Delft University of Technology

Influencing factors for condition-based maintenance in railway tracks using knowledge-based approach

Jamshidi, Ali; Hajizadeh, Siamak; Naeimi, Meysam; Nunez, Alfredo; Li, Zili

Publication date
2017

Document Version
Final published version

Published in
Proceedings of the First International Conference on Rail Transportation

Citation (APA)
Jamshidi, A., Hajizadeh, S., Naeimi, M., Nunez, A., & Li, Z. (2017). Influencing factors for condition-based maintenance in railway tracks using knowledge-based approach. In *Proceedings of the First International Conference on Rail Transportation: ICRT2017*

Important note
To cite this publication, please use the final published version (if applicable).
Please check the document version above.

Copyright
Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy
Please contact us and provide details if you believe this document breaches copyrights.
We will remove access to the work immediately and investigate your claim.

This work is downloaded from Delft University of Technology.
For technical reasons the number of authors shown on this cover page is limited to a maximum of 10.

2017
ICRT
International Conference on Rail Transportation

First International Conference on Rail Transportation
Chengdu, China, July 10-12, 2017

Influencing factors for condition-based maintenance in railway tracks using knowledge-based approach

Ali Jamshidi[1], Siamak Hajizadeh[1], Meysam Naeimi[1], Alfredo Núñez[1], Zili Li[1]
[1]Railway Engineering Section, Delft University of Technology, Delft, 2628CN, The Netherlands.

Abstract: In this paper, we present a condition-based maintenance decision method using knowledge-based approach for rail surface defects. A railway track may contain a considerable number of surface defects which influence track maintenance decisions. The proposed method is based on two sets of maintenance decision factors i.e. (1) defect detection data and (2) prior knowledge of the track. A defect detection model is proposed to monitor surface defects of the track including squats. The detection model relies on track images and Axle Box Acceleration (ABA) signals to give both positions of severity and defects. To acquire the prior knowledge, a set of track monitoring data is selected. A fuzzy inference model is proposed relying on the maintenance factors to give the track health condition in a case study of the Dutch railway network. The proposed condition-based maintenance model enables infrastructure manager to prioritize critical pieces of the track based on the health condition.
Keywords: Condition-based maintenance decision, Rail surface defects, Bayesian model

1 Introduction

To optimally manage the railway assets, an appropriate combination of infrastructure monitoring and maintenance improves the performance of the entire network and extend life cycles of railway assets. In order to analyze problems, consequence prediction of potential train delays plus ranking different maintenance decisions are required. Condition-based models can be used to estimate the influence of maintenance decisions in the infrastructure performance. In The Netherlands, with one of the most intensively used railway networks, ProRail manages the railway infrastructure including railway tracks (2800 line kilometers, 6830 kilometers of tracks), tunnels and viaducts (5100), overhead wiring (4500 kilometers), switches (7508), signaling system, safety control system, and stations (388) [1]. To find the proper trade-off between maintenance costs and optimal performance of the railway infrastructure is difficult, not just due to complexity of the whole railway system, but also because of the interaction between infrastructure manager and the set of third parties in charge of the monitoring and maintenance tasks in the field. In the case of the Dutch track infrastructure, maintenance includes the considerable portion of the infrastructure manager budget, nearly the 44.5% of the total budget [2].

Rolling contact fatigue (RCF) reduce the life cycle of the railway track. In the Dutch railways, huge amount of money is allocated to solve RCF-related problems. Among all type of RCFs, squats are a type of RCF that appear on the top of rails. To detect severe squats, Typically three methods are employed: eddy current testing, ultrasonic and human inspector. This paper relies on a new method that detects both light and severe squats, using axle box acceleration (ABA) measurements. Relying on the detection algorithm from ABA signals, a condition based maintenance strategy is proposed, so to reduce the cost of myopic strategies.

Although a defect detection method could give indication of the track status, infrastructure manager requires prior knowledge of the track to (1) have all influencing factors for the estimation of the track health condition, (2) analyze interdependency between the track observations and the prior knowledge and (3) give future view of the track performance. Thus, prior knowledge of the track can significantly influence the track health condition and consequently the track maintenance planning.

Thus an analysis of influencing factors should be taken into account to give at the most a proper prospect of the infrastructure health condition. Moreover, track related assets like bridges and level crossings could influence the track health condition due to interdependency between track and the assets, in particular for a long track.

2 Methodology Description

In this paper, we propose a condition-based maintenance methodology taking into account both the observation acquired by a defect detection method and the prior knowledge of the track. At the first, the idea is to measure infrastructure performance by defining rail-related KPIs (Key Performance Indicators). As mentioned in the introduction, the defect observation is provided by ABA signals which are matched with video frames taken from the track. As an example, channels of the ABA signals are shown together with related video frames in Fig. 1.

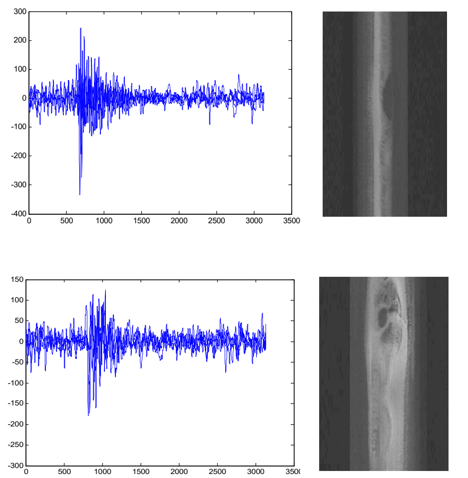

Fig.1: ABA signals matched with video frames

A knowledge based fuzzy model is developed to give a single value as global KPI. Then influencing factors are investigated. The intention is to find correlation between defect observation and all influencing factors of the track prior knowledge. The defect appearance is defined in terms of defect position on the track and defect severity. The correlation then indicates which pieces of the track are prone to be defective. Once interdependency between the influencing factors and the defect appearance is acquired, a set of track maintenance rules is generated to present all possible scenarios of track condition in a given maintenance time horizon. The infrastructure manager then is able to plan maintenance decisions relying on the track performance (see Fig.2).

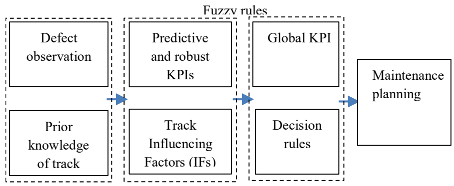

Fig. 2 Flowchart of the proposed methodology

3 Squats In Railway Infrastructure

Squat growth relies on the dynamic contact between wheels and rails. Squats can be defined into three classes including light, moderate and severe in terms of severity [3]. Many measurements of all classes of squats have been performed by our group at Technical University of Delft over the last years, including in field and on-board measurements.

This type of RCF defects tend to grow on top of the running band. For the Dutch tracks, if the size of a typical rail defect exceeds a critical size, it may grow into a squat [4] and defects below this threshold are considered as trivial defects. Furthermore, squats in tracks with a higher mega tonnage (MGT) per year are also more likely to evolve faster than in less occupied tracks. To analyze the squat detection outputs, visual length of each individual squats (L_i) are considered to give a criterion as severity. The severity is categorized into three different stage of squat growth in which A and B, C and RC are light squat, medium squat, sever squat and squat with high potential of risk derailment respectively.

The full track of the Meppel-Leeuwarden is used to show the proposed methodology in Fig. 2. The track is partitioned in four segments called j_1, j_2, j_3 and j_4. The partitions can be adapted according to the maintenance plans or other design considerations. The partitions in this paper, are all around 10 kilometers long, except the last one which is 15 kilometers long.

4 KPIs For Rail Health Condition

The use of key performance indicators (KPIs) can show an explicit way of track deterioration in which different scenarios are provided to explain stochasticity of the squat growth. However, the monitoring of the a single squat's evolution is not practical in terms of the maintenance operations. Hence, an aggregated information of the given KPI over bigger track segments can give more practical decisions on infrastructure manager's maintenance plans. Regarding squats, we propose key performance indicators (KPI's) based on the number of different types of squats including A, B and C squats and the number of squats with potential risk of rail break called RC squats, at different time t and different growth scenario h where A, B and C address light squats, moderate squat and severe squat respectively. Furthermore, as considerable amount of B and C squats nearby each other indicate a group of safety risk to track, a KPI is proposed based on density of squats B and C.
To facilitate the analysis of indicators, a global KPI is considered per segment by using a fuzzy inference system that combines all of the proposed key performance indicators. To acquire the global KPI, a set of fuzzy rules is generated to define all possible combinations of the given squat KPIs. Deterioration is ranked by a score between zero to two, where zero means the track is heathy and two indicates an unhealthy condition of the track [5].

$$KPI_j^{Rail}(k) = \frac{\sum_{h\in\{h_1,h_2,h_3\}} \sum_{t=k}^{k+N_p} w_h.w_t.y_{h,j}^M(t)}{\sum_{h\in\{h_1,h_2,h_3\}} \sum_{t=k}^{k+N_p} w_h.w_t} \quad (1)$$

where $KPI_j^{Rail}(k)$ is global KPI, w_h is growth weight per scenario, J is track segment, h is growth scenario in three different scenarios (h_1, h_2, h_3), $y_{h,j}^M(t)$ is fuzzy KPI of the fuzzy rules and w_t is a weight exponentially showing time effect on the KPIs. The global KPI is considered over time (t) from $t=k$ till $t=k+N_p$. In this way, we aggregate different KPIs into a single one, that captures together stochasticity and evolution over time.

5 Influencing factors

After obtaining global KPI for each segment, second part of the methodology is taken into account in which correlation between defect observations and prior knowledge of the track is studied. For this purpose, a set of influencing factors (IFs) can be defined to express prior knowledge of the track. The intention is to estimate influence of (1) train velocity, (2) train acceleration and deacceleration and (3) track geometry.

6 Maintenance decision rules

Fig. 3 shows the flowchart showing contribution of the maintenance rules in the proposed methodology divided in 4 steps. In Step 1, major track condition influencing factors, IFs, are presented to give prior knowledge of the track. Step 2 presents the interdependency analysis between the influencing factors with the observation of the ABA measurements. The aim is to investigate on how the influencing factors are related to the observations. For this purpose, a FE modelling is carried out to show authenticity of the interdependency analysis. In Step 3, a fuzzy inference system is proposed. A set of possible condition rules, $r = r_1, r_2, ..., r_i$, is generated to build up the inference system estimating the track health condition relying on the step 2. Finally in Step 4, maintenance planning is proposed based on the track health condition (will be explained in chapter 6). For this purpose, the track can be divided to k segments, $j = j_1, j_2, ..., j_k$ to give detailed vision of the track condition for each segment. Infrastructure manager then gets informed of each segment's status within a maintenance time horizon. Once the segment requires maintenance operations either for grinding or rail replacement, the maintenance intervention is requested. A maintenance decision model is provided to analyze track positions in terms of the grinding and the replacement decisions.

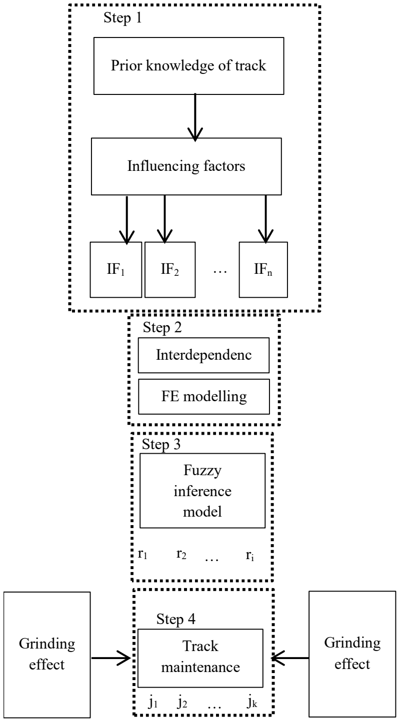

Fig. 3: Maintenance decision rules using prior knowledge of track

7 Maintenance planning

Two different maintenance countermeasure are considered for treating squats: grinding and rail replacement. The optimum maintenance strategy for a variety of conditions can be derived using the factors that predict the growth of cracks due to surface defect. Also, understanding of crack evolution process is key for running a safe and cost-efficient railway. Field observations show that evolution over time of squats is stochastic, with different growth rates that sometimes it can be stopped by grinding action or by the normal wear on the rail. In order to incorporate explicitly in the model the stochastic behavior of squat evolution, based on real data obtained by years of track visits in the Dutch railway, a robust model was proposed with three different growth scenarios: slow, average and fast evolution.

7.1 Rail grinding operation

In the railway field, a large number of squat A in early stage of development are good candidate for grinding. As planning the maintenance for each of them is not possible, we syggest to combine light squats into certain form of squats. To do that, we use fuzzy clustering as an unsupervised classification method that considers sets of light squats based on their kilometer positions. Those sets are called clusters, and the squats within the same cluster are very likely to be near to each other, while their position is different to squats in other clusters. Hence, maintenance plan can be based on those conceptual regions defined by the clusters instead of fixed regions that are not related with the amount of defects.
Different fuzzy clustering method are available in the literature. In this paper, we have selected the method called fuzzy c-means. This method requires to know in advance the desired number of clusters. In case this is unknown, a sensitivity analysis can be perform to optimize the number of clusters [6]. In this paper, fuzzy c-means algorithm optimizes a distance criterion over a data set of squat locations. This data is unlabeled, and K is the number of data points. In the optimization, it is minimized the within cluster spread of squats on the rail, and it is maximized the inter cluster separation. From the fuzzy clustering approach, a data point will belong to all the clusters but with a different membership degree. The closer to the center of the cluster, the nearest the membership will be to 1. In the paper [6] we proposed to use an α criterion for grinding, related to the coverage percent of the cluster. Fig. 4 shows the corrective grinding zone proposed over the track using four clusters. The parameter %α is the coverage percent of the clusters. Red markers on the x-axis represent squats, and the arrows in blue the proposed grinding position for the selected %α.

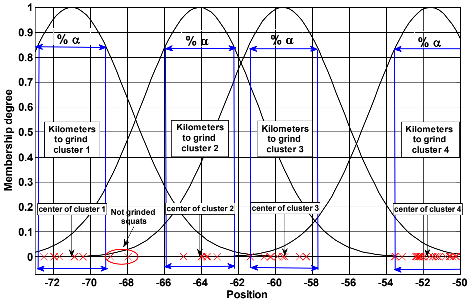

Fig. 4: decision zones for corrective grinding in four clusters with forty percent coverage [6]

7.2 Rail replacement operation

When the squat is severe enough and cracks are grown considerably, grinding is not solution anymore [5]. Thus, replacement is the only solution. Replacement of the full track is too much costly, so an optimal decision making for when and where the rail should be replaced is important.
In the paper [5], wo different cases of replacement are investigated. First, squat growth between welds where all the squats will disappear after replacement. The model assumes that no squats will appear during a long horizon by considering that new developed squats can be detected in the next measurement campaign. The second case explains growth on the welds a period after replacement. The exact time instant when the growth starts is related to quality of the weld. This means that for those welds that have good quality, the starting point would be much later.

8 Conclusion

In this paper, a condition-based maintenance decision method is proposed relying on a fuzzy inference model for railway track infrastructures. The methodology considers the squat observation and the prior knowledge of the track. The purpose is to give an estimation of track health condition to infrastructure manager in a maintenance time horizon. At the first stage, we acquire global KPI per rail segment. Then, A knowledge based system is defined to infer interdependency between the changes of track knowledge using IFs and appearance of surface defects by using ABA signals over the track.. Thus, the critical pieces of the track are taken into account with a proposed maintenance planning in terms of rail grinding and rail replacement. The results enable the infrastructure manager to ease the consideration of the track health condition to efficiently operate the maintenance decisions. Data of a track in the Dutch railway network is provided to depict the benefits of the proposed methodology.

Acknowledgement

Research sponsored by the NWO/ProRail project “Multiparty risk management and key performance indicator design at the whole system level (PYRAMIDS)”, project 438-12-300, which is partly financed by the Netherlands Organisation for Scientific Research (NWO) and by the Collaborative Project H2020-MG-2015-2015 GA-398 636237b Needs Tailored Interoperable Railway - NeTIRail-

References

Leijten, M. and Koppenjan, J. (2010). “Asset management for the Dutch railway system.” Next Generation Infrastructures Conference Systems of Eco Cities, Shenzhen, China.

Zoeteman, A. (2006). “yardstick for condition based and differential planning of track and turnout renewal: A major step towards full decision support” Proceedings of the 7th world congress on railway research (WCRR), Fairmont The Queen Elizabeth in Montréal, Canada.

Li, Z., Molodova, M., Zhao, X., Dollevoet, R. (2010) “Squat treatment by way of minimum action based on early detection to reduce life cycle costs” Joint Rail Conference, Urbana, Illinois, USA. pp. 305-311.

Molodova, M., Li, Z., Núñez, A., and Dollevoet, R. (2014). “Automatic detection of squats in the railway infrastructures.” IEEE Transactions on Intelligent Transportation Systems. 15, 5:1980-1990.

Jamshidi, A., Núñez, A., Dollevoet, R., and Li, Z. (2016). “Robust and predictive fuzzy key performance indicators for condition-based treatment of squats in railway infrastructures.” Infrastructure Systems. 04017006. DOI:

10.1061/(ASCE)IS.1943-555X.0000357.
Jamshidi, A., Núñez, A., Li, Z., and Dollevoet, R., (2015). "Fuzzy maintenance decision support for treating squats in railway infrastructures." Joint Rail Conference (JRC). American Society of Mechanical Engineers. California, USA.