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Track Geometry Estimation and Prediction Tool Combining Onboard Monitoring and Measurement Vehicle Data

Wolfgang Birk, Jesper Westerberg, Per-Olof Larsson-Kråik, Wolfgang Lachnit (SOB)

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TRACK GEOMETRY ESTIMATION AND PREDICTION TOOL COMBINING ONBOARD MONITORING AND MEASUREMENT VEHICLE DATA

Wolfgang Birk[1,2,♦], **Jesper Westerberg**[1], **Per-Olof Larsson-Kråik**[2], **and Wolfgang Lachnit**[3]

[1] Predge AB, Vastra Varvsgatan 11, SE-97236 Lulea, Sweden
[2] Lulea University of Technology, SE-97187 Lulea, Sweden
[3]Schweizerische Südostbahn AG, Bahnhofplatz 1a, 9001 St. Gallen, Switzerland
♦ Corresponding author: wolfgang.birk@predge.se, +46 725390909

ABSTRACT

Infrastructure owners monitor changes in the track geometry to safeguard operation and to plan maintenance activities. Usually, track geometry is monitored using specialized measurement vehicles assessing the track several times a year to establish information on the development of a specific locations along the track. In this paper, a prediction tool is proposed and described that combines information from the measurement vehicles with measurements of onboard monitoring systems on regular trains to estimate and predict the properties longitudinal level and twist. Further, static asset configuration and information on the infrastructure is used in the decision making to provide actionable insights. The tool provides an improved resolution in time for track geometry properties and predictions on how these properties develop in the future including information on the uncertainties.

It will be discussed how data from different sources with irregular sampling need to be preprocessed to be combined and harmonized. Moreover, in what way different principles from data science, machine learning and estimation theory can be combined with domain knowledge to enable a better analytics and decision making. To support engineers, it is shown how a decision support tool for maintenance can be tailored and used. Finally, the tool and approach are showcased and benchmarked on track systems in Europe, where both onboard monitoring data and data from measurement trains is available. The results indicate that such a tool provide improved actionable insights to practitioners.

INTRODUCTION

A high level of availability, reliability, and service quality with high robustness against unexpected events, is required to meet the demand on today's railways (Isam, Ricci and Nelldal, 2016). Forecasting the future status of the track geometries are essential for Infrastructure Managers (IM) to evaluate the effect of various maintenance strategies on track reliability, availability, safety, and risk management. Track geometry represents a significant part of the maintenance cost for an IM and is also a safety issue (Arasteh-khouy, Larsson-Kråik, Nissen, 2016). The quality of the track is mainly represented by the track geometry parameters, cant, alignment, longitudinal level, twist and gauge.

To monitor quality, track geometry measurement trains are employed and/or data from on-board systems from service train and locomotives might also be used. But good predictions require enough high-quality data, sufficiently verified and preprocessed. Only then measurement train (MT) and onboard monitoring (OBM) data can be combined, allowing for significant better prediction as compared to MT data alone according to Hunn et. al (2020).

The condition monitoring data gives then support IM's to evaluate if the different geometry parameter levels are exceeding the predetermined safety or maintenance limits. At predefined geometry levels maintenance actions will be implemented to restore the track geometry to an acceptable level. To manage track geometry, several maintenance actions are employed. Condition monitoring and inspections actions give input data to support decision on restore the quality of the geometries. Other maintenance activities are tamping, manual intervention and stone-blowing. The most applied maintenance action to remedy a degraded track geometry is tamping.

Andrade and Teixeira (2016) developed an optimisation model with two objective functions, to identify the optimum limit that minimises both the total maintenance cost and delay. In another research study, Arasteh Khouy, Larsson-Kråik, Nissen, and Kumar (2016) proposed a cost model for the determination of cost-effective maintenance limits. They considered the costs related to inspection, corrective tamping, operational capacity loss and the risk of accidents due to poor quality of the track geometry. The authors assumed that when the standard deviation of the longitudinal level reaches a certain limit, trains need to reduce their speed and the cost due to the capacity loss should be considered in the cost model. They concluded that a specific ‘cost-effective maintenance limit’ needs to be determined for different track quality classes.

It is the believe of the authors that aggregating information from all available sources, on-board monitoring, measurement vehicles, inspections, and train-driver reports is needed to determine deviations from the ideal condition and the appropriate actions to be taken. Hence, track geometry is characterized by multiple information sources and parameters which need to be assessed in both temporal and spatial domain rendering a complex decision-making problem.

This study contributes to the development of how data from different sources with irregular sampling is preprocessed, combined, and harmonized. Different principles from data science, machine learning and estimation theory are combined with railway domain knowledge to enable a better analytics and decision making for track engineers. It is further shown how the analytics results can be used for decision support for maintenance of permanent way.

The paper is organized as follows. First, the challenges and needs in relation to decision making for condition-based maintenance are discussed. Thereafter, the modeling assumption of the condition degradation is presented. The authors then propose an analytics approach harmonizing different data sources including the measurement models. These are then the basis of the decision support approach and how deviations for the maintenance planning are determined, followed by a discussion of a real-life case. The paper is conclusion by a summary and an outlook.

CHALLENGES AND NEEDS

Maintenance is applied to ensure reliability, availability, and safety of the railway infrastructure. It has been shown that a large fraction of maintenance work is caused by degradation in the geometrical parameters longitudinal level and twist, as reported by Ripke and Feng (2018, p.18) for speed levels up to 140 km/h and 280 km/h. This motivates that there should be an emphasis on these parameters when it comes to the analytics of the track geometry data.

The European standard EN 13848-5 (2008) has determined the following three maintenance limits for different defects, based on different permissible speeds: Immediate Action Limit (IAL), Intervention Limit (IL), and Alert Limit (AL). Exceeding the IAL value requires taking measures to reduce the risk of derailment to an acceptable level, by typically taking one of the following actions: (i) closing the line, (ii) reducing speed, (iii) correcting the track geometry. Exceeding the IL value requires corrective maintenance such that the IAL shall not be reached before the next inspection. Finally, exceeding the AL requires assessment of the track geometry condition and considering it in the regularly planned maintenance operations. The IAL considers the track-vehicle interaction, as well as the risk of unexpected events, and as such is normative.

The AL and IL are linked with the type of IM maintenance policy being implemented and are informative. This means that IM may set various ILs and ALs based on their maintenance policy to achieve the desired safety, ride quality and lower life cycle cost.

Therefore, the five safety-relevant track geometry parameters listed above must be measured in periodical time intervals and compared with their corresponding IAL. But how to determine an appropriate and effective IAL? – In practice a variety of parameters must be considered:

- the maximum time interval to be assumed between two measurements, resulting from the availability and quality of MT or OBM data, respectively.
- the maximum intervention time between any measurement exceeding the IAL and its corresponding maintenance work that curates the IAL violation, given by assumptions on lead times for planning maintenance action, including machine ordering times, maximum number of maintenance actions to be carried out simultaneously, the maximum number of IAL violations per measurement, and so forth.
- the maximum degradation rate to ensure further track degradation to avoid speed restrictions and derailment risk. If the aging rate changes, leading from a prior “good” super-/substructure to a more degraded class, something unexpected must have happened or is about to happen. Water inleakage or neighboring civil construction may be reasons for that.
- the maximum speed of the track
- eventual further safety margins

Hence, for a given measurement and maintenance strategy, the IAL ensures that safety limits are kept at any time. For availability, cost optimization or even investment decision, more data from other sources might need to be integrated into the decision making, as proposed by Marshnig & Holzfeind (2013). But the question is how to define deviations and quantify the impact.

MODELING AND MEASURING TRACK GEOMETRY AND ITS DEGRADATION

Train loaded tracks are exposed to static loading and superimposed high-frequency load variations from trains. When unloaded, the track will not return exactly to its original position but to a position very close to the original one (Dahlberg 2004). Accumulated loading cycles, from train passages, will add up to small non-elastic deformations of the track geometry, differently in different parts of the track, resulting in a new track position. This phenomenon is called differential track settlement. The track alignment and the track level will then change with loading, position along the track and with time. Depending on the ballast and substructure composition, the wavelength of these irregularities will be of the order of meters up to hundreds of meters. The uneven track will induce low-frequency oscillations of the train. Hence, the imposed dynamic load variations from the train will increase, giving an increase in track settlement. The settlement is caused by the repeated traffic loading. The settlement severity depends on the quality and the behavior of the ballast, the sub-ballast and the subgrade. Track settlement occurs in two major phases. In phase one, directly after tamping, when the track position has been adjusted to a straight level, the settlement is relatively fast until the gaps between the ballast stones have been reduced and the ballast is consolidated. The second phase of settlement is slower and there is a relationship between this slow settlement speed and accumulated load (time) (Dahlberg 2004).

To study dynamic behavior of railway ballast track, a variety of physics of failure models have been proposed in the literature. Models of railway ballast as a continuum, whose behavior can be predicted when excited by the combination of quasi-static and dynamic loadings from the trains is complex. Deeper understanding of the railway ballast track dynamic behavior requires an integration of field measurements and theoretical analysis (Shi, Zhao, Zhang & Guo 2020).

In practice the standard deviation of the geometry measurements is used to control the need for Preventive Maintenance (PM) activities, and isolated defects are used for Corrective Maintenance (CM) actions. Soleimanmeigouni, Ahmadi and Kumar (2018) investigated and documented a review on track geometry prediction and found a broad spectrum of data-driven predictive models. Other published track geometry degradation models include linear function (Andrade, Teixeira. Hierarchical (2013), Caetano, Teixeira (2016) and Khajehei, Ahmadi, Soleimanmeigouni, et al. (2019), exponential functions (Quiroga, Schnieder (2012), Famurewa, Xin, Rantatalo, et al. (2015), stochastic model gamma process (Meier-Hirmer, Riboulet, Sourget, et al. (2009)), Wiener process (Soleimanmeigouni, Ahmadi, Letot, et al. (2016)) and Letot, Soleimanmeigouni, Ahmadi, et al. (2016)) and Markov chain (Bai, Liu, Sun, et al. (2015)) These different models can be used to predict the degradation of a track section over time.

However, condition prediction of a linear asset includes time domain and spatial domain for monitoring and modelling. A prediction of track geometry must then include section-to-section (spatial) of variation of the track in the degradation parameters. Predicting a section-to-section variation in the degradation parameters is a complex task and include factors such as type of traffic, environmental condition, track configuration and structure, maintenance history.

Lasisi, Attoh-Okine (2019) report on using machine learning techniques for geometry degradation. Machine learning techniques can be a good candidate for capturing the section-to-section variation in geometry degradation parameters. Fuqing (2011) reports on failure diagnostics using support vector machine and Karlaftis, and Vlahogianni (2011) reports on using neural networks. To accurately predict track geometry degradation, one need to consider the section-to-section variation in the degradation rate

ANALYTICS SCHEME FOR TRACK GEOMETRY

The basis of the analytics scheme is threefold. First, the data from the different measurement sources for the same geometric property need to be combined, and second, the measurements need to be aligned (harmonized) in time with the help of predictions and a horizon for the remaining useful life of a selected segment need to be determined.

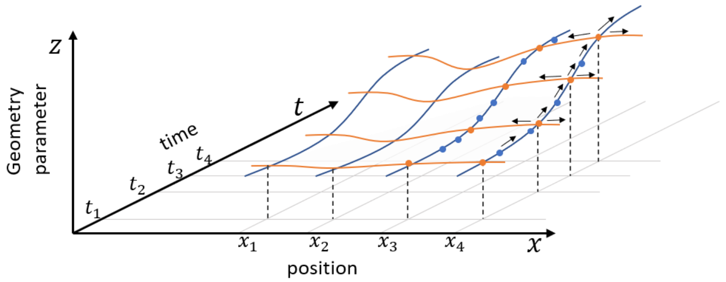


Figure 1: Principal sketch for the analytics approach to combine different measurement sources. Evolution of a point in the track in time (blue), shape of the track in terms of a geometry parameter at a time instance (orange) in space, continuous track monitoring data points (blue dots), measurement train data points (orange dots).

In Figure 1, the geometrical shape of a track segment at the locations $x_1$to x_4 and over time at the instances t_1 to t_4 is depicted, showing a change of the shape over time. At certain fixed time instances t_i the track is measured using a measurement train (MT) with sophisticated measurement equipment acquired data for every point along the track (indicated by the orange dots). In between these measurement campaigns from on-board monitoring (OBM) is performed which occurs more irregular in time but at a far higher recurrence rate (indicated by the blue dots). These measurements might have a lower quality in terms of accuracy and precision but would also miss certain locations.

The approach is therefore to perform a combined fusion and prediction to assess the threshold fulfillment and quantification of a horizon in time until the threshold is achieved, as depicted in Figure 2

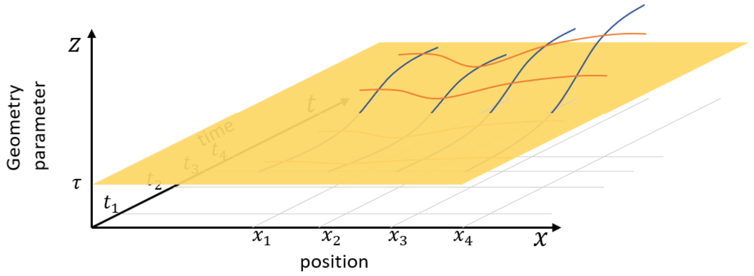


Figure 2: Track geometry surface and its relation to a threshold plane with a predefined τ.

Moreover, the approach would also enable a harmonization of track shape information. As can be seen in Figure 1 along the position x_4 OBM data points can be used in the stepwise consolidation and prediction steps in accordance with the black arrow. Each of the position along the track can use data as it becomes available to combine it with the predictions based on prior measurement data. While all measurements are affected by uncertainties and noise, prior measurement together with a degradation model can be used to determine an improved estimate of the true geometry parameter. The geometry parameters will hereafter be referred to as $\theta(x,t)$, depending on position and time, with $\theta(x,t) \in \mathbb{R}^m$ and m indicating the number of considered geometric parameters.

Assuming a dynamic model of the parameter variation would comprise the parameter, its rate of change and the acceleration of change, where the acceleration would be induced by exogenous inputs. Such a model could be stated as

$$\frac{\partial^2\theta}{\partial x^2}(x,t)+\frac{\partial^2\theta}{\partial t^2}(x,t)=u(x,t), \tag{1}$$

where $u(x,t)$ represents the exogenous inputs, which could be all the factors discussed by Dahlberg (2004). If there is limited knowledge about the exogenous factors available and further assuming that each of the position x may behave independently, the model can be simplified to

$$\frac{\partial^2\theta}{\partial t^2}(x,t)=\mathrm{v}(x,t), \tag{2}$$

where ν can be represented as a stochastic process to represent the exogenous inputs as variations. This stochastic process could be further simplified to a distribution, like a gaussian distribution.

Preprocessing of Measurement Data

Tracks are traditionally monitored using measurement trains with recurring measurement campaigns for a complete infrastructure. With the development of low-cost sensor solutions that can acquire data about the infrastructure using regularly operating trains, measurement becomes available at a far higher rate.

Measurement train data

The measurement of geometric properties by the measurement train is assumed to be governed by the following measurement equation,

$$z_{MT}(x,t) = f(\theta(x,t),x,t) + \eta_{MT}(x,t), \tag{3}$$

where f is a function that maps the geometric parameters to a measurement signal depending on the location and time. Thereby, the position dependencies and time variation of the measurement process can be considered. The stochastic function η_{MT} reflects the measurement uncertainties and can also be depend on position and time. Commonly, a gaussian distribution is assumed but by introducing time and position dependency a gaussian process could be used instead.

In the most simplistic case (3) can be reduced to

$$z_{MT}(x,t) = \theta(x,t) + \eta_{MT}, \tag{4}$$

where η_{MT} can be understood as a vector of independent gaussian distributed variable $\mathcal{N}(0,\sigma_{MT}^2)$ with variance σ_{MT}^2 for every geometric parameter. Here we also assume that the measurement trains provide bias-free measurements of $\theta(x,t)$ with zero mean.

Continuous track monitoring data

Even for the OBM measurement data the same reasoning applies, and the following initial and simplified measurement model can be assumed,

$$z_{OBM}(x,t) = f_{OBM}(\theta(x,t),x,t) + \eta_{OBM}(x,t), \tag{5}$$

$$z_{OBM}(x,t) = \theta(x,t) + \eta_{OBM}, \tag{6}$$

Similarly, a variance for η_{OBM} can be assumed as σ_{OBM}^2. Since OBM is often based on accelerometer data, a bias could be encountered for some of the geometric parameters and thus the gaussian distribution would not have zero mean and instead is μ_{OBM}.

Introducing the measurement models in this way adds flexibility to the analytics through their hyper parameters. Since more detailed models for the measurement equations are not known for the time being, the analytics will consider the simplified models in (4) and (6). The model uncertainties are then reflected by the gaussian distribution and its parameters.

Data Fusion and Prediction

As it is discussed the individual measurements for a certain position along the track are provided by two different sources. These sources provide measurements of different qualities, quantified in terms of the variance of the measurement and a potential bias.

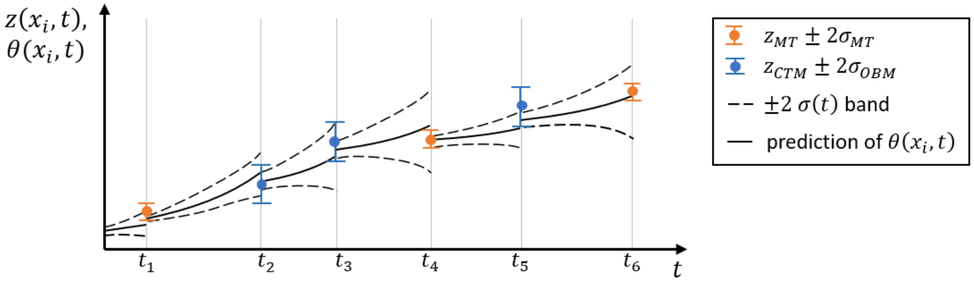


Figure 3: Sketch of the combined data fusion and prediction approach for track geometry data

Using Bayesian inference-based approach as described in Gustafsson (2001) the model in (2) can be used in combination with (4) and (6) to perform a joint data fusion and prediction. The conceptual sketch of the approach is depicted in Figure 3. There, the prediction of the parameter $\theta_j(x,t)$ at a specific location x_i is consolidated at time t_1 with the measurement $z_{MT}(x_i,t_1)$ using the covariance of the prediction $\theta_j(x,t_1|t_0)$ and the measurement variance σ_{MT}^2. The consolidated posterior is then used for the prediction using the degradation model until the next measurement becomes available at t_2, where the next consolidation occurs, at this time using $z_{OBM}(x_i,t_2)$.

Since the variance of the measurements differs, the data fusion will consider the quality of the measurement at every step enabling the use of time varying quality indicators like the variance.

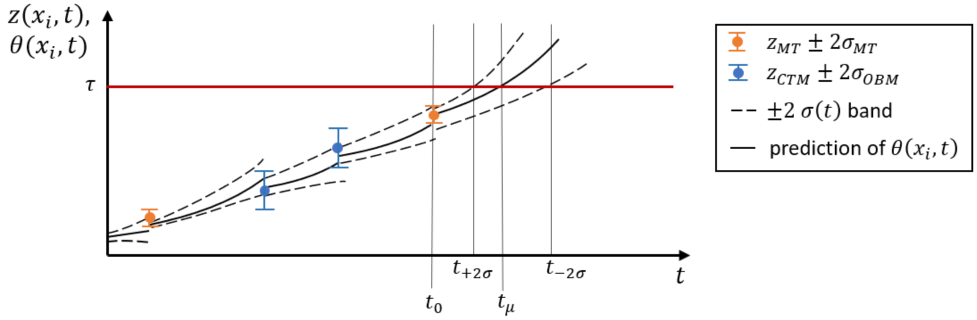


Figure 4: Quantification of the horizon until an arbitrary limit will be achieved in the future

Moreover, the prediction can also be used to quantify the horizon until a limit is achieved, namely AL and IAL. Since the predictions are derived including their covariances, it is possible to determine the likelihood that a limit is reached at a certain point in time in the future. In Figure 4, a prediction is performed at time point t_0 and using the nominal and the 2σ prediction it is not only possible to determine nominal time horizon but also the timeframe with a 95% likelihood of reaching the limit. In addition, the likelihood for reaching the limit at the latest or at the earliest can also be determined. Thus, the decision support tool can be tailored to consider the probabilistic properties of the predictions and connect them with operational aspects.

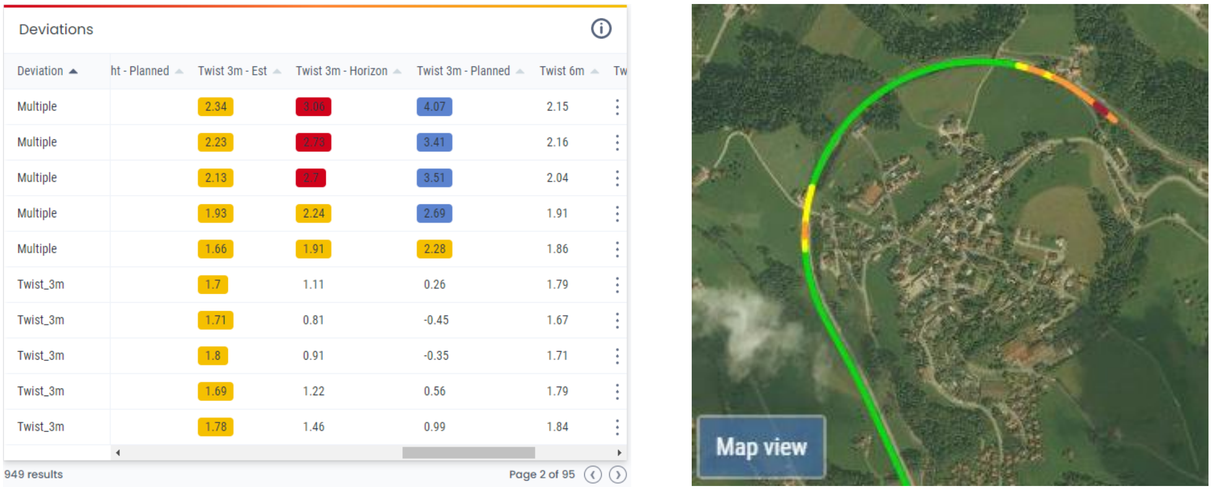
DECISION SUPPORT FOR MAINTENANCE PLANNING

A predictive decision support is dependent on an adequate data acquisition, sophisticated analytics and understanding of the decision-making context and needs. This study focused on three main roles, operational asset manager, strategical asset manager and data analyst. The decision support should support operational maintenance decisions, such as tamping, and hence recommend actions and present relevant deviations. From the broad range of use-cases targeting these roles only, flexibility in the underlying architecture and preventing limitations throughout the solution is an important consideration.

As previously described, several different maintenance and safety limits such as IAL, IL and AL are defined for the infrastructure. These limits serve different purposes, targets different roles and are more and less open for re-evaluation. To manage this, a dynamic way of implementing the thresholds is required. Besides the dynamic thresholds, these limits may vary along the track due to different track properties or environmental factors. This introduces requirements on data integration and harmonization between multiple types of data. Condition and asset data are obvious to include, but also business and maintenance data are important to give the users the full picture for their decision making. To be able to relate and stack all different types of data to the same linear asset, relying on a consistent asset description is crucial.

Introducing further analytics, prediction horizons, rate of change and probabilities are additional parameters to include beside the estimated absolute geometry values. Hence, horizons as an indicator on when certain thresholds will be reached, probabilities for the risk management aspects, and rate of change in the form of speed and acceleration as another view on the track condition.

Having all these parameters and thresholds, defining deviations is not an obvious task. Hence, before providing complete operational insights to the users they are provided with tools to test and evaluate different deviation definitions. With these tools users can test different definitions and evaluate the outcomes. Then as the definitions settle, further steps can be taken, integration into the operational decision-making process, mapping corresponding actions to deviations etc. In figure Y two ways of viewing and evaluating deviations can be seen. To the left a more detailed view on deviations for a track section, the deviations are defined based on both current values and predicted values at various time instances. To the right an aggregated geographical view of the deviations is presented.


(a)

Deviations

Deviation ▲	ht - Planned	Twist 3m - Est	Twist 3m - Horizon	Twist 3m - Planned	Twist 6m	Tw
Multiple		2.34	3.06	4.07	2.15	
Multiple		2.23	2.73	3.41	2.16	
Multiple		2.13	2.7	3.51	2.04	
Multiple		1.93	2.24	2.69	1.91	
Multiple		1.66	1.91	2.28	1.86	
Twist_3m		1.7	1.11	0.26	1.79	
Twist_3m		1.71	0.81	-0.45	1.67	
Twist_3m		1.8	0.91	-0.35	1.71	
Twist_3m		1.69	1.22	0.56	1.79	
Twist_3m		1.78	1.46	0.99	1.84	

949 results

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(b)

Figure 5: Example of deviations. (a) shows grouping of deviations by continuous track positions and multiple deviating parameters from both estimates and predictions. (b) Geographical view of outcome on selected deviation definitions

RESULTS AND OBSERVATIONS

To evaluate the analytics and decision support, the tools has been applied on data from a real-life infrastructure of Südostbahn AG in Switzerland. The selected track segment was a 4 miles long stretch on line 870 between Mogelsberg and Brunnadern. Data was collected from both measurement trains and OBM for the longitudinal level (left and right, including 110 yards moving average) and twist (wavelengths from 3.3 yards to 19.8 yard).

The MT data is usually acquired once or twice per year, while the OBM data is acquired by regular trains and thus far more often. The OBM data is available since 2019, where at the time of writing only one data point was available for 2019. The data during 2020 and until March 2021 was more regularly available. Further the Bayesian inference algorithm was also tuned to assume a larger variance for the OBM data compared to the variance of the MT data, emphasizing a potentially larger uncertainty in that type of data.

For the selected track segment, the data is fused and predicted for individual positions with a position resolution of one meter (approx. 3 ft) with the help of the data that has be acquired over the years from MT or OBM. The temporal domain is discretized with a one-day resolution, which means that the fusion and prediction is performed jointly removing the need to bin measurements to different time instances. The result is a high resolution in the time domain, which is usually unnecessary fine grained with regards to the dynamics of the degradation. For storage purpose the data was then decimated to a one-month resolution using the nearest neighbor approach.

(a) (b)

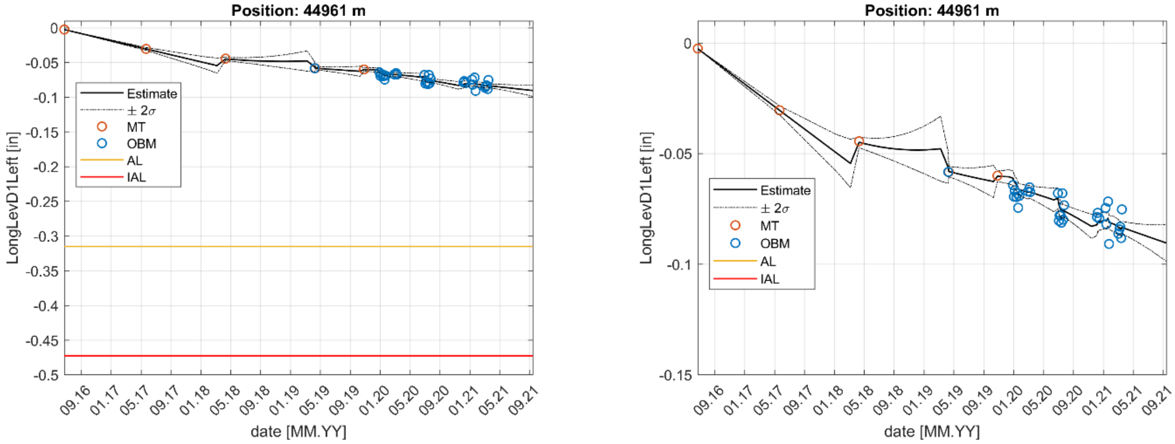

Figure 6: Fusion and prediction of the longitudinal level left for position 44961m along the track combining OBM and MT data. Limits for alarms and actions are indicated. (a) shows the fused and predicted trend in relation to the limits. (b) shows a close-up on the fusion of the data sources.

In Figure 6, the longitudinal level of the left rail is depicted over time, where both raw measurement data, estimated/fused data, and predicted data is depicted. The prediction of the next measurement point given including the covariance of the prediction, which is clearly widening the longer the prediction is time. As soon as need measurements are available the prediction and the measurement are combined to form the next estimate. While the OBM data points exhibit a higher covariance, they are occurring more often and enable a better data fusion and also prediction. It can be seen that the covariance of the trend is smaller as a result.

(a) (b)

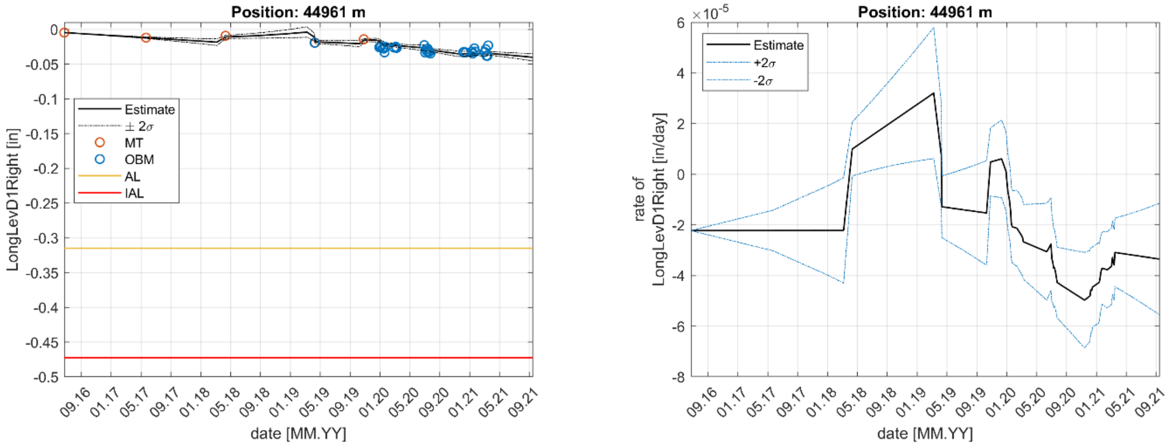

Figure 7: Fusion and prediction of the longitudinal level right for position 44961m along the track combining OBM and MT data. Limits for alarms and actions are indicated. (a) shows the fused and predicted trend in relation to the limits. (b) shows the estimated rate of degradation with covariance bands.

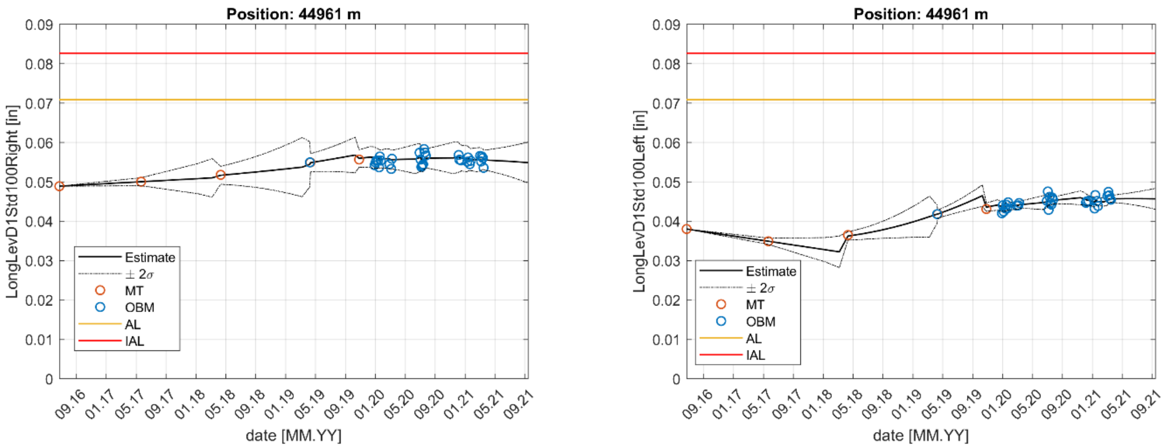
(a) (b)

Figure 8: Fusion and prediction of the longitudinal level using a moving average over 328ft for position 44961m along the track combining OBM and MT data. Limits for alarms and actions are indicated. (a) Right, (b) Left

Both in Figure 6a and Figure 7a, a negative trend can be observed for both left and right, but it is still far from close to any of the established values for AL and IAL. Nevertheless, the trend seems to be well established. In Figure 7b, the estimated degradation rate is shown which can exhibit large jumps due to the sparse data of the MT data, which improves with the OBM data.

When the focus is on larger spatial segments, the 100m-moving average (328 ft) is of interest as shown in Figure 8. While there was an early on trend towards the limits, the OBM data shows a clear slowing of that trend which is also reinforced by the sheer number of OBM data that aligns towards a stable level.

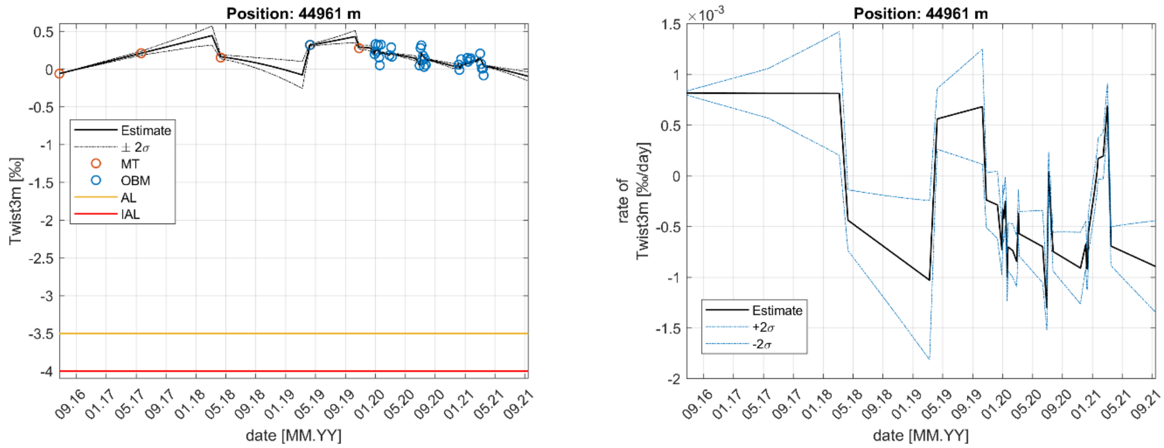
(a) (b)

Figure 9: Fusion and prediction of the twist with 10ft wavelength for position 44961m combining MT and OBM data. Alarm limits are indicated. (a) Twist in per mille, (b) degradation rate in per mille per day.

As already pointed out the twist is also an important parameter, and the fusion and prediction are shown in Figure 9 along with the rate of the degradation. Here the covariance of the prediction becomes small as the covariance associated with the model uncertainty is assumed to be quite small. As a result, the fusion and prediction does not rely too much on the OBM data in that case. Note, the assumed variance can also be time varying and considering other exogenous affects.

Figure 10 to Figure 12 provides a 3D plots of the complete 328ft long stretch for the three discussed parameters longitudinal level (left and right) and twist. Clearly, values of the longitudinal level along exhibits some variation in the spatial domain which can be expected and is in magnitude not very large.

Interestingly, the estimated rate show large variation which could be used as an indication for some exogenous effects that have an impact on the degradation. Root causes for this spread have to be investigated. Among apparent reasons are track usage (e.g., in tons per year), curve radius, substructure condition etc. It was proposed to define a set of such reasons and to divide them into appropriate classes. Data gets binned for any combination of these classes, called "standard elements", as proposed by Marschnig & Vidovic (2019). Using standard elements, a much smaller spread is expected. Using models like this will help both understanding data and optimizing fit algorithms, and thus helps predicting the time when levels like IAL or IL will be reached.

(a) (b)

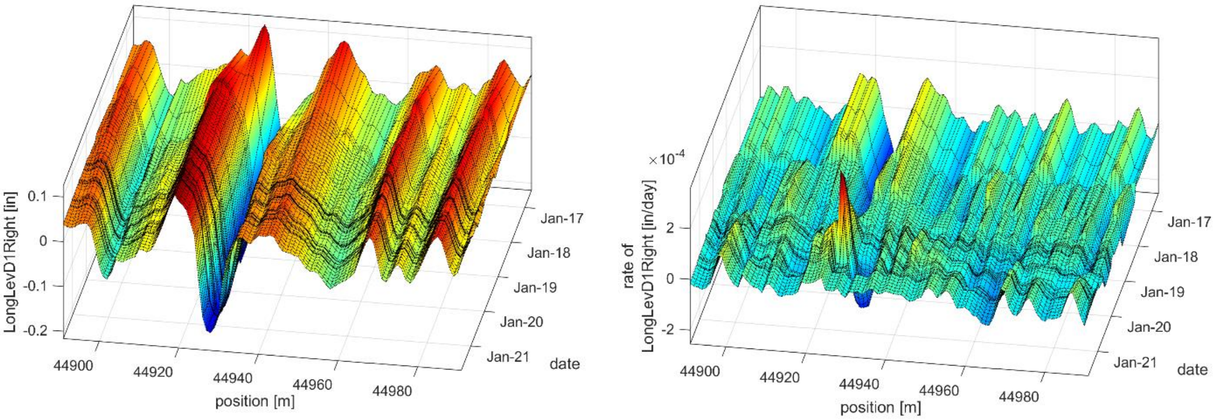

Figure 10: Predicted and consolidated fused data from OBM and MT. (a) Longitudinal level of the right track, (b) Rate of change of the longitudinal level of the right track. Color code: Green close to zero, blue negative, yellow orange positive.

(a) (b)

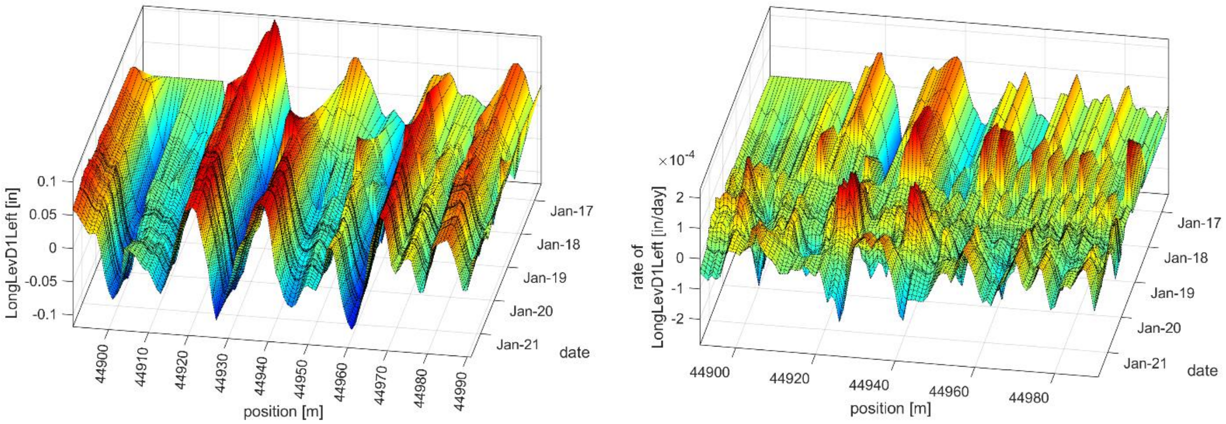

Figure 11: Predicted and consolidated fused data from OBM and MT. (a) Longitudinal level of the left track, (b) Rate of change of the longitudinal level of the left track. Color code: Green close to zero, blue negative, yellow orange positive.

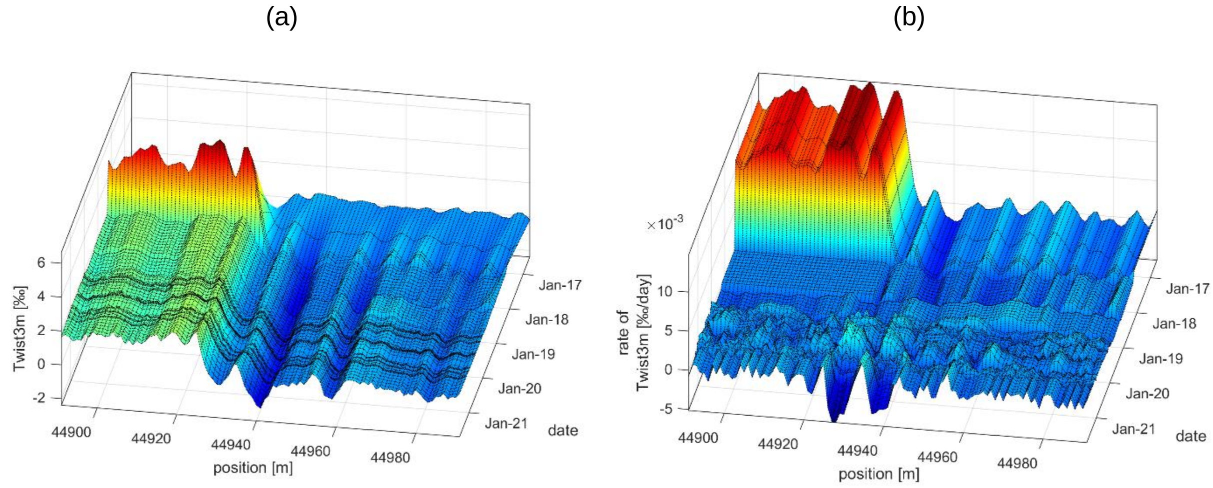

Figure 12: Predicted and consolidated fused data from OBM and MT. (a) Twist with 3m base length, (b) Rate of change of twist with 3m base length. Color code: Green close to zero, blue negative, yellow orange positive.

CONCLUSION

In this paper a methodology and a tool to support the decision making in maintenance planning for maintenance of way is proposed. The work is based on the reported challenges in literature and standards, and the needs of maintenance planner and infrastructure managers. The genuine highlight of the paper is the data fusion approach that combines measurement train data with on-board monitoring data and provides predictions with uncertainty information. The analytics approach then reduces the complexity for the decision making as several data sources are combined into one data source for decision making. Further, a decision support for maintenance planning is suggested which requires a proper definition of the deviations for the decision making. These definitions highly depend on the maintenance strategy and operation aspects of the infrastructure manager.

In its current for the analytics and decision support tool need to be validated using field data from inspections. Further, an aggregation scheme and optimization approach need to be realized to propose a actions on the basis of the deviations.

REFERENCES

Alemazkoor, N., Ruppert, C. J., & Meidani, H. (2018). Survival analysis at multiple scales for the modeling of track geometry deterioration. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 232(3), 842–850.

American Railway Engineering and Maintenance-of-Way Association. (2006). Manual for Railway Engineering. Chapter 2, Part 1. Definitions. (Report No. 4). USA.

Andrade, A.R., Teixeira, P.F. (2013) Hierarchical Bayesian modelling of rail track geometry degradation. Proceedings of the institution of mechanical engineers, part F. J Rail Rapid Transit. (2013), 227(4):364–375.

Andrade, A. R., & Teixeira, P. F. (2016). Exploring different alert limit strategies in the maintenance of railway track geometry. Journal of Transportation Engineering, 142(9), 04016037. doi:10.1061/(ASCE)TE.1943-5436.0000867

Andrews, J. (2013). A modelling approach to railway track asset management. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 227(1), 56–73. doi:10.1177/0954409712452235

Andrews, J., Prescott, D., & De Rozieres, F. (2014). A stochastic model for railway track asset management. Reliability Engineering & System Safety, 130, 76–84.

Arasteh Khouy, I., Larsson-Kråik, P., Nissen, A., & Kumar, U. (2016). Cost-effective track geometry maintenance limits. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 230(2), 611–622.

Bai, L., Liu, R. Sun, Q., et al. (2015) Markov-based model for the prediction of railway track irregularities. Proceedings of the Institution of Mechanical Engineers, Part F. J Rail Rapid Transit. (2015), 229(2):150–159.

Caetano, L.F., Teixeira, P.F. (2016) Predictive maintenance model for ballast tamping. J Transp. Eng. (2016);142(4):04016006.

Can Shi, Chunfa Zhao, Xu Zhang & Yunlong Guo (2020) Coupled discrete-continuum approach for railway ballast track and subgrade macro-meso analysis, International Journal of Pavement Engineering

Cardenas-Gallo, I., Sarmiento, C. A., Morales, G. A., Bolivar, M. A., & Akhavan-Tabatabaei, R. (2017). An ensemble classifier to predict track geometry degradation. Reliability Engineering & System Safety, 161, 53–60.

CEN, (2005). Railway applications -Track- Track geometry quality - Part 5: Geometric quality assessment; EN 13848-5:2005.

Dahlberg, T. (2004). Railway track settlements-a literature review, Report for the EU project SUPERTRACK, Division of Solid Mechanics, IKP, Linköping University, Sweden, BriteEuram project SUPERTRACK, Contract No G1RD-CT-2002-00777

Famurewa, S.M., Xin, T., Rantatalo, M., et al. (2015) Optimisation of maintenance track possession time: a tamping case study. Proceedings of the Institution of Mechanical Engineers, Part F. J Rail Rapid Transit. (2015), 229 (1):12–22.

Fuqing, Y. (2011) Failure diagnostics using support vector machine. Doctoral thesis / Luleå University of Technology, (2011), ISSN 1402-1544, ISBN: 978-91-7439-366-8 (printed), URN: urn:nbn:se:ltu:diva-17188, , DiVA, id: diva2:990187.

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

Hunn, S., Züger, S., Nerlich, I., Schlatter, C., Wolter, K.U., (2020) Onboard Monitoring in der Schweiz, ein Gemeinschaftswerk dreier Bahnen. ZEVrail 144 (04).

Islam, D.M.Z., Ricci, S. & Nelldal, BL. (2016) How to make modal shift from road to rail possible in the European transport market, as aspired to in the EU Transport White Paper 2011. Eur. Transp. Res. Rev. 8, 18.

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.

Karlaftis, M.G.Vlahogianni E.I. (2011). Statistical methods versus neural networks in transportation research: differences, similarities and some insights. Transp Res Part C Emerging Technol. (2011), 19(3):387–399.

Khajehei, H., Ahmadi, A., Soleimanmeigouni, I., et al. (2019) Allocation of effective maintenance limit for railway track geometry. Struct Infrastruct Eng. (2019), 15(12):1597–1612.

Khosravi, M., Soleimanmeigouni, I., Ahmadi, A., Nissen, A. (2021), Reducing the positional errors of railway track geometry measurements using alignment methods: A comparative case study. Measurement, Volume 178, 109383, ISSN 0263-2241.

Loidolt, M., Marschnig, S., Vidovic, I., Veit, P., (2020) Das Performance Regime (RL 34/2012/EU) als Tool zur Systemoptimierung. ZEVrail (2020), 144 (9).

Lasisi, A., Attoh-Okine, N. (2019) Machine learning ensembles and rail defects prediction: multilayer stacking. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering. (2019), 5(4):04019016.

Letot, C., Soleimanmeigouni, I., Ahmadi, A., et al. (2016) An adaptive opportunistic maintenance model based on railway track condition prediction. IFAC-PapersOnLine. (2016), 49(28):120–125.

Marschnig, S., & Holzfeind, J. (2013). Verursachungsgerechte Kostenzuordnung der Fahrbahnerhaltungsarbeiten am Beispiel des Verschleissmodells der SBB. ZEV rail Glasers Annalen, 137(JAN), 14-21.

Marschnig, S., & Vidovic, I. (2019). Estimating future tamping demands using the Swiss Wear Factor. In 12th World Congress on Railway Research: Railway Research to Enhance the Customer Experience

Meier-Hirmer, C., Riboulet, G., Sourget, F., et al. (2009) Maintenance optimization for a system with a Gamma deterioration process and intervention delay: application to track maintenance. Proceedings of the Institution of Mechanical Engineers, Part O: J Risk Reliab. (2009) , 223(3):189–198.

Prescott, D., & Andrews, J. (2013). Modelling maintenance in railway infrastructure management. Paper presented at the meeting of Reliability and Maintainability Symposium (RAMS), 28–31 January 2013, Florida, USA.

Quiroga, M.L., Schnieder, E. (2012) Monte Carlo simulation of railway track geometry deterioration and restoration. Proceedings of the Institution of Mechanical Engineers, Part O: J Risk Reliab. (2012), 226(3):274–282.

Rripke, B., Feng, J., (2018) D4.1 Report on track/switch parameters and problem zones. Project report of the H2020 Sift2Rail JU project IN2SMART, Grant Agreement GA 730569. Available at https://cordis.europa.eu/project/id/730569/results.

Sharma, S., Cui, Y., He, Q., Mohammadi, R., & Li, Z. (2018). Data-driven optimization of railway maintenance for track geometry. Transportation Research Part C: Emerging Technologies, 90, 34–58.

Soleimanmeigouni, I., Ahmadi, A., Letot, C., et al. (2016) Cost-based optimization of track geometry inspection. 11th. Milan, Italy: World Congress of Railway Research; (2016).

Soleimanmeigouni, I., Ahmadi, A., Kumar, U. (2018). Track geometry degradation and maintenance modelling: a review proceeding of the institution of mechanical engineers, part F. J Rail Rapid Transit. (2018), 232(1):73–102.