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A decision support approach for condition-based maintenance of rails based on big data analysis☆

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ABSTRACT

In this paper, a decision support approach is proposed for condition-based maintenance of rails relying on expert-based systems. The methodology takes into account both the actual conditions of the rails (using axle box acceleration measurements and rail video images) and the prior knowledge of the railway track. The approach provides an integrated estimation of the rail health conditions to support the maintenance decisions for a given time period. An expert-based system is defined to analyse interdependency between the prior knowledge of the track (defined by influential factors) and the surface defect measurements over the rail. When the rail health conditions is computed, the different track segments are prioritized, in order to facilitate grinding planning of those segments of rail that are prone to critical conditions. In this paper, real-life rail conditions measurements from the track Amersfoort-Weert in the Dutch railway network are used to show the benefits of the proposed methodology. The results support infrastructure managers to analyse the problems in their rail infrastructure and to efficiently perform a condition-based maintenance decision making.

1. Introduction

The increase in train traffic and axle loads affect the health conditions of railway infrastructure. Hence, efficient infrastructure monitoring and maintenance is among the major concerns of infrastructure managers in order to improve the performance of railway operations (Åhrén and Parida, 2009). As such, infrastructure health conditions should be monitored and considered in the maintenance decision making process. Effective management of infrastructure health conditions is crucial to guarantee the desired asset quality level (Parida and Chattopadhyay, 2007; Gandomi and Haider, 2015; Zywiel and Oberlechner, 2001). It also plays an important role in meeting the demands for the whole system performance when the infrastructure is upgraded e.g. when increasing traffic capacity, the maintenance regime should be adapted to avoid compromising safety and infrastructure health requirements. To keep the infrastructure system working at an effective level, a conditions-based maintenance system is required not only to consider the actual heath conditions but also evolution during the maintenance decision horizon (Jamshidi et al., 2017b; Li et al., 2014).

Condition-based monitoring is used in railway infrastructures to estimate the actual health conditions of the assets, so that degradation processes can be effectively controlled. It helps to keep the infrastructure manager continually informed of the estimated health of the railway infrastructure. Condition-based monitoring is supposed to collect information that will allow an effective

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operation by reducing maintenance cost, eliminating unnecessary operations, and focusing on places where the problems are located and where they will be in the coming period. Furthermore, the enhancement in usage of the railway infrastructure needs a systematic monitoring plan to keep the trains running safely by considering all related data influencing the health conditions. The data for a typical railway infrastructure includes a large amount of frequent measurements from the monitoring systems of the assets involved in the railway operations. To ensure the required performance level, a huge amount of data should be collected, transmitted, processed, and properly stored so that it can be used as historical information. This whole process reflects a transition from raw infrastructure data into actionable maintenance knowledge. Therefore, the database constituted from continuous monitoring will become larger and larger over time and applying big data analysis approaches is inevitable (Fumeo et al., 2015). In order to design proper maintenance plans in railways, it is necessary to explore and analyse the growing amount of data and to extract useful information. To do so, different sensors can be used to collect the data obtained in railway track monitoring at different times, environmental conditions, and frequencies. These data can exhibit different characteristics: (1) discrete or continuous, (2) spatial or temporal, (3) signal and images among others (Lasisi and Attoh-Okine, 2018; Attoh-Okine, 2017; He et al., 2013; Liu and Dick, 2016; Ghofrani et al., 2018).

In condition-based maintenance for railways, the monitoring data are mostly collected periodically with regular sampling intervals. For some critical assets, the monitoring can be adapted to other possible needs including continuous measurement. The essential concept for the monitoring data is to take the degradation of the infrastructure into account, in particular for critical infrastructure like rails. This paper focuses on rail conditions monitoring, which has a critical role in the network performance (He et al., 2015, 2013). In an intensively used network, a considerable amount of the maintenance budget has to be allocated for the rail, e.g., in the Dutch railway network, this amounts to almost half of the annual maintenance budget (approximately 60.000 euro/km) (Zoeteman et al., 2014). As a high percentage of failures are directly related to the rail, it is important to assess the rail conditions in order to obtain a proper condition-based maintenance approach. More specifically, the health conditions analysis involves detecting the rail surface defects that can potentially result in rail breaks and derailment in extreme cases (Liu et al., 2011, 2012; Islam et al., 2016; Xu and Zhai, 2017).

Rolling contact fatigue (RCF) affects the health conditions of the rail due to the contact in the interface between wheel and rail (Makino et al., 2016). RCF is a generic term describing a range of rail surface defects and has been an interesting challenging research topic, in particular the influence of RCF on maintenance decision making (Sciammarella et al., 2016). Moreover, its influence is related to other factors including traffic type, train speed, traffic load, rail/wheel profile, train characteristics, and maintenance policy (Popović et al., 2013). Once RCF appears, it induces considerable dynamical forces on the rail surface, and subsequently cracks are initiated and propagated from the surface (Zhuang et al., 2018; Makino et al., 2012). The most important cause of the appearance of defects is the large number of trains passing over rail critical components, most significantly at welds, joints, and switches (Molodova et al., 2014). Early detection of surface defects is important to mitigate induced maintenance costs as well as unforeseeable consequences of rail breaks. There are different methods to diagnose the conditions of rail defects, including ultrasonic measurements (Fan et al., 2007), eddy current testing (Song et al., 2011), and guided-wave based monitoring (Mariani et al., 2013). In this paper, the focus is on a type of rail surface defect called squat. The costs for treating these defects in the Dutch railway network are considerably high (more than 5000 euro/km per year) (Molodova et al., 2014). The maintenance of squats should be different according to their severity. For late-stage squats, a rail replacement plan is a proper decision while for the light squats, grinding a thin layer from the rail surface is the most effective solution. Hence, when all residual damages are removed, grinding is effective and the rail will be turned to a healthy condition. To optimally plan grinding operations, condition-based maintenance relying on early detection of the squats is required. Although a defect detection method could give an indication of the health of the rail, the infrastructure manager requires prior knowledge to (1) be aware of all influential factors, (2) analyse interdependency between the rail observations and the influential factors, and (3) obtain a future view of the track conditions. In this paper, we relate influential factors to the rail health conditions to show the effect of the track characteristics in the rail observations. Hence, by having knowledge about the track characteristics, potential risks about the rail can be anticipated due to the effect of the influential factors on the appearance of defects and consequently on the rail health conditions. Therefore, an analysis of influential factors should be taken into account to give at the most a proper prospect of the infrastructure health conditions.

Mixed Integer Linear Programming (MILP) is a common approach for track maintenance scheduling. An MILP model is developed in Wen et al. (2016) for optimal condition-based preventive maintenance for a single track divided into multiple segments, considering various economic and technical factors such as train speed limits and track quality. The optimal planning of routine maintenance activities and projects like grinding to minimize maintenance costs and track possession time for a single track is formulated as an MILP in Budai et al. (2006). The optimal scheduling of rail, sleeper, and ballast renewal at a network level is formulated as an MILP problem in Caetano and Teixeira (2016) to minimize the expected life-cycle cost and track unavailability. In Peng and Ouyang (2014), the optimal clustering of track maintenance jobs into projects to minimize total maintenance costs for the network of track is recast as a Vehicle Routing Problem (VRP). The track maintenance problem considering different priorities for each section in the railway network is formulated as an VRP with customer costs in Heinicke et al. (2015). A time-space network model is developed in Peng and Ouyang (2012) for the optimal scheduling of capital maintenance projects like rail replacement. A metaheuristic based on simulated annealing is developed in Santos and Teixeira (2011) to determine the optimal tamping length of a tamping machine, minimizing the associated logistic costs and fixed machine costs. In this paper, we use a simplified MILP model to optimize the rail grinding decision plan into clusters that can be related to the actual conditions of the rail. The proposed MILP model not only uses different clusters for determining the most critical pieces of tracks, but also simultaneously takes time and budget constraints into account. Moreover, the model benefits a new method for estimating rail health conditions as an input data. This eases implementing the condition-based maintenance strategy, reaching an effective maintenance plan in terms of rail health conditions