CLOUD-BASED EMAINTENANCE SOLUTIONS FOR CONDITION-BASED MAINTENANCE OF WHEELS IN HEAVY HAUL OPERATION

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SUMMARY

The Swedish ore line, began in 1898 and was completed and operational by 1902. The line was later electrified and remains so to this day. A study on wheel-rail interaction, to optimize wheel and rail profiles on the Malmbanan and Ofoten lines states that there is a need to develop and apply limit values for the allowable length of single and multiple cracks on wheels. Herein, all stakeholders in the railway organization have to be involved. Provisioning of an integrated decision support system for track and vehicle contributes to increased efficiency and improved effectiveness of the maintenance process, which in turn enables achievement of business excellence. However, an integrated decision support process for maintenance is highly dependent on appropriate information logistics which enables information provisioning to various maintenance stakeholders. One emerging approach for development of eMaintenance solutions is utilization of cloud-based technologies. Cloud-based eMaintenance solutions promises smooth information logistics for maintenance decision support. Hence, the purpose of this paper is to propose an approach for condition-based maintenance decision-making relating to railway vehicle wheels, based on a cloud-based eMaintenance solution. The paper also demonstrates how the proposed approach can be implemented for estimation of Remaining Useful Life (RUL) of railway vehicle wheels.

1. INTRODUCTION

The Swedish ore line, began in 1898 and was completed and operational by 1902. The line was later electrified and remains so to this day. Unlike its global counterparts, the mining company LKAB, neither owns nor manages the track infrastructure; these are under the control of the Swedish Transport Administration. Each car carries a 100 tonne pay load, equaling 30 tonnes axle load, and each train set consists of 68 cars.

A study on wheel-rail interaction, to optimize wheel and rail profiles on the Malmbanan and Ofoten lines states that there is a need to develop and apply limit values for the allowable length of single and multiple cracks on wheels. Herein, all stakeholders in the railway organization have to be involved. Moreover it is known that wheel impact detector data can be used to determine bogie performance to determine the optimum use of data from these detectors in day-to-day vehicle maintenance decisions [1].

Due to the deregulated Swedish market decision support systems tend to address track and vehicle assets separately.

As a result, functional requirements are needed to ensure system integrity from a technical perspective. An integrated decision support system that optimizes the system as a whole is desireable. Furthermore, there is a need that important factors such as rail and wheel profiles are optimized to achieve a system that shall be able to determine optimum maintenance profiles [2].

An integrated decision support system for track and vehicle contributes to increased efficiency and improved effectiveness of the maintenance process, which in turn enables achievement of business excellence.

However, an integrated decision support system for maintenance is highly dependent on appropriate information logistics which enables information provisioning to various maintenance stakeholders [3]. Appropriate information logistics can be realized through eMaintenance solutions. eMaintenance solutions for maintenance decision support can be developed based on different approaches, technologies, and methodologies (see e.g. [4]). One of the emerging approaches for development of eMaintenance solutions is utilization of cloud-based technologies. Cloud-based eMaintenance solutions promises smooth information logistics for maintenance decision support.

Hence, the purpose of this paper is to propose an approach for condition-based maintenance decision-making relating to railway vehicle wheels, based on a cloud-based eMaintenance solution. The paper also demonstrates how the proposed approach can be implemented for estimation of Remaining Useful Life (RUL) of railway vehicle wheels.

2. CLOUD BASED EMAINTENANCE SOLUTIONS

The development and implementation of eMaintenance solutions, in combination with measurement systems, and control of appropriate wheel and rail profiles enables optimization of wheel and rail maintenance in heavy haul operations. Hence, “early warnings” for railway maintenance stakeholders to make fact-based decisions of key factors in the deterioration processes of wheels is supported [2].

Maintenance and renewal of wheel-sets account for a large proportion of the costs for railway rolling stock. Factors including wheel surface damage, fleet availability and vehicle design are important to be considered. Managing these factors efficiently, has significant beneficial implications on a vehicle’s service life, track damage, environmental and life cycle costs. Condition monitoring of wheel-sets will therefore support the optimization of maintenance and renewal regimes [5].

An analysis of wheel profile wear and its consequences on the Spoornet coal export line found that attention to the wheel/rail interface is of utmost importance [6], and that development of technical solutions to implement an effective wheel/rail interface management strategy is essential. The success of such a strategy depends on coordinated efforts between all stakeholders. Rolling stock and infrastructure engineers must develop and apply a holistic strategy to manage the wheel/rail interface.

3. DESCRIBING DIFFERENT INTERACTING PARAMETERS

Wheel defects can be divided into four major groups: surface defects, polygonization, profile defects and subsurface defects [7].

Wheel profile parameters such as flange thickness, flange slope and hollow wear are important wheel parameters. By combining wheel impact force data and wheel profile measurement, the data indicate that more than half of the wheel impact defect warnings can be removed by setting the wheel maintenance limit to a flange height of 30.46 mm instead of 34 mm. Thereby, the amount of capacity-consuming reactive measures is reduced [8].

Railways around the world are now using data from wayside detectors to implement vehicle maintenance strategies and in turn increase safety by detecting and mitigating the ‘bad actors’. In Brazil, VALE uses a wheel profile detector on the Estrada de Ferro Vitoría Minas (EFVM) line. Wheel profile has a strong influence on vehicle dynamics, especially on safety parameters such as wheel rail contact (L/V). The results show that it is possible to set the limits used by wayside detectors to identify ‘bad actors’ and to increase the overall safety [9].

System capacity increases, such as axle loads, are systematically being implemented, [10]. This has been possible due to improvements in metallurgy, larger rail cross sections, development of new rail/wheel profiles, and the extensive use of track lubrication and grinding.

Further, life prediction is important and different criteria are designated to predict the life span of components under wear, such as the wheel profile. Wheel wear is one of the important problems in the railway industry, especially from the point of safety, maintenance, and replacement cost [11].

Wayside condition monitoring systems support diagnosis of failures and faults in rolling stock, in order to increase quality, to reduce factors like delays, damage to infrastructure, serious accidents, and unnecessary costs. Wayside measuring and monitoring systems are readily available on the market and they make use of different types of sensing technologies. The generated data from these systems provides the basis for maintenance decision making related to the actual condition of the rolling stock, such as wheels, axle bearings and bogie performance. The cost of wheel and rail maintenance for heavy traffic such as ore lines can be up to 50% of the total rail/wheel system maintenance cost [12, 13, 14].

Models developed to simulate real field phenomena are often designed for specific problems and cannot be extrapolated to the general situation. In this paper a hybrid approach is chosen, which can describe both continuous and discrete dynamic behaviour. Such models often combine physics of failure (continuum mechanics) models and statistical observations. A data driven model is often based on a set of observations and assumptions concerning the generation of the observed data. A hybrid model has the benefit of encompassing a larger class of models within its structure, allowing for more flexibility in modelling different phenomena.

The first known hybrid wheel/rail model, combining operational data based on true wheel/rail profiles, and advanced continuum mechanics on Malmbanan operation was developed to understand wear and plastic deformation of wheels and rails in 2003. The importance of matching measured wheel and rail profiles in order to obtain good agreement between measured and simulated contact forces was emphasised and reported in [15].

The challenge is in combining the outcomes of technical condition monitoring data with maintenance activities. The use of a combination of way-side condition monitoring and train/track simulation in maintenance planning provides a powerful tool to predict changes in wear due to different rail/wheel profile strategies. Simulations, in combination with condition based field observations, clearly suggest possibilities to find longer wheel life [16].

Any change to the wheel/rail profile will change the response of a vehicle. Hence, condition monitoring of the wheel/rail interface is needed to evaluate wheel/rail profile degradation rate and prediction of its future profiles. The wheel/rail profile estimation can be carried out using linearized simulation functions [17].

Seeking to optimize the wheel maintenance strategy one needs to determine the wheel failure distribution and its predicted evolution. Thus, service life of a railway wheel can be significantly increased if one understands and monitors failures and its damage development [18].

Re-profiling intervals of railway vehicle steel wheels have been scheduled according to manufacturer guidelines which are experience-based. Today, accurate condition monitoring tools are available for predicting wheel wear and wheel-set lifetime. Tools are now available to predict the evolution of the wheel profiles for a given railway system, as a function of the running distance. Such a tool is applied to realistic operation scenarios in order to assess the effect of service conditions on the wheel wear progression [19].

Faults related to wheels do have an impact on capacity. Such information can be used to develop prognostic health management strategies. Data are processed to find patterns providing input to develop maintenance, monitoring, and inspection strategies for wheels. and also The provided information also supports prognostic and health management system , which can be used to enable proactive maintenance [8].

4. TRADE OFF VALUES

Condition monitoring is seen as a contributing factor in enabling rolling stock to perform with high capacity, [20].

Moreover, condition monitoring of rolling stock enables engineers to convert monitoring data into useful information. Railway system availability and reliability can then be improved. The most expensive component on wagons are the wheels. The ability to predict maintenance demands, long before the actual wheel is required for maintenance action, is thus very valuable. Accurate predictions enable more cost-effective maintenance operations as inventory, and storage costs are limited [21]. Wheel maintenance status has a significant impact on efficiency of an operation. For heavy haul railways this is especially true. Higher axle loads and demands for higher throughput have challenged the limits within the wheel/rail interface. The importance of monitoring and evaluating wheel profile is to identify and eliminate profiles that cause high stresses. A hollow wear criterion is effective, however additional criterion based on the gauge side false flange gradient can further reduce the stress state. Applying a hollow wear limit, in this case 2 mm, gives significant reduction in the wheel/rail contact stresses, [22]. Furthermore, significant reduction in contact stresses is also possible by applying gauge side false flange gradient criteria. The findings also clearly identify the shape of the wheel wear as the critical parameter to be addressed in further suspension and wheel profile design development.

Wheels are termed hollow when wheel wear at the center of the wheel tread is worn below the level of the end of the tread. There is an optimum cost level for removing hollow wheels from service. From an economic perspective, the optimum economic removal criterion for North America is when wheels have reached 3 mm hollow wear. This limit corresponds to the development of a negative slope to the rolling radius and the consequent loss of steering [23].

5. ESTIMATION OF THE WHEEL WEAR

In [13] it is shown that wear transitions can occur and a number of wear regimes emerge; mild, severe, and catastrophic. These develop depending on lubrication/friction, contact conditions and material properties for the wheel and rail contact. In this paper, the following parameters are studied: flange wear and hollow wear. These parameters can develop different stages of wear rate regimes under operation. Different parameters will then have different wear rates depending on their maintenance and operations status.

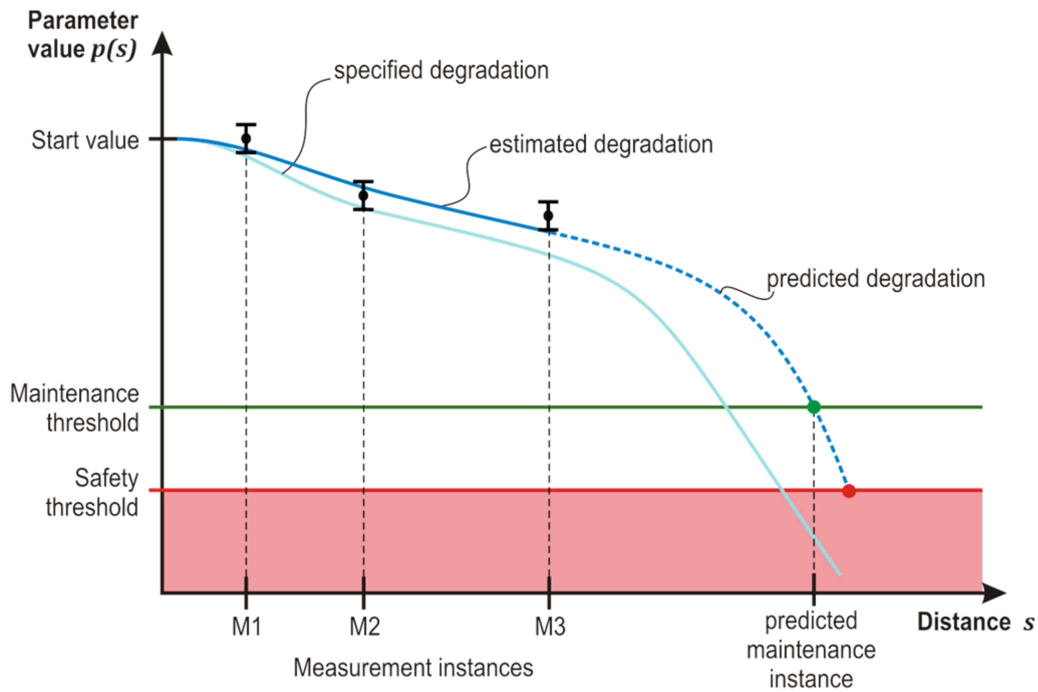

Figure 1: Conceptual sketch for the estimation and prediction scheme for the wheel profile data and its relationship with maintenance and safety thresholds.

Principally, this means that the wear of an arbitrary wheel profile parameter p follows a constant wear rate model for a covered distance s and therefore is a function of s.Introducing the vector $\boldsymbol{p}(s)$ as

$$\boldsymbol{p}(s) = \begin{bmatrix} p(s) \\ \frac{\partial p(s)}{\partial s} \end{bmatrix}, \quad (1)$$

a dynamic wear model can be stated as

$$\frac{\partial \boldsymbol{p}(s)}{\partial s} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \boldsymbol{p}(s) + \boldsymbol{v}(s) \quad (2)$$

Here, the states are assumed to be uncertain which is expressed by $\boldsymbol{v}$ which is normally distributed $\boldsymbol{v} \sim \mathcal{N}(0, \boldsymbol{Q})$ with covariance matrix $\boldsymbol{Q}$.

Essentially, $\boldsymbol{v}$ allows the state vector to change at certain rates. Clearly, a vehicle (car or locomotive) which is running at a certain speed $\frac{ds}{dt}$ will cover the distance $s = \frac{ds}{dt} \cdot t$. Under the assumption of constant speed $\frac{ds}{dt}$, the model in (2) can be rewritten as a time dependent model instead and yields

$$\frac{\partial \boldsymbol{p}(t)}{\partial t} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \boldsymbol{p}(t) + \boldsymbol{v}(t) \quad (3)$$

Now, an estimation and prediction scheme can be developed which makes use of wheel profile measurements including their known variance to estimate the profile parameter p.

In turn, the estimated profile parameter in combination with the wear model can be used to predict the evolution of the profile parameter ahead of covered distance s or operation time t. Such a scheme is depicted in Figure 1.

Using a typical estimation scheme like a Kalman filter [27] or similar, the predicted parameter value (blue solid line) at a measurement instance will be combined with the measurement value (black) at that instance. When the predicted and measured value are combined into an estimate of the true parameter value, the variance in these contiguities is used. For the prediction a combination of the manufacturer based specified degradation is used with the degradation model.

The prediction model can then also be used to predict the evolution of the parameter in question beyond the measurement instances and can be compared with maintenance and safety thresholds. From this the remaining useful life of a wheel in relation to a certain parameter can be derived.

It is important to note that both predictions and estimates do not only comprise the parameter value but also the probability density function. Consequently, confidence intervals and other statistical information on the parameter can be derived.

Moreover, the estimation and prediction scheme can be executed in real-time while considering the history of measurements, estimates, and predictions. The granularity of the predictions can be adjusted using the sample interval, either in time or space, and will not depend on the regularity of the measurement instances.

6. PRELIMINARY EVALUATION

In order to evaluate the estimation and prediction concept, data from the eMaintenance database was extracted. The data comprised all locomotives and cars that travel the Malmbana and are under the responsibility of MTAB, which is the transport company of LKAB.

The data spans a time period between April 2012 and December 2014 and included more than two million data records.

For the preliminary evaluation, the scheme is implemented on a desktop computer that is provided with the data.

It needs to be noted that the implementation is tailored such that autocoding methodologies can be used to generate modules that are implementable on virtually any platform.

In Figure 2, an example of the estimation and prediction results are given. The data sequence is relative to the start date and time of the data acquisition as mentioned before.

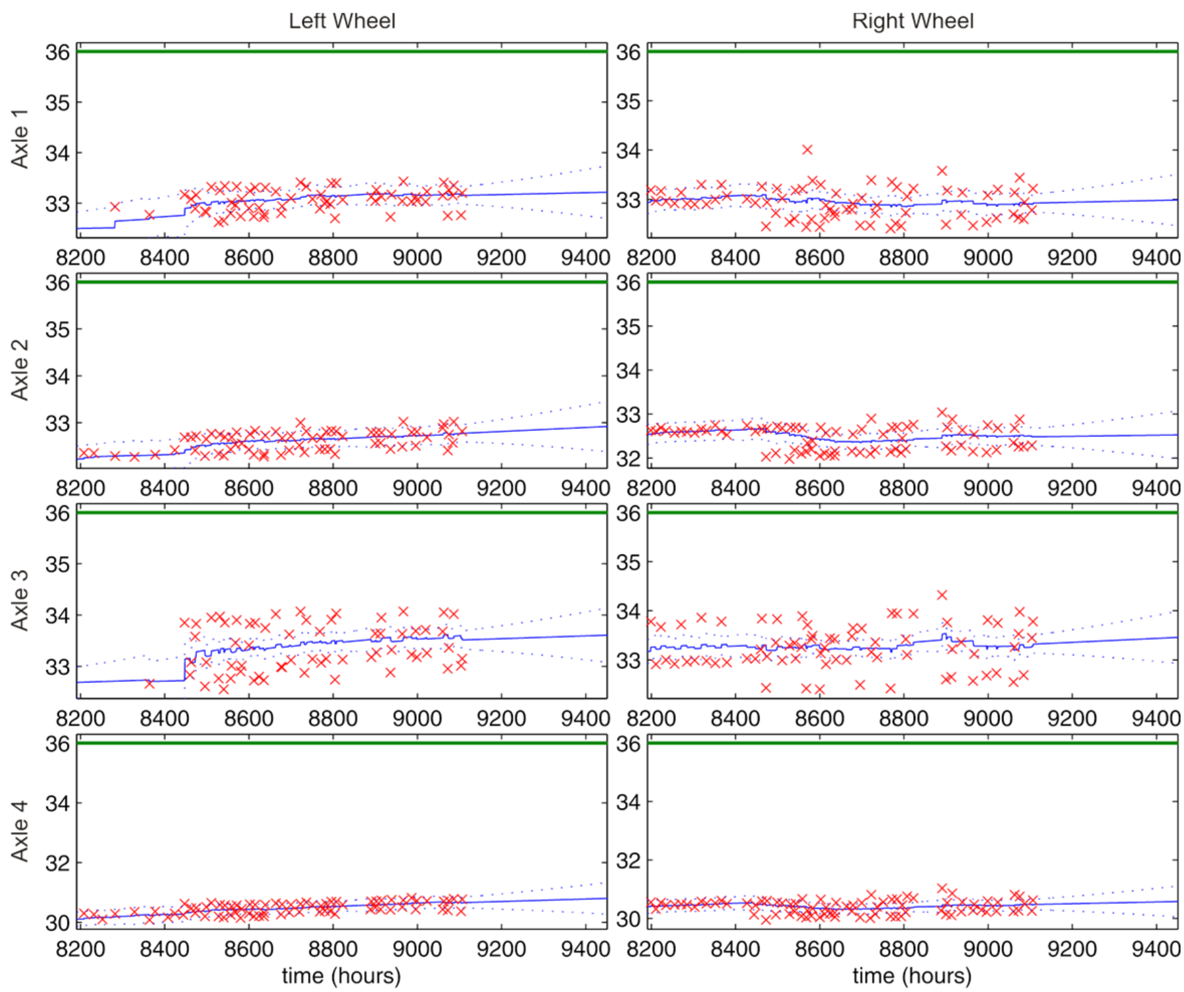

Figure 2: Estimation and Prediction of the flange height for wheels on car 4761 of MTAB. Maintenance threshold (green solid), Measurements (red crosses), Estimated and predicted parameters (blue solid), 95% confidence region (blue dotted).

The data in Figure 2 is for the car 4761 and the right wheel on the first axle. For the wheel profile data there are currently three parameters with associated maintenance thresholds, namely flange height, flange thickness and flange slope.

It is worthwhile to note that the scheme is only making use of the historic information, which means that the estimated values at measurement instances is only using prior information. Further, between measurement instances the scheme is running in a prediction mode which essentially predicts the evolution of the parameter.

Looking at the flange height in Figure 2 reveals that the estimate (blue solid line) is not coinciding with measurement values. This is due to the fact that the estimate is derived using the measurement variance and the variance of the prediction. In the figure the variance is related to the 95% confidence lines (blue dotted line). Between the time instances 8100 and 8300 in the plot, there are only two measurement instances, while the measurements are more frequent after 8400 hours.

Clearly, in between two measurement instances the scheme is just running a prediction. It can also be seen that the confidence intervall is increasing during that time which means that the variance of the prediction is increasing. In other words, the prediction is becoming less trustworthy.

In addition to the estimation and prediction of the parameter values, the wear rate is estimated. Thus, the scheme automatically adapts to different wear regimes as indicated before. Still, measurements are needed to perform the adaptation.From a validation perspective these plots are only indicative, they prove that the estimation does follow the measurements nicely while not following the variability of the measurements. This is highly intentional, since the estimation should be insensitive to measurement noise and imperfection. Especially, measurement outliers should not have an effect on the estimate.

In Figure 2 only the parameter flange height is depicted, but for all the wheels on the car. The information which is available is similar to the one in Figure 2,but in this picture it can be easily seen which of the wheels is closer to the maintenance threshold.

Essentially, this would be the left wheel on axle 3, which is closest to the maintenance threshold. Nevertheless, all wheel are still rather far away from the maintenance threshold. Since the 95% confidence interval has a rather large distance from the threshold is can be concluded that the likelihood of hitting the maintenance threshold based on the current estimates is far less than 2.5%.

7. CONCLUSIONS

The purpose of this paper is to propose an approach for condition-based maintenance decision-making related to railway vehicle wheels, based on a cloud-based eMaintenance solution.

It can be concluded that an approach based on using a typical estimation scheme such as a Kalman filter or similar can be used to enable condition-based decision-making in railway maintenance.

The paper has also demonstrated that by implementing the proposed approach the estimation of Remaining Useful Life (RUL) of railway asset can be achieved.

Furthermore, the study has shown what the estimation and prediction capabilities of an eMaintenance solution can look like. A preliminary evaluation of the estimation and prediction scheme has been conducted and the indications for the usefulness of the scheme are positive.

A more formal validation of the estimation and prediction performance of the scheme is yet to be conducted. Additionally, the underlying algorithms need to be further analyzed and compared with state-of-the-art algorithms in the area.

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