile measurements and impact forces could add a purpose also for bearings.

Wayside detectors are normally integrated with RFID-readers and axle counting capabilities. Having RFID-tagged vehicles it is then possible to keep track on condition data for a specific bearing position on the vehicle. The bearing mounted at this position, however, might change over time. To avoid this limitation, it is of high importance to have access to information on maintenance activities. Having information about mounts and dismounts of specific bearing individuals, it is possible to relate acquired data not only to a bearing position but to an individual bearing. This will allow for more sophisticated analytics and a better decision support in the end.

## Analytics Scheme

In this section the analytics scheme is discussed which makes use of data from wayside detectors. While wayside detectors are few but measure all vehicles that pass by, there is a large effect from ambient factors on the measurement data. As a result, the data need to be pre-processed to mitigate the effect of ambient factors on the data. If the preprocessing is not properly conducted the wayside data will not only reflect the information relating a potential damage but also the ambient factors.

Resultingly, direct detection schemes that would merely assess the raw data from the detector could generate false detections or missed detections for a damage because of the distortion added by the ambient factors. While there is no direct issue with the wayside detector, the information could be apprehended as unreliable or inconsistent.

An example for this phenomenon could be the measured axle box temperature by the hot box detector. Depending on the ambient outdoor temperature, the axle box temperature will be raised or lowered by the effect of the ambient temperature. Thus, the measured temperature is then a function of the bearing temperature and the ambient temperature. If a decision on the bearing condition is to be made based on the measured temperature, the measurement need to be preprocessed first to compensate for the ambient temperature effect.

### Preprocessing of wayside data

There need to be a specific preprocessing scheme in place for every wayside detector type. Preferably, there is a physical model in place describing the measurement principle and the relation to the ambient effects. Otherwise, approximations need to be used.

*Hotbox detector*

For the Hotbox detector a measurement model for the measured temperature $z_T(t)$ is assumed which is a function of the bearing temperature $T_B(t)$ and a temperature effect which is depending on the outdoor temperatures but also operational characteristics of the train and installation related aspects of the detector, denoted as an ambient temperature effect $T_A(t)$. Moreover, the measurement will be affected by a noise term $\eta(t)$ and a general model can be stated as

$$z(t) = f\big(T_B(t), T_A(t)\big) + \eta(t) \tag{1}$$

Assuming that $f$ can be approximated by two additive components then (1) can be restated as

$$z(t) \approx f_1\big(T_B(t)\big) + f_2\big(T_A(t)\big) + \eta(t) \tag{2}$$

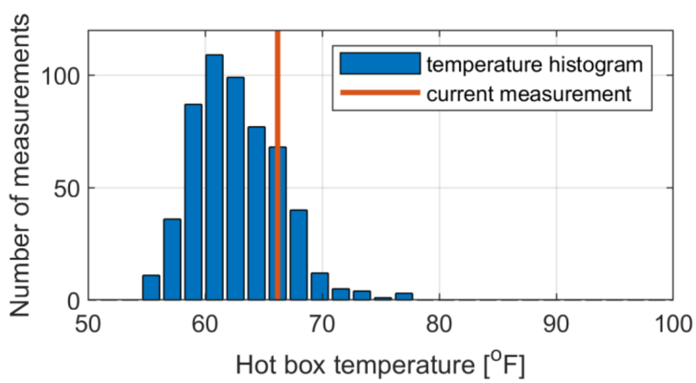


Figure 1: Example for a hotbox measurement and the temperature histogram for a train passage at a hox box detector station. The data is from a freight train on the iron-ore line in Northern Sweden.

When a train with several vehicles passes by a detector station, then it can be assumed that all bearing boxes have experience the same ambient temperatures, which means that all bearing temperatures should be biased by the term $f_2\big(T_A(t)\big)$. If the number of damaged bearing boxes, by exhibiting a raised temperature $T_B(t)$, is small in relation to the number undamaged bearings, then the distribution of $z(t)$ should have a clear peak relating to the effect of $f_2\big(T_A(t)\big) + \eta(t)$. Thus, the expectation of $z(t)$ can be used to compensate the hot box measurement and therefore be used as the preprocessed measurement.

$$\hat{z}(t) = z(t) - E(z(t)) \tag{3}$$

In order to derive $\hat{z}(t)$ it is necessary to collect the measurements from all axle boxes for one passage of a train, compute the expectation and then compensate the measurement.

In Figure 1, the temperature histogram is depicted along with the current measurement. There, the expectation can be extracted as the peak value, which is $E\big(z(t)\big) = 60.8^{\text{o}}F$, and the current measurement for one of the axle boxes is $z(t) = 66.2^{\text{o}}F$. Accordingly, the preprocessed measurement $\hat{z}(t) = 5.4^{o}F$ implying a slightly increased temperature in relation to the expected value, but not deviating sufficiently to be characterized as an outlier in relation to all the other axle box temperature.

The advantage of preprocessing the measurements in this way makes measurements from different detector stations comparable and thus allows them to be analyzed more consistently. In Figure 2, the probability density function for the original data from different detector stations but for the same axle box has shown. The differences are quite subtle, but for this case the density around the center has become more dominant for the processed measurements. Note that the processed data measurements are no longer absolute temperature values but deviations around a varying nominal value.

*Bearing acoustics detector*

In contrast to the hot box detector, bearing acoustics detectors produce already processed data sets. While the hot box detector is affected by certain phenomenon acoustic emissions mainly affected by the location, installation properties of the site as well as weather conditions and thus, are processed by the detector already. Usually, the detector is providing data on different bearing components in terms of acoustic emission in certain predefined frequency ranges. Those frequency ranges for the processing performed by the detector are also depending on the speed of the train while passing the detector station.

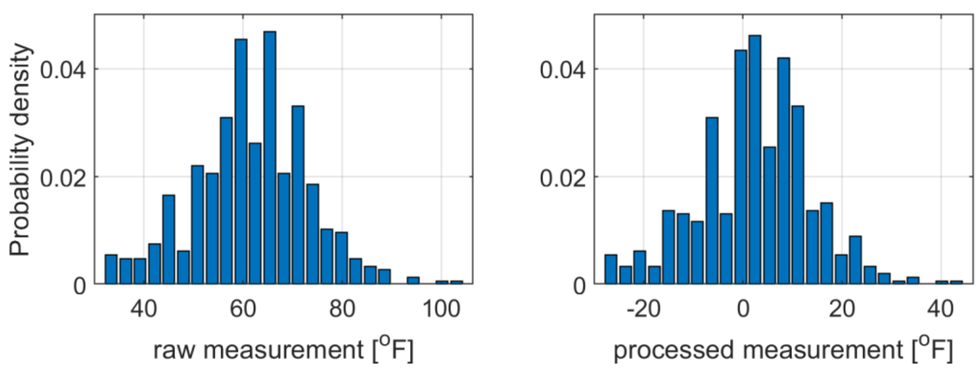


Figure 2: Probability density of a time series combining different detector station readings for one and the same axles box.

Since acoustic emissions are analyzed by the detector other acoustic emissions also contribute to the overall assessment of the acoustic signal. The detector is also affected by weather and seasonal variations when it comes to intensities of the acoustic emissions and how they are propagated through air to the sensor system of the detector. But in contrast to the hot box measurements, the data is already a deviation measurement and further preprocessing is not needed in that case.

**Detecting changes relating to bearing damages**

When a bearing is in good condition deviation measurements should be distributed around zero, where the variations are mostly related to the measurement principle itself and noise that is affecting any measurement. As a result, if the expectation value of the distributed measurement is changing or if the variations of the distribution change, then either the detector has changed its behavior, or the observed bearing has changed its behavior.

When multiple detector stations are considered in the analytics of a specific bearing, then a change would merely create and outlier in relation to the other detector stations. Thus, if there is a consistent change in the distribution, then the change should be attributed to a change in the bearing. Moreover, combining different measurement principles like bearing acoustics together with hot box measurements enables a better damage indication when both indicate consistent changes in the behavior, then the hypothesis of a change in the bearing is further strengthened.

It is now assumed that changes in the bearing acoustic data and hot box data need to occur. A simplifying assumption is now that both data sources are normally distributed

$$\begin{aligned}\hat{z}_{BA}(t) &\sim N(\mu_{BA}(t), \sigma_{BA}(t)) \\ \hat{z}_{HB}(t) &\sim N(\mu_{HB}(t), \sigma_{HB}(\mathrm{t}))\end{aligned} \tag{4}$$

where $\hat{z}_{BA}(t)$ and $\hat{z}_{HB}(t)$ are preprocessed measurements for bearing acoustics and hot box, respectively, and $\mu_{\blacksquare}(t)$ is the time varying mean and $\sigma_{\blacksquare}(t)$ the time varying standard deviation of the respective measurements.

An adverse change in the bearing condition will then be reflected in the change of the mean and the standard deviation. Both parameters could be used to detect changes over time. A typical change detection method that can be applied is the CUSUM detector as described in Gustafsson (2000) and proposed by Page (1954). For this end, for each point in time $t_k$ an estimate of $\mu_{\blacksquare}(t_k)$ and $\sigma_{\blacksquare}(t_k)$ is derived by evaluating $\hat{z}_{BA}(t)$ and $\hat{z}_{HB}(t)$ over a historic time frame of length $\Delta t$ and thus is $(t_k - \Delta t, t_k]$. The window length $\Delta t$ then becomes a hyper parameter in the detection. The CUSUM detector can be stated as follows

$$g(t_k) = \max\left(g(t_{k-1}) + s(t_k) - \gamma, 0\right) \tag{5}$$

In (5), s$(t_k)$ represent $\mu_{\blacksquare}$ and $\sigma_{\blacksquare}$ and are the input to the CUSUM detector and $g(t_k)$ is the filter version of input, on which the decision is taken using a threshold comparison like $g(t_k) > \tau$ to establish a damage event. The parameter $\gamma$ is the forgetting factor in the change detection. Thus, there are two additional hyper parameters, the forgetting factor $\gamma$ and the detection threshold $\tau$. For each $\mu_{\blacksquare}$ and $\sigma_{\blacksquare}$ a hyper parameter set $\{\Delta t, \gamma, \tau\}$ need to be tuned.

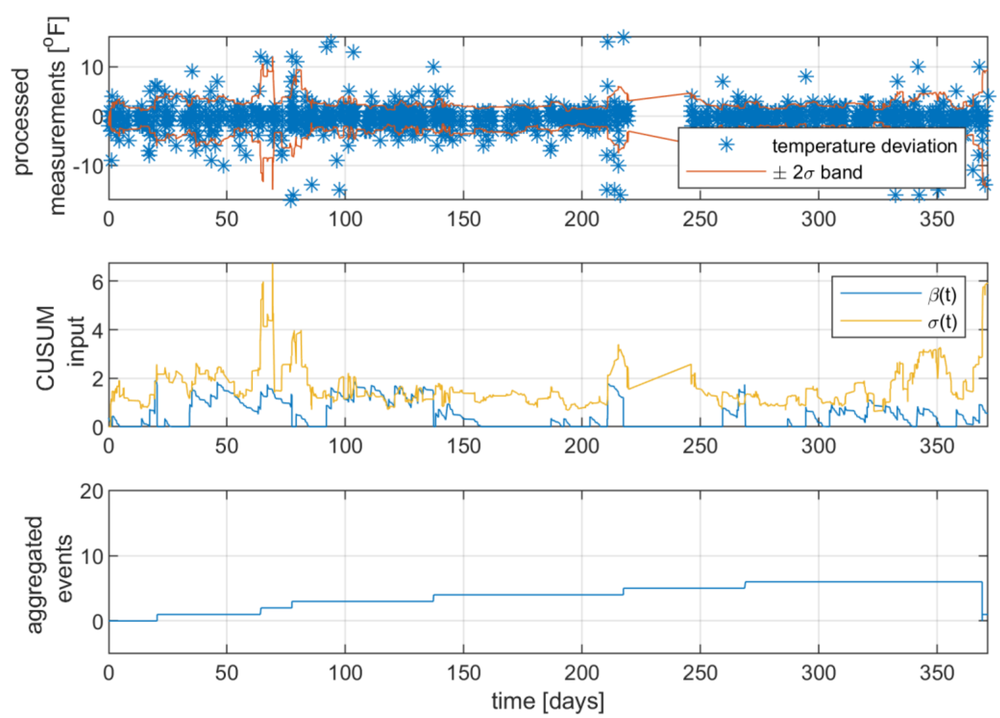


Figure 3: Application of the analytics scheme on hot box measurement for one bearing of a freight vehicle on the iron ore line in Northern Sweden.

According to Jin et. al. (2013), high bearing temperature can also be interpreted as an indication for a bearing damage event, but it is not a monotone rising function of the time of use. Moreover, the instantaneous contribution of such a damage event fulfills the following proportionality

$$\beta(t) \sim e^{\frac{-b}{\hat{z}_{HB}(t)}} \tag{6}$$

Similarly, a CUSUM detector can be established for $\beta(t)$ and used to quantify the direct contribution of high bearing temperature on the bearing life. In Figure 3, an application of the detection scheme on processed hot box measurement data is shown. There, two CUSUM detectors are used for $\sigma_{HB}(t)$ and $\beta(t)$. In the processed measurements plot it can be seen how the processed measurements are varying and how the standard deviation is depending on time. The resulting $\sigma_{HB}(t)$ and $\beta(t)$ are then used in the CUSUM detector which produces damage events. These events are then aggregated. Based on the aggregated damage events a decision support can now be provided.

### Decision Support For In-Field Damage Prevention

A predictive decision support is dependent on an adequate data acquisition and sophisticated analytics, but the value created is determined only by the effect the solution has on the decision-making process. By that, it is highly relevant to identify the relevant users and understand their needs and limitations. This to ensure that the provided information fulfills a need and can be easily interpreted.

For this case, focusing on bearings, with many data sources and indications involved it cannot be assumed that users should evaluate each indication separately and aggregating this by themselves. Also, targeting users working close to the vehicles, having extensive railway knowledge, but limited analytics and IT knowledge, the decision support must be built from the railway perspective focusing on components firstly and not types of data and analytics.

Having introduced multiple factors as relevant indications of a deviating bearing, a clear view on their relation and impact on the bearing condition is also needed. Since all information considered for this decision support are not directly translated to the current condition of the bearing, an initial step is to separate the indications based on this. From the available data in this case, bearing acoustics and hot-box data are classified as directly related to the bearing condition whereas wheel condition data, weather data and axle load is seen as secondary factors impacting the life length. This separation of the indicators can classify them into two barriers. One which focuses on a longer perspective and factors weighing up over time as important when considering the life length, such as loads, speed and weather conditions. The other focusing on damages already established with existing indications on decreased capability in the form of higher temperatures and vibrations. Both together covers a larger portion of faults that can be detected as a kind of layered detection. Each individually could also be relevant for different user with different time perspectives in focus.

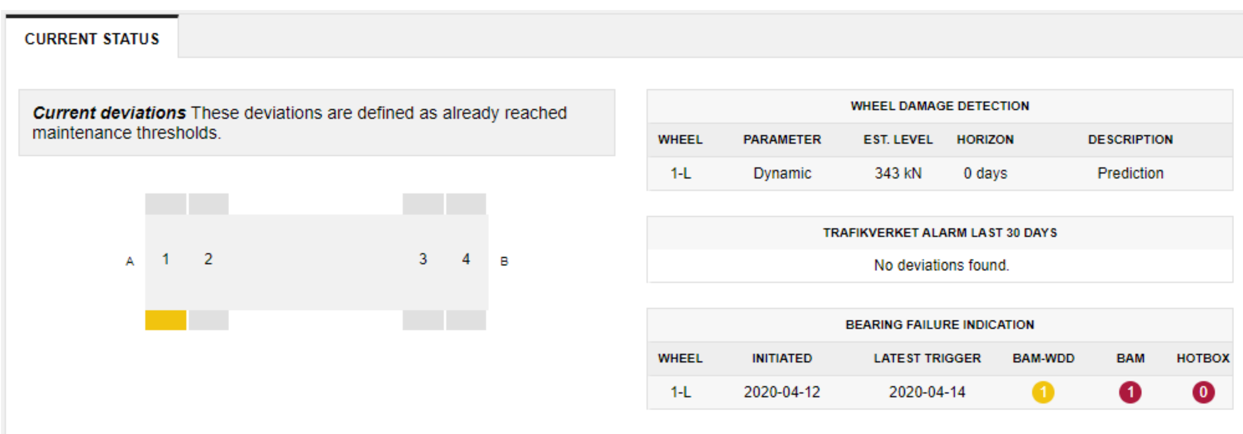


Figure 4: Screenshot from a decision support solution providing aggregated bearing damage indications

To not overwhelm users in the first step and gain a bit of trust and confidence while gaining experiences and feedback on the solution, the focus is on the short-term indications. These indications, generated by the analytics on hot-box and bearing acoustics data presented in the previous chapter, should highlight bearings with established damages. From this the user should be able to determine if the bearing is running hot or has increased noise. Regarding the acoustic noise, it is not in this case concluded how noise from damaged wheel affects the acoustic data for the bearings. Hence the bearing acoustics indications is extended and separated into two, BAM-WDD and BAM. The first one indicates that increased noise in the bearing has been identified at a time when there is also an assumed wheel damage on the wheel identified by de detection approach presented in Birk et al (2019). The second one, BAM, is an indication that the bearing has increased noise but no identified wheel damage on the same wheel position.

In figure 4 an example how this aggregated bearing indication could look like is presented. The aggregated indication weighs in detections from hot-box and bearing acoustics over time, counts the number of times each type has triggered a detection and keeps track on the initial detection of any type and the latest.

This aggregated bearing failure indication is a single point of information for all bearing related wayside information. Taking decisions based on this information the user has the full picture and can learn and identify correlations between the different indicators over time.

It is worth mentioning that this indication is not intended to replace available safety thresholds provided by the infrastructure owner. It is solely a complementary solution to this.

### Validation Using Real Life Case Data

The proposed decision support scheme needs to be validated to prove its performance and also ensure that the scheme enables better decision making than single data source decision making. Trust in the decision making is gained when the decision support scheme provides few false positive indications together with few missed indications.

False positives generate costs for unnecessary inspections and are detrimental for the trust in the decision support solution. It is therefore important to combine several indicators with high individual false positive rates in an appropriate manner to reduce the total number of false positives. The reasoning is based on the notion that bearing failures occur rarely but create immense damages, while inspections are costly and time consuming. Reducing the false positive by introducing an approach that is conservative when it comes to the generation of alarms is essential, while balancing the missed bearing failures.

#### Validation principle

The validation of the decision support is complicated and requires several activities over a longer period, where it is likely that bearing damages will develop and become detectable using inspections of the bearings. It is also necessary to align the validation efforts with time-based maintenance and inspection intervals such that the bearings are traceable throughout operation, to avoid conflicts between the validation efforts and legally required maintenance practices.

The validation should provide a quantification and understanding of the performance aspects:

- **True positive** is the event of the correct indication of a bearing damage which is confirmed by standard inspection and maintenance practices. It means that a wagon which receive an indication need to be shunted out for inspection of the bearing.
- **False positive** is the event of the incorrect indication of a bearing damage which could not be confirmed by a standard inspection and maintenance practices. Here it must be noted that there might be a bearing damage present, but it was not yet possible to confirm it. Clearly, the timing of the inspection, namely when a wagon is shunted out for inspection and maintenance is a factor here.
- **True negative** is the event of correctly not providing an indication. A metric can be established by annotating if a wagon is inspected and maintained according to standard practice does not exhibit a bearing damage and that there is no indication of a bearing damage in the decision support as well. The extra effort lies in the cross referencing between maintenance protocols and the history of indications by the decision support.
- **False negative** is the event of a missed indication, when there is a bearing damage. A metric can be established like for true negatives by cross referencing maintenance protocols, or in the unfortunate event that a bearing damage leads to an incident on route.

The validation protocol therefore needs to include several stakeholders in the validation process, like maintenance engineers, shunting personal, and operators at the railway undertakers. These roles need to have access to the decision support system and the information, which is not directly available, usually maintenance protocols, need to be introduced into the information flow of the validation.

At the time of writing, the validation process is established at a Scandinavian freight operation and the first samples for the validation statistics are established.

**Observations during the validation process**

For the validation, the analytics scheme was preliminarily tuned meaning that the hyper parameters of the individual detectors were setup and the decision support scheme aggregates and visualizes the indications for the selected freight operation. Further, the personnel affected by the validation process were instructed and trained to perform the needed additional supporting tasks.

During the validation efforts several aspects surfaced. First, the tuning of the multi-indicator scheme is a quite intriguing challenge, since it not all damages might exhibit an indication in all indicators and thus, it has to be decided what is the earliest point in time when a shunting for the inspection shall occur. There is also an interplay with the selection of the hyper parameters. It should also be noted that the validation is performed in life-operation, which means that unnecessary shunting creates additional costs for the railway undertaker that must place work orders on the maintenance contractor.

Second, there is the hypothesis that wheel damages like for example RCF damages or wheel flats could generate indications form the bearing acoustic detectors. Such indications would be misleading for the validation of the bearing damage scheme, while they are still appropriate to be highlighted. In Figure 5, an example from the collected and processed data is shown. There are clear similarities in the trends of the dynamic force measured by a wheel impact load detector and the raise in the standard deviation of the RMS for a frequency band in the bearing acoustic detector. Clearly, the RCF damage on the wheel seems to generate changes in acoustic emissions and can therefore distort the bearing damage indications.

Therefore, it was decided to introduce information on wheel damage in the decision support as a disclaimer, as can be seen in Figure 4.

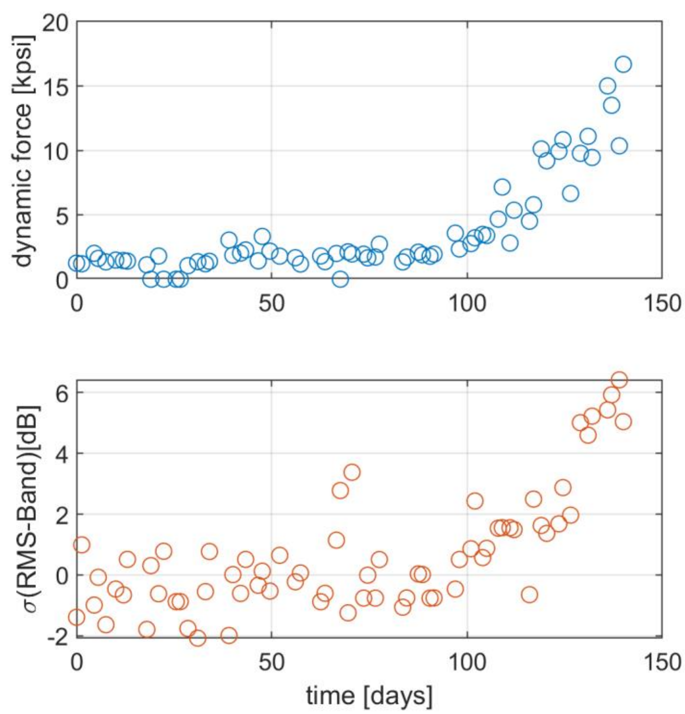


Figure 5: Comparison of the dynamic force trend form wheel impact load detector in relation to the standard deviation of the RMS of the bearing acoustics measurement.

## Conclusion

In this paper a novel analytics and decision support scheme is proposed that can be used to detect and predict the onset of bearing damages. It is shown how data from multiple way-side detectors of different kinds, like hot box, bearing acoustics and wheel impact load detectors, can be combined to provide indications to railway undertakers. Using the indicators, the wagons can be shunted appropriately to maintenance contractors to increase availability and safety along the routes.

The analytics scheme uses a statistical normalization of detector information and subsequent generation of a bearing damage event time series reflecting the abnormal condition of a specific bearing on a rail car. The decision support solution is implemented in a cloud-based service provided as a SaaS which reflects each bearing tracks the condition throughout the operation of a railcar.

The solution is applied to a heavy haul operation in Scandinavia during more than one year and validation statistics is still collected to get an exact understanding of the performance in terms of true and false positives. The next steps are to fully integrate the different stakeholders in the decision support solution and when sufficient trust is gained by all stakeholder to fully automate the decision making.

## References


Birk, W., Dittmann, T., Karim, R., Westerberg, J. (2019) Experiences from the detection and prediction of wheel damages on railway vehicles in operation. 13th International Heavy Haul Association STS Conference, June 10-15, Narvik, Norway.

Corni, I., Symonds, N., Birrell, C. E., Katsamenis, O. L., Wasenczuk, A., & Vincent, D. (2017). Characterization and mapping of rolling contact fatigue in rail-axle bearings. *Engineering Failure Analysis*, *82*, 617-630.

Corni, I., Symonds, N., Wood, R. J. K., Wasenczuk, A., & Vincent, D. (2015). Real-time on-board condition monitoring of train axle bearings.

Gustafsson, F. (2000). *Adaptive filtering and change detection* (Vol. 1). New York: Wiley.

Jin, G., Matthews, D., Fan, Y., & Liu, Q. (2013). Physics of failure-based degradation modeling and lifetime prediction of the momentum wheel in a dynamic covariate environment. *Engineering Failure Analysis*, *28*, 222-240.

Karim, R., Birk, W., & Larsson-Kråik, P. O. (2015). Cloud-based emaintenance solutions for condition-based maintenance of wheels in heavy haul operation. In *International Heavy Haul Association: The 11th International Heavy Haul Association Conference will be held 21-24 June 2015 in Perth 21/06/2015-24/06/2015*. International Heavy Haul Association.

Nagatomo, T., & Toth, D. G. (2006). Investigation of the bearing damage progression starting from cone creep of a railroad axle journal bearing. *Quarterly Report of RTRI*, *47*(3), 119-124.

Page, E. S. (1954). Continuous inspection schemes. *Biometrika*, *41*(1/2), 100-115.

SKF Group. (2012). Railway Technical Handbook. *SKF: Gothenburg, Sweden*, 25-35.

Su, Y. T., & Sheen, Y. T. (1993). On the detectability of roller bearing damage by frequency analysis. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, *207*(1), 23-32.

Symonds, N., Corni, I., Wood, R. J. K., Wasenczuk, A., & Vincent, D. (2015). Observing early stage rail axle bearing damage. *Engineering Failure Analysis*, *56*, 216-232.

Tsukahara, H., Aime, W., Burle, A., Chavance, D., & Mouille, E. (2013, November). Innovative application of Acoustic Bearing Condition Monitoring in High Speed Train Depots. In *World Congress on Rail Research, Sydney*.