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# Probabilistic Defect-Based Risk Assessment Approach for Rail Failures in Railway Infrastructure

**Ali Jamshidi*. Shahrzad Faghih Roohi**, Alfredo Núñez*, Robert Babuska**, Bart De Schutter**, Rolf Dollevoet*, Zili Li***

** Section of Railway Engineering, Delft University of Technology, Stevinweg 1, 2628CN Delft, The Netherlands (email: A.Jamshidi@tudelft.nl; A.A.NunezVicencio@tudelft.nl; R.P.B.J.Dollevoet@tudelft.nl; Z.Li@tudelft.nl)*
*** Delft Center for Systems and Control, Delft University of Technology Mekelweg 2, 2628CD Delft, The Netherlands (email: S.FaghihRoohi@tudelft.nl; R.Babuska@tudelft.nl; B.DeSchutter@tudelft.nl)*

Abstract: This paper develops a defect-based risk analysis methodology for estimating rail failure risk. The methodology relies on an evolution model addressing the severity level of rail surface defect, called squat. The risk of rail failure is assessed by analyzing squat failure probability using a probabilistic analysis of the squat cracks. For this purpose, a Bayesian inference method is employed to capture a robust model of squat failure probability when the squat becomes severe. Moreover, an experimental correlation between squat visual length and squat crack depth is obtained in order to define four severity categories. Relying on the failure probability and the severity categories of the squats, risk of future failure is categorized in three different scenarios (optimistic, average and pessimistic). To show the practicality and efficiency of the proposed methodology, a real example is illustrated.



*Keywords:* Squat, Railway track, Bayesian inference, Failure risk, Severity analysis

## 1. INTRODUCTION

In the recent years, railways has been promoted in the whole world as a means of reducing road traffic congestion and emission levels. In order to keep the trains running without disruptions, an efficient maintenance policy based on risk assessment of the different components of the infrastructure is essential to anticipate problems before they occur.

Among all railway infrastructures, the track plays an important role in the entire railway system. In the Netherlands almost half of the maintenance budget is allocated to track maintenance (Zoeteman, 2014). The purpose of the budget is to keep the track at a high reliability level. Moreover, a robust track maintenance plan can facilitate infrastructure management by capturing a set of realistic cases of component degradation. Then, the infrastructure manager would be able to define which scenarios are the most relevant to consider and how to manage the track maintenance in a maintenance time horizon. As a high percentage of the railway system failures occur in the tracks, analysing the failure risk caused by surface defects is crucial for the track maintenance plan (Burstow et al., 2002; Zhao et al., 2006; Liu et al., 2001; Hassankiadeh, 2011). The idea of this paper is to analyse the effect of one common defect in railway networks called squat. To assess a defect-based risk, two major factors must be taken into account. First, the track stochastic variables such as the growth rate of defects where the rail structure deteriorates as the traffic passes along the rails. Second, the spatial characteristics of the track since the track characteristics vary in space. The idea is to capture the evolution rate of the squat when the growth can affect the track reliability and where the track is prone to rail failure. Moreover, in extreme cases, the squat could pose a safety threat due to potential derailment (Prescott et al., 2013).

In this paper, risk of rail failure is assessed relying on a probabilistic approach using a Bayesian inference method. The Bayesian approach provides robust inferences together with a more realistic treatment of growth rate uncertainties. A few studies have been carried out on the application of Bayesian methods in safety of railway infrastructures. Andrade et al. (2015) employ Hierarchical Bayesian models to predict the evolution of the main quality indicators related to railway track geometry degradation including the standard deviation of longitudinal level defects and the standard deviation of horizontal alignment defects. The goal is to use the modelled indicators in planning of track maintenance operations. An investigation on railway ballast failures is done by Lam et al. (2014) using Bayesian inference to analyse uncertainty induced by measurement errors of vibrations in the ballast failure zones. Two integrated frameworks for track degradation and rail maintenance decisions are proposed relying on Bayesian networks in (Bouillaut el al. 2008; Mahboob, 2014). A nonparametric Bayesian approach with a Dirichlet Process Mixture Model is used to facilitate reliability analysis in a railway system by Mokhtarian et al. (2013). Train accident consequences can be modelled by Bayesian networks where human errors and track degradation are addressed (Bearfield et al., 2005, Marsh, 2004; Castillo at al., 2015). This paper is organized as follows. In Section 2, a short background on the squats is presented. Section 3 addresses the Bayesian model of rail failure. Section 4 presents the risk assessment model together with a real-life example. Finally, in Section 4, conclusions are presented.


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## 2. SQUAT IN RAILWAY INFRASTRUCTURES

Surface defects can affect track availability. Those rolling contact fatigue (RCF) defects can be classified as rail corrugation, squats, head checks, shatter cracking, vertical splits, head horizontal splits, and wheel burns (Magel , 2001). Appearance of those defects results in the increase of maintenance operations needed, more frequent track monitoring required, and rail failure when not detected in time in the worst case.

In this paper, we investigate squats, which are surface-initiated defects. The squats are observed in tracks, either ballast tracks or slab tracks, and in all possible traffic volumes (Kaewunruen et al., 2014). Fig 1 shows a reference photo of severe squats with cracks already propagated beneath the rail surface.

Fig 1: Example of severe squats on a rail

Typically, the squats evolve from indentations into defects with surface cracks growing along the depth beneath the rail surface (Li et al., 2010). Once the squat gets severe in terms of crack depth and visual length, the train ride quality and safety become considerably low (Remennikov and Kaewunruen, 2008). In practice, squats can be detected and analysed using different methods, such as inspection using human inspectors, on-board measurements via photo/video records, axle box acceleration (ABA) measurements, and other non-destructive testing (NDT), such as ultrasonic and eddy current testing. While axle box acceleration (ABA) measurements are efficient in detecting both early stage and severe squats (Molodova et al. 2014; Li et al. 2015), in this paper the focus is the analysis of severe defects in terms of crack lengths. Thus, we rely on ultrasonic and surface photos of the defects.

Ultrasonic (US) testing is currently one of the most extensively employed automatic inspection technique for squats. This method can only be used to reliably detect cracks with depths higher than 4 mm, depending on the instruments. When a rail includes squats with cracks larger than 4 mm, the evolution of the defects generates a potential risk of the rail failure. This paper employs US measurements to model crack growth of squat. In the next two sections, the rail failure probability model is presented.

## 3. BAYESIAN MODEL FOR RAIL FAILURE

Bayesian methods are widely used as a statistic technique to evaluate robustness in stochastic data behaviours in particular, for analysis of hazard rates with a small number of data samples. Potential benefits of the Bayesian approach in comparison with the usual Maximum Likelihood Estimate (MLE) method are computationally explained by Ahn et al. (2007). The MLE is an effective tool to estimate hazard rate as long as a sufficient amount of data is available. Using the MLE, a single point value for the failure rate, which maximizes the likelihood function, can be estimated. However, our prior beliefs about the likely values for the failure rates are not injected into the estimation model with the MLE. In contrast to the MLE, Bayesian inference treats failure rates as random variables. Thus, the difference is that in the Bayesian model, the estimation output is a probability density function rather than a single point as in the MLE.

In Bayesian inference, prior knowledge and beliefs about unknown parameters are represented by the probability density distribution $\pi_0(\lambda)$, and statistical observations $y$ have the likelihood $f(\mathrm{y}|\lambda)$ where $\lambda$ is the failure rate. Then, according to Bayes' theorem, the posterior distribution of rail failure probability is expressed as:

$$\pi(\lambda|\mathrm{y}) = \frac{f(\mathrm{y}|\lambda)\pi_0(\lambda)}{f(\mathrm{y})} \propto f(\mathrm{y}|\lambda)\pi_0(\lambda) \tag{1}$$

Let us assume that the failure probability is constructed by considering a nonlinear regression model over the crack depth. The data include observations of the crack depth, the number of cracks with the same depth, and the number of cracks with the growth above 4 mm (see Fig 2). The nonlinear regression model shows the likelihood distribution of parameters $a$ (intercept) and $b$ (slope) in the Bayesian inference model:

$$f(y\,|\,(a,b)) = \exp(-1/(a+b\cdot y)) \tag{2}$$

where $y$ is the crack depth. When no prior information is available about the values of parameters $a$ and $b$, we assume uniform prior distributions (Faghih-Roohi et al., 2014):

$$\pi_0(a) = Uniform(A_1, A_2) \tag{3}$$

$$\pi_0(b) = Uniform(B_1, B_2) \tag{4}$$

By Bayes' theorem, the joint posterior distribution of the model parameters is proportional to the product of the likelihood and the priors. Monte Carlo methods are often used in Bayesian data analysis to describe the posterior distribution. The objective is to generate random samples