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# Key performance indicators using a robust prediction modelling to treat squats in railway infrastructures

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## Abstract

This paper proposes a growth model for squats in railway infrastructures for design of key performance indicators (KPI’s) in a maintenance time horizon. The main idea of the paper is to make the growth model robust and predictive by the capturing all possible growth scenarios over time. The squats are detected using an axle box acceleration (ABA) measurement system. A methodology is proposed to estimate visual length of squats using the power spectral density of the ABA signal. Next, a robust model is employed for predicting the visual length, including fast, average and slow growth prediction scenarios. The purpose of using the robust model is to consider stochastisities in the squat growth in order to cover the most important uncertainties. Relying on the prediction model, five KPIs are defined to reflect track condition over time, in 5 different segments of the track Eindhoven-Weert in the Dutch railway network. By using the proposed prediction model, infrastructure manager will be able to plan a condition based maintenance for tracks.

**Keywords:** Squat, key performance indicators (KPI’s), ABA measurement.

# 1 Introduction

The design of key performance indicators (KPI’s) to facilitate optimal maintenance decisions in the Dutch railway network is not always easy, due to the fact that it encompasses approximately 2,800 km of track and 388 stations and it is intensively used because of increasing high demand. This intensive use brings some negative consequences to the infrastructure, such as the appearance of surface defects that grow faster with an increase in mega tonnage (MGT). Thus, in the case of maintenance of surface defects, to achieve a robust performance, decisions should include explicitly at least two factors: (1) stochastic variables, such as the tonnage and the degradation rate of defects over time, and (2) the distributed characteristics of the track, because infrastructures vary per location [1]. To ensure the proper functioning of railway tracks, both the temporal and the spatial characteristics of the track need to be considered in the KPI's design for maintenance decisions.

Squats are a type of RCF (Rolling contact fatigue) that appear on the rails. To detect squats, the following methods are usually employed: eddy current testing, ultrasonic measurements, human inspection and axle box acceleration (ABA) measurements. The ABA measurement is capable to detect both the early stage squats and severe squats on the rail [2]. In this paper, we rely on the use of the ABA measurement system to detect the squats on the rail. The main idea of the paper is to propose a condition-based model using the KPIs in every segment of track (called a partition). To capture the most important possible defect growth scenarios, a model is employed for predicting the squat visual length including fast, average and slow growth prediction scenarios. The purpose of using the model is to consider stochastisities in the squat growth in order to cover the main uncertainties. The prediction power of the model is validated by real data taken from the track Eindhoven-Weert in the Dutch railway network. In the design of KPI's, the importance for the worst-case scenario (rapid squat growth) is weighted more strongly than other scenarios, whereas combining different models would result in a less conservative and more realistic and generic robust maintenance strategy. In the KPIs model, number and density of squats are taken into account over a prediction horizon by calculating assuming the three growth scenarios.

The paper is structured as follows. In the Section 2, first a brief introduction on the squat is presented and the ABA detection methodology is described. In Section 3, the proposed squat growth model is presented. In Section 4 the KPIs description at a track partition level and the experimental results are discussed. Conclusions and further research are in Section 5.

# 2 The track health monitoring using ABA measurement technology

## 2.1 A brief background on squats in railway infrastructures

Squat as a type of rail surface defect appear on the running band. For Dutch tracks, if the size of a rail surface defect reaches a certain size, it could grow into a light squat called *A* squat and defects below this threshold are considered as trivial defects [3]. In case the squat gets severe, it would be a *B* squat or a *C* squat in the worst case. Moreover, mega tonnage (MGT) can affect squats growth such that a higher MGT can accelerate evolution process of the squats. It means that tracks with less occupation could have less amount of squats. In [4], it is shown that at least 40MGT of traffic is necessary for the development of seed squats, and approximately 100MGT is required for squat to become a defect of concern.

## 2.2 Squat monitoring using ABA measurement technology

Among common measurement technologies of surface defects on the rail including eddy current testing, ultrasonic measurements, visual inspection, we use ABA measurements. The reason to use the ABA measurements is that we need a technology qualified to detect squats in an early stage. In this detection algorithm, the squat location and the severity are estimated by wavelet spectrum analysis and advanced signal processing methods. By adopting ABA energy signal and the understanding of vibration caused by the wheel-track behavior, the severity level of the squat can be predicted. To employ the ABA in the prediction model of the squats, a model is used to get visual lengths calculated from the maximum power spectral density gained by the ABA signals. The goal is to evaluate how the visual length measurement model works. The obtained length measurements are used as input for the prediction model to capture the stochastisities in growth within three different growth scenarios as explained in the next section.

# 3 Squat growth model description

## 3.1 Estimation of the squat's length by ABA measurements

Since the squat's length grows over time when the squat gets severe, for assessment of the squats growth it is necessary to estimate the squats length at various time instants. Therefore, this section presents the model for estimation of the length of squats by ABA measurements.

In [5] it has been observed that some frequency components of the ABA signal are related to the length of squats. Particularly, the power spectral density at 300 Hz increases with the growth of the squat's length. In the real-life measurements the frequency characteristics of ABA may vary at different locations. For this reason the maximum power spectral density in the frequency band between 200 Hz and 400 Hz, denoted by $P$, was used for estimation of the length:

$$P = \max_{200 \le f \le 400} \left\{ PSD_{ABA}\left(f\right) \right\} \tag{1}$$

The data obtained from the track Eindhoven – Weert used for the investigation of the relationship between the power spectral density and the length are in **Error! Reference source not found.**.

Table 1: The field data: visual lengths of squats, measured ABA and the power spectral density in frequency band around 300 Hz.

| Squat | Length, mm | ABA, $m/s^2$ | P |
|---|---|---|---|
| 1 | 24 | 89.8 | 66.0 |
| 2 | 9 | 10.5 | 0.3 |
| 3 | 23 | 27.3 | 27.4 |
| 4 | 18 | 24.3 | 2.3 |
| 5 | 19 | 27.6 | 4.8 |
| 6 | 21 | 21.8 | 6.1 |
| 7 | 18 | 31.0 | 4.0 |
| 8 | 23 | 25.0 | 9.4 |
| 9 | 23 | 21.1 | 3.5 |
| 10 | 18 | 17.6 | 3.2 |
| 11 | 19 | 45.4 | 7.9 |
| 12 | 31 | 65.5 | 107.4 |
| 13 | 13 | 15.5 | 1.9 |
| 14 | 35 | 48.2 | 46.2 |
| 15 | 29 | 20.5 | 28.2 |
| 16 | 24 | 30.4 | 10.4 |

The data listed in **Error! Reference source not found.** is presented in Figure 1. It can be seen from this plot that the relation between the squat’s length $L$ and the power spectral density $P$ is similar to a power function. Therefore, a model for estimation of the length was constructed as follows:

$$L = 13.371 P^{0.2012} \text{ [mm]} \quad (2)$$

The coefficient of determination $R^2$, which is a measure of how well the model approximates the real data points, is 0.8 for this model.

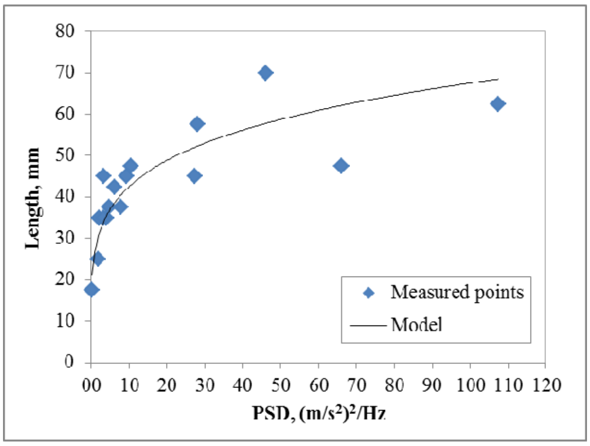



Figure 1: The model for estimation of the length of squats.

## 3.2 Squat growth prediction model

In this paper we propose the use of three piece-wise linear model to capture the stochasticities of different growth scenarios relying on the squat visual lengths calculated based on the PSD. The measurements are collected from the track Eindhoven- Weert. The upper bound of the interval reflects a worst case scenario in growth, while the lower bound shows a slow grow scenario as shown in Figure 2.

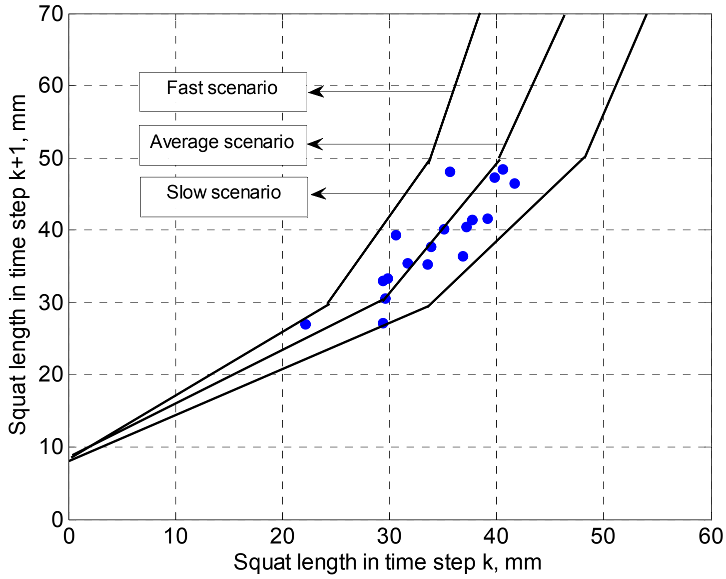



Figure 2: Squat robust growth scenarios for the track Eindhoven- Weert.

The general problem of squat evolution is as follows. Let’s consider different squat growth scenarios $h = h_1, h_2, h_3$, time steps $t = k, k+1, k+2, \ldots, k+N_p$ at measuring time step *k*. The prediction model for the growth of a squat can be written as:

$$\hat{L}_i^h\left(k+1\right) = f_j^h\left(L_i(k)\right), \quad x_i \in \left[x_j, x_{j+1}\right) \tag{3}$$

where $\hat{L}_i^h(k+1)$ is an estimation of length of the squat *i* located in the track partition $j$ at the time step *k+1* considering scenario *h*, $x_i$ is the location of the squat *i*, and the partition *j* is defined between the kilometre positions $x_j$ and $x_{j+1}$.

Once the model is obtained, slow growth scenario and fast growth scenario are estimated as lower and upper level of the average growth scenario.

# 4. KPIs for track health condition

Number of squats can be used by a predictive tool to support the infrastructure manager’s decision on how to keep controlled the squat growth over time. Together with the squat numbers, significant density of B and C squats can represent a high potential risk to track safety. According to the squat detection and modelling tool, number of squats and density of B and C squats are used as key performance indicators (KPI’s).

A vector including all the KPIs called $y_{h,j}(t)$ can be defined to cover the proposed KPI’s in terms of time step *t*, scenario *h* and track partition *j*:

$$y_{h,j}(t) = \left[y_{h,j}^1(t), y_{h,j}^2(t), y_{h,j}^3(t), y_{h,j}^4(t), y_{h,j}^5(t)\right]^T \tag{4}$$

where $y_{h,j}^1(t)$, $y_{h,j}^2(t)$, $y_{h,j}^3(t)$, $y_{h,j}^4(t)$ and $y_{h,j}^5(t)$ are number of *A* squat, number of *B* squat, number of *C* squat, number of *RC* squat and density of *B* and *C* squats, respectively.

Squat number KPIs can be defined as follows:

$$y_{h,j}^1(t) = \sum_{h=1}^{3} \sum_{t=k}^{k+N_p} N_h^A(t) \tag{5}$$

$$y_{h,j}^2(t) = \sum_{h=1}^{3} \sum_{t=k}^{k+N_p} N_h^B(t) \tag{6}$$

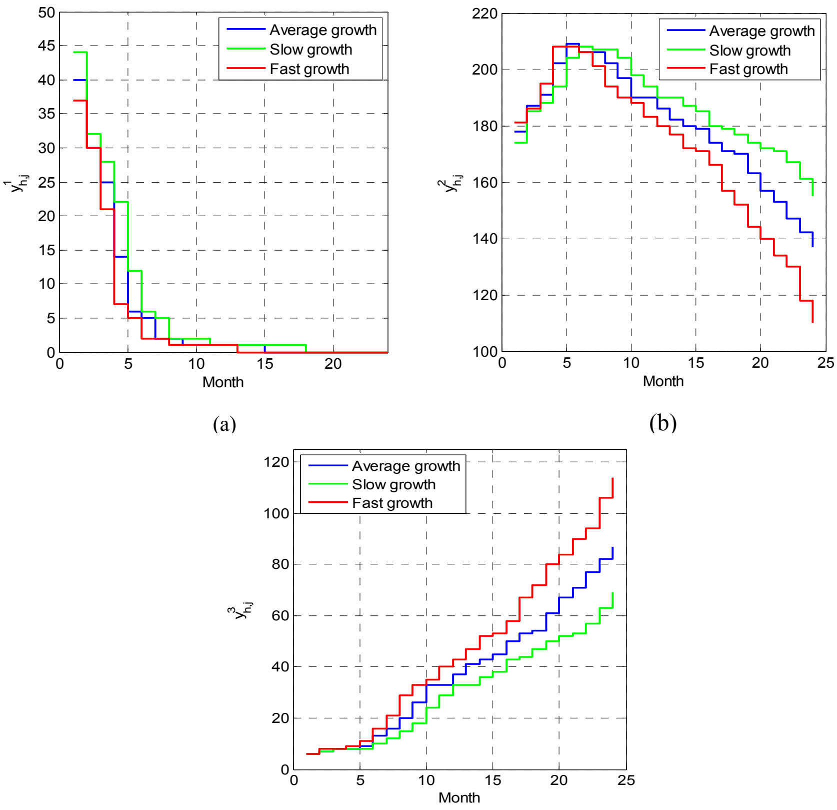
$$y^3_{h,j}(t) = \sum_{h=1}^{3} \sum_{t=k}^{k+N_p} N_h^C(t) \tag{7}$$

$$y^4_{h,j}(t) = \sum_{h=1}^{3} \sum_{t=k}^{k+N_p} N_h^{RC}(t) \tag{8}$$

Density indicator of *BC* squat can be expressed as:

$$y^5_{h,j}\left(t\right) = \sum_{h=1}^{3} \sum_{t=k}^{k+N_p} d_h^{BC}\left(t\right) \tag{9}$$

Figure 3 shows number of *A* squat, *B* squat and *C* squat over 24 month from the moment of measurement assuming no new squat will appear over time.




(a) (b) (c)

Figure 3: Number of squats over time according to three proposed growth scenarios where (a), (b) and (c) show *A* squats, *B* squat and *C* squat over time, respectively.

Relying on the prediction model, we present the KPIs for squats on the entire left rail track between Eindhoven and Weert, which was measured in March 2014. In this paper, the track is divided into five partition, $j=1,\dots,5$. It is supposed that no maintenance is performed during the prediction horizon. Table 2 shows the result of the KPIs predictions for next 24 month considering three different scenarios.

Table 2 : Prediction of number of *A* squat, *B* squat, *C* squats and *RC* squats over the track Eindhoven – Weert.

| Evolution scenarios | Squat type | T=0 | T=6 | T=12 | T=18 | T=24 |
|---|---|---|---|---|---|---|
| Slow growth | A | 49 | 6 | 1 | 0 | 0 |
| | B | 169 | 208 | 190 | 177 | 155 |
| | C | 5 | 10 | 33 | 47 | 69 |
| | RC | 1 | 1 | 2 | 4 | 6 |
| Average growth | A | 49 | 5 | 1 | 0 | 0 |
| | B | 169 | 206 | 186 | 170 | 137 |
| | C | 5 | 13 | 37 | 54 | 87 |
| | RC | 1 | 1 | 3 | 6 | 16 |
| Fast growth | A | 49 | 2 | 1 | 0 | 0 |
| | B | 169 | 206 | 180 | 152 | 110 |
| | C | 5 | 16 | 43 | 72 | 114 |
| | RC | 1 | 2 | 4 | 8 | 35 |

Figure 4 depicts the proposed model for the squat evolution in terms of length, mm, over track position after 24 months, just as an example. The idea is to see the growth model covering all the KPIs features, containing number and density of squats. The track Eindhoven – Weert is partitioned into 5 different partitions in which figures a, b, c, d and e present Partition 1, Partition 2, Partition 3, Partition 4, Partition 5, respectively. Each letter is notated by 1, 2 and 3 showing slow growth scenario, average growth scenario and fast growth scenario respectively. Moreover, those squats that exceed 50 mm, where squat is in dangerous zone prone to real break, are shown by red colour.

Figure 5(a) shows how density of *BC* squats is distributed over the track of around 27 km. To visualize the track position, a simple map of the track Eindhoven-Weert is presented as shown in Figure 5(b). Track Partition 5 is the one concentrating the highest number of squats, with the highest density of predicted severe of defects.

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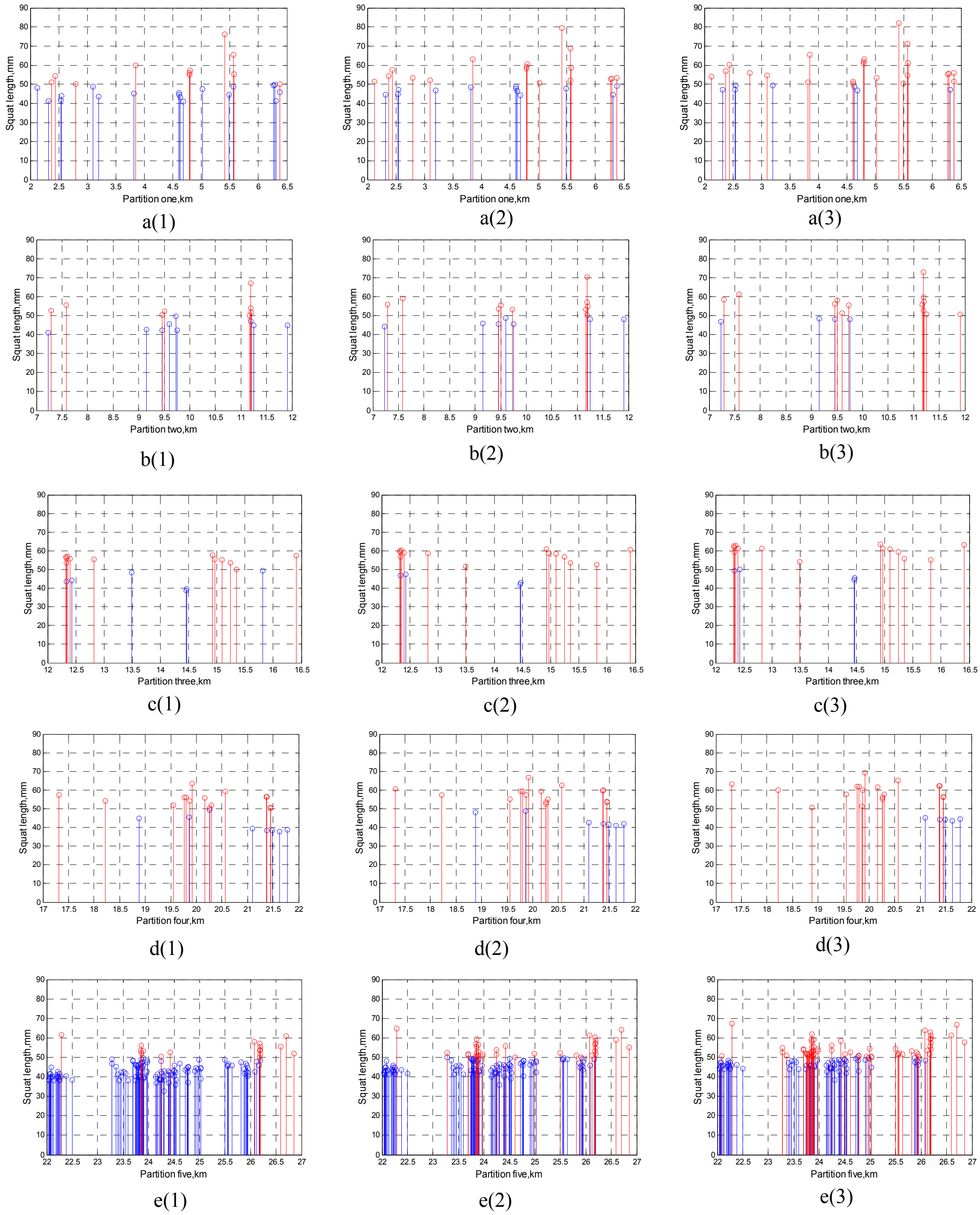


Figure 4: Squat length prediction after 24 months over the five track partitions.

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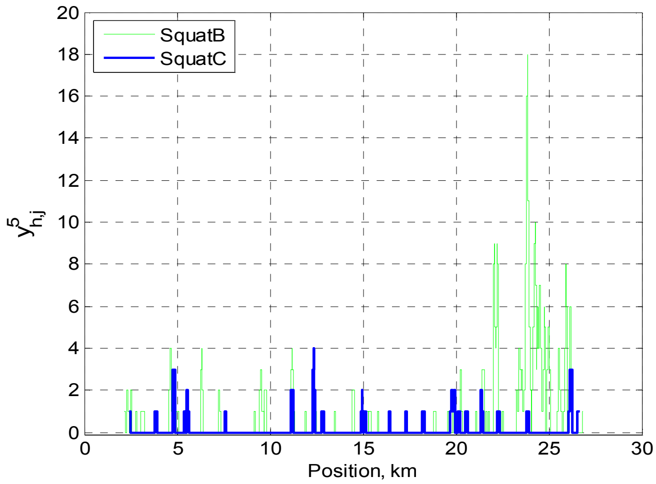


(a)


(b)

Figure 5: (a) Density of *BC* squats over the track position, (b) map of the track Eindhoven-Weert.

## 5. Conclusion and future research

In this paper a methodology for design of predictive and robust KPIs for squats is developed. The idea is to use energy signals estimated by the ABA to get visual length of squats by using the maximum power spectral density in a specific frequency band.

The methodology is employed to construct a prediction modelling in order to monitor the track condition over a time horizon per track partition. The idea of using the robust prediction model is to capture all the possible growth scenarios. The KPIs obtained by the prediction model are defined for the track Eindhoven-Wert. In future studies, we will consider optimization-based methodologies to reduce optimally the life cycle costs using the KPIs.

## References

[1] A. Jamshidi, A. Núñez, Z. Li, and R. Dollevoet, “Maintenance decision indicators for treating squats in railway infrastructures”, Proceedings of the 94th Annual Meeting of the Transportation Research Board, Washington, USA, January 11-15 2015.

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

[3] Z. Li, M. Molodova, X. Zhao, and R. Dollevoet, "Squat treatment by way of minimum action based on early detection to reduce life cycle costs", Proceedings of the 2010 Joint Rail Conference, April 27-29, Urbana, Illinois, USA, pp. 305-311, 2010.

[4] S. Grassie, "Squats and squat-type defects in rails: the understanding to date", Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 226 (3):235-242.

[5] M. Molodova, Z. Li, A. Núñez, and R. Dollevoet, "Signature tunes of squat", Submitted to Mechanical Systems and Signal Processing, September, 2014.