MAINTENANCE DECISION INDICATORS FOR TREATING SQUATS IN RAILWAY INFRASTRUCTURES

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Abstract

In this study, we use a defect prediction-based methodology to support maintenance decisions for railway infrastructure that are related to surface defects known as squats. The performance and cost-effectiveness of possible squat maintenance countermeasures are assessed by analysing scenarios for the evolution of detected squats. Thus, indicators are identified that can enable an infrastructure manager to determine which sections of the track are healthy and which sections require grinding or replacement. To support the decision-making process, a fuzzy expert system is developed to determine the health condition of the tracks and cluster of squats, to facilitate corrective maintenance planning. The benefits of the developed approach are demonstrated by considering a section of the Groningen-Assen track of the Dutch railway network.

INTRODUCTION

Asset management plays a vital role in railway networks because a major part of the budget for railway infrastructure is related to maintenance. A typical railway network consists of several assets: tracks, switches, culverts, bridges, tunnels, light systems, embankments, yards, heating systems, different types of detectors, track locks, boards, signalling systems, power lines, stations, an overhead contact system, level crossings and vehicles. All of these assets require different types of maintenance that are specific to each asset. In the Netherlands, the railway network encompasses approximately 2,800 km of track and 388 stations. The intensive use of the Dutch railway network makes efficient track maintenance crucial for the performance of the entire railway system. Forty-four percent (the major part) of the maintenance budget is related to track maintenance (Zoeteman, 2006).

To achieve a robust railway track maintenance decision system that can be used by an infrastructure manager, two primary factors must be considered: (1) stochastic variables, such as the tonnage and the evolution rate of defects in time, and (2) the distributed characteristics of the track, because infrastructures vary in space. To ensure the proper functioning of railway tracks, both the temporal and the spatial characteristics of the track need to be considered in maintenance decisions. To achieve optimal maintenance, early detection of the defects is essential to reduce the high cost of corrective maintenance and the disastrous consequences of rail breaks on the entire performance of the railway.

Various defects can affect the tracks. Rail defects can be classified as rail corrugations; rolling contact fatigue (RCF) defects, such as squats; shatter cracking; vertical splits; head horizontal splits and head wheel burns. These defects can be detected using different methods, such as non-automatic inspection using human inspectors, photo/video records, and non-destructive testing (NDT), such as ultrasonic and eddy current testing. In this study, we investigate squats, which are surface-initiated defects. These squats are detected using an axle box acceleration (ABA) system that was developed by our group at the Delft University of Technology in the Netherlands (Molodova et al., 2014). After defect detection, countermeasures must be used to prevent/correct the effect of the squats. The evolution of the squats depends on the dynamic wheel-rail interaction in a nonlinear stochastic system. Thus, the decision-maker should consider these dynamics in determining which sections of the track are healthy and which regions require preventive or corrective maintenance.

In this study, we use different predictive indicators to evaluate the cost-effectiveness of potential squat maintenance countermeasures. The use of these indicators simplifies the analysis for decision-making. Light squats that appear with a high density are categorised as A squats. Thus, we define an indicator, which is based on a fuzzy c-mean, that creates clusters of A squats. Grinding planning is thus recommended for these conceptual track sections with a high density of A squats. For more severe squats, we define an indicator that is based on the density of squats. This indicator is combined with a predictive model to determine the impact of the squat on the health of the track, in particular where the risk of rail break is highest. Therefore, these indicators can provide an infrastructure manager with tangible information on the squats in the entire infrastructure, which the infrastructure manager can use to predict/decide which parts of the track are healthy and which parts require grinding or replacement.

BACKGROUND ON SQUATS IN RAILWAY INFRASTRUCTURE

A squat is a type of RCF defect, which was little known in Europe until approximately 30 years ago. Squats were identified as a distinct type of failure in the 1970s. This defect was thus named because it appears as if a heavy gnome has squatted on the rail. These squats are most commonly observed on the running band of a straight track and for large curves, independent of the type of track (Li et al., 2008). Squats are usually associated with one of the following features: corrugation, welds and small periodic indentations in the rail running surface (periodic squats).

There are three categories of squats. Figure 1 shows photographs of these three classes of squats: light (A squats), moderate (B squats) and severe (C squats). An A squat appears as a simple imprint with a black spot. A B squat has a ‘V-shaped’ crack with black spots on both sides of the crack. A C squat has cracks with wavelengths between 20 to 40 mm and has a big black spot. The squat growth depends on the dynamic contact between the wheels and the rails.

All simple defects do not grow into squats. The size of a rail surface defect on a Dutch track must exceed a critical size to grow into a squat. For tracks in the Netherlands, this critical size ranges from 6–8 mm for visual inspection (Molodova, 2014). Defects below this threshold are considered to be trivial. In a severe squat with a network of surface and subsurface cracks, the maximum depth of the squat is 16 mm, and the squat length significantly exceeds the typical size range of squats of 2-6 cm. Squats in different infrastructures generally exhibit similar characteristics (Li et al., 2010). These defects can be detected in straight lines or gentle curves and in locations with high driving traction. One of the most challenging aspects of studying squats is that they are usually isolated in different parts of the infrastructure.

Our practical experience with squats has shown that squats in an early stage of development can be effectively treated using a grinding machine. Once the squat has developed cracks, the squat tends to reappear in the same location where it was before grinding. Generally, more severe squats tend to evolve faster than squats in the early stages of growth. In terms of mechanisms for generating squats, the more loaded is the track, the more likely are “seed” squats to develop. Squats on tracks with a higher megatonnage per year are also more likely to evolve at a faster rate than those on less occupied tracks. In this study, we develop a model to capture these characteristics of squats.

Squat monitoring system

Ultrasonic testing is currently the most extensively employed automatic inspection technique for squats. This method can only be used to reliably detect cracks with depths above 5–7 mm. Eddy current testing can be used to detect surface cracks at depths ranging from 0.1 to 2.5 mm. Surface defects that do not have cracks cannot be easily detected. Therefore, ultrasonic testing and eddy current testing are not suitable for detecting early-stage squats (Li et al. 2010). Another health monitoring system for railway tracks is based on ABA measurements. An ABA system can be used to detect defects such as corrugation, squats and poor quality welds. An ABA system offers the advantages of having a lower cost than other type of detection methods, being easy to maintain and can be implemented onboard in-service operational trains to monitor track conditions (Li et al., 2008; Molodova et al., 2014). Other significant advantages that

ABA offers over similar measurement systems include the ability to detect defects without cracks, the absence of complicated instrumentation and the ability to indicate the level of the dynamic contact force.

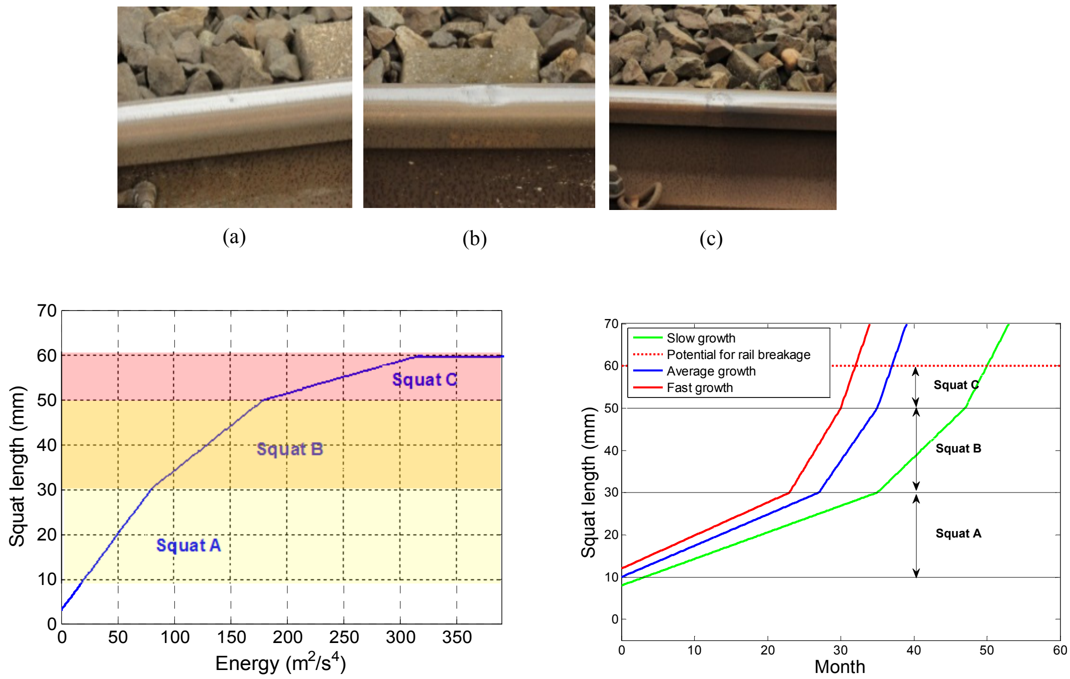
The parameters that affect the detection of squats when using ABA include the train speed, the squat location on the track relative to the sleeper and the track design (Molodova et al., 2014). Molodova (2013) investigated the feasibility of detecting early-stage squats using an ABA prototype and could detect squats by analysing the frequency content of the signals. Finite element (FE) modelling showed that the relevant frequencies for squats (signature tunes) were 300 Hz and 1060–1160 Hz, with a brief maximum high-frequency response of 2000 Hz. However, in practice, the useful frequency band for the detection of light squats ranges from 1000-2000 Hz (Molodova et al., 2014).

An infrastructure manager could monitor the energy of the ABA signal to detect and predict the evolution of squats over time. Thus, we develop an experimental correlation between the squat length and the energy of the ABA signal (see Figure 1.d) by measuring photographs that were taken during track visits and ABA on-board train measurements for different tracks of the Dutch railway. We also develop a simple method to convert an ABA energy signal to the level of severity of the squat. In this method, the squat location and the severity of the squat are obtained using wavelet spectrum analysis and advanced signal processing methods. The evolution of the squats depends on the tonnage of the track. We analyse a case study in which approximately six months is required for an A squat to evolve into a B squat. This evolution is a stochastic process that is determined by different exogenous factors. We also investigate evolution scenarios for squats to capture general stochastic characteristics.

Squat growth

The optimum grinding strategy can be determined for a variety of conditions using models that predict the growth of surface rail cracks caused by surface defects (Hyde and Fletcher, 2010). Understanding the crack evolution process is critical to ensure safe and cost-efficient railway operation.

Many factors can affect the growth process of squats. These factors interact with each other, making it difficult to model the squat growth evolution process. For instance, the growth of seed squats can be spontaneously halted by the wear of the commercial trains or by grinding. Late-stage squats with developed cracks are frequently too deep to be completely removed by grinding, and squats reappear in the same spot after some months. These factors and other factors, such as tonnage, make it difficult to predict the stochastic mechanism of squat growth evolution. Photographs were taken in the field (every six months from 2007 to 2012) and measured to obtain a cloud of data points to derive a relation between the squat length and the month. The data show that the larger is the defect, the higher is the rate of growth. The observations also reveal that different squats have different rates of growth. We propose three different evolution scenarios: (1) slow growth, (2) average growth and (3) fast growth. Figure 1.e shows the three evolution scenarios over time for a particular squat.



(a) (b) (c)

(d) (e)

FIGURE 1: Representative photographs of (a) a light squat, (b) a moderate squat and (c) a severe squat. (d) Squat length as a function of the energy value of the ABA signal and (e) squat evolution scenarios in time (months)

Figure 1.e shows that the squats exhibit a maximum growth of 30 mm in the first months. The majority of the squats with lengths ranging from 10 to 30 mm contain no cracks or contain only shallow cracks: these squats are classified as A squats. The wavelengths (the squat lengths) of squats ranging from 30 to 50 mm grow rapidly and cracks develop. The squats in this regime are classified as B squats. The ensuing growth is accelerated by the network of cracks that develops beneath the squat. Squats with this level of severity are classified as C squats.

The successful removal of squats by grinding requires that the grinding is performed when the squats are between 10-30 mm in length, when no cracks exist or when the cracks are shallow. The slow growth rate at this stage leaves sufficient time for planning and actions; otherwise, the squat may enter the rail break zone, which corresponds to squat lengths beyond 60 mm. Theoretical scenarios and piecewise functions are developed to capture the primary nonlinearities in the growth evolution of the squats. These curves are fit using data that were collected in a specific case study over a six-year period; however, these curves can be adapted to other types of tracks. The developed models can be employed to predict squat evolution with time to formulate robust maintenance strategies, which include stochastic effects for different scenarios. In a min-max robust strategy, 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.

MAINTENANCE ACTIONS

Most squats initiate from rail top defects, such as indentations and corrugations. No effective measures are available to prevent the appearance of such squats, and the most practical way to treat squats is to remove them (Li et al., 2010). Once squats are detected, two maintenance actions can be considered: grinding and track replacement. To facilitate maintenance planning, fixed-track partitioning is used to organise the desired maintenance actions and obtain performance indicators for each partition.

Each 200-m track section is generally characterised in terms of the particular features of the track infrastructure (Andrade and Teixeira, 2011). The potential deterioration rates of different track sections are determined by partitioning the track using the associated radii and stations. Curves with radii greater than 1,800 m are considered to be straight tracks. Figure 4.a is a schematic of the fixed partitioning scheme. Stations can serve as suitable references in partitioning; however, the remainder of the track should be partitioned such that the infrastructure manager can interpret the results easily. In this study, five generic partitions are considered, just to facilitate the explanation of the example. In a real-life implementation we suggest the partitioning design to be according similar characteristics of tracks and radii. In the figure, $H_i(t)$ indicates the set of key performance indicators for monitoring the health of the partition i of the track, which is defined as the track between x_i and x_{i+1} km of the track.

Grinding

A rail-grinding program is a critical component of profile optimisation in any rail maintenance program (Magel and Kalousek, 2002). Dutch railways typically have a cyclic grinding regime. Research studies have shown that rail grinding plays an important role in the reducing the effects of rail degradation, including the prevention of derailments. The majority of RCF cracks are removed by grinding. Therefore, early detection of RCF rail defects is extremely important to prevent derailment. When squats are detected at an early stage, and the degradation is minor, tracks can be easily treated by grinding a thin layer from the surface. For A squats (light squats) and simple defects, grinding the rail top can be an effective corrective measure (Li et al., 2008). The most important benefit of grinding is that the maintenance and life cycle cost of the tracks are reduced.

Grinding severe squats generally results in the reappearance of squats at their original location, even if all of the visible effects at the surface are removed by grinding. Figure 2.a shows the squat evolution before and after grinding. Note that grinding is not efficient for cracks deeper than 5–7 mm. In the figure, A squats are located in the effective zone for grinding, such that these squats have a zero length after grinding (i.e., these squats will disappear from the model). Squats that are near moderate levels of severity are located in the ineffective zone for grinding. After grinding, these squats will not disappear, and their rate of evolution will be determined by the specific scenario, as shown in Figure 1.e. Grinding severe squats delays rail replacement but may accelerate squat evolution, because the cracks beneath the squats are not treated.

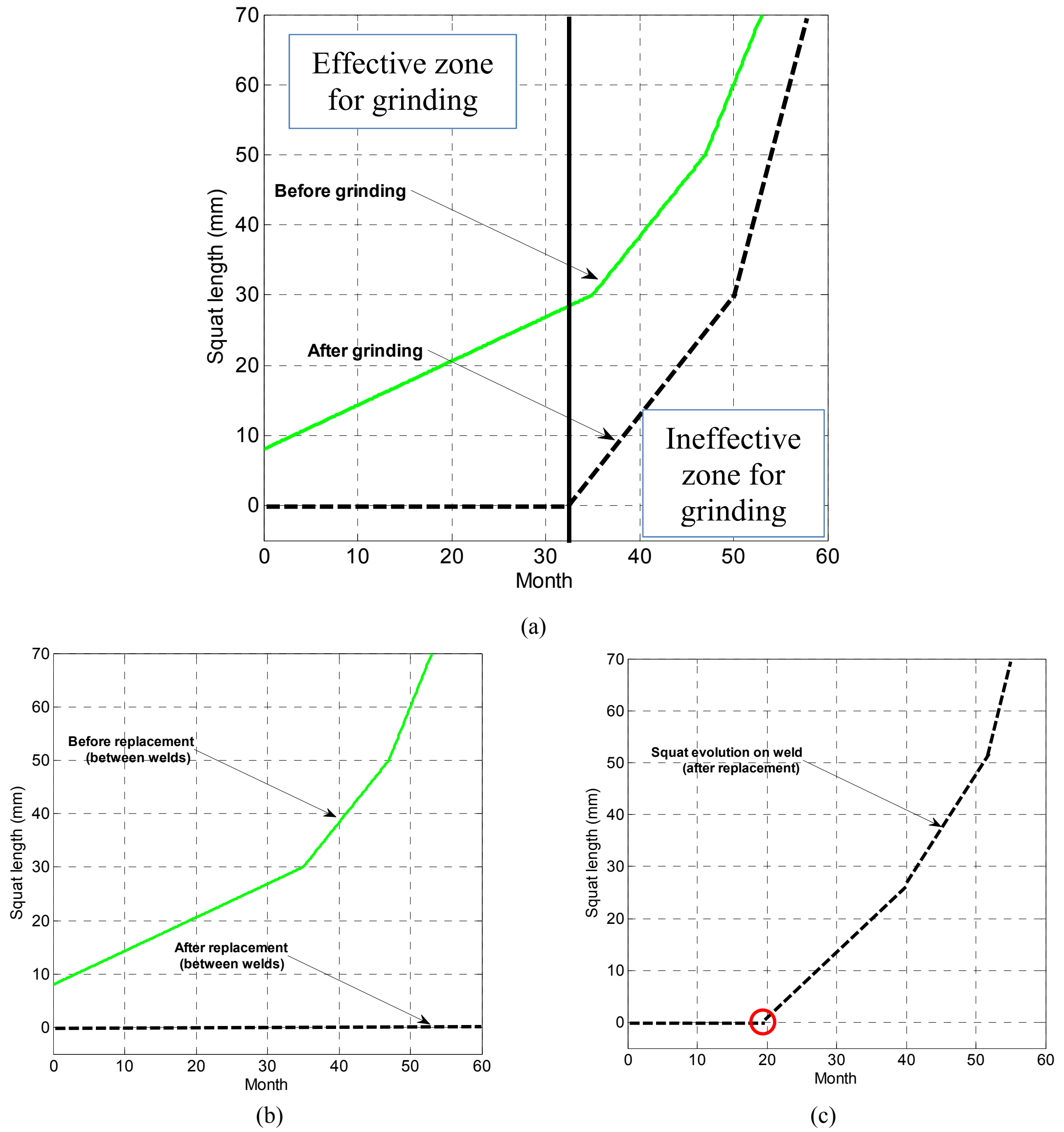


FIGURE 2: (a) Comparison of squat growth before and after grinding. (b) Squat evolution between welds (before and after rail replacement) and (c) squat evolution of welds after rail replacement: red circle shows the starting point of the growth of the defect, which depends on the quality of the weld

Rail replacement

Replacing rails with lengths greater than 110 m is known as rail replacement. Rail replacement may be employed for severe squats (C squats), especially at switches and crossings. Rail replacement is based on several factors. Rails are frequently replaced based on their life, tonnage, wear limit and fatigue. Weather conditions are also an important factor. Determining the optimal rail replacement interval is a critical issue for rail industry players (infrastructure managers, contractors and operators).

Rail replacement is only performed when absolutely necessary because it has a high cost and affects the performance of the entire system. Welds are used to join rail sections. The use of different materials increases the likelihood of weld deterioration. Welds account for approximately 25.5% of the total number of rail breaks (Lewis and

Olofsson, 2009). There are two primary types of welding: (1) alumino-thermic welding and (2) flash-butt welding. Alumino-thermic welding is generally used to repair rail breaks and involves the generation of a superheated liquid metal by an exothermic reaction between iron oxide and aluminium powders. Flash-butt welding is used for re-railing and renewals. In this method, two rail sections are brought together, and resistance heating is employed to soften and melt the rail edges (arcs form across the interface, resulting in flashing). Manual metal arc welding is used for rail repair: an arc is struck between the rail and a consumable electrode, thereby depositing molten metal onto the rail (Lewis and Olofsson, 2009).

Figure 2.b and 2.c shows squat evolution before and after rail replacement. Figure 2.b shows the response between welds, showing that all of the defects prior to replacement (independent of the defect size) disappear after replacement. As shown in Figure 2.c, the model predicts that squats will be initiated at the weld. The exact moment at which this deterioration occurs depends on the quality of the weld. Our prediction horizon obviates making an estimate of this variable (which is shown as a red circle in Figure 2.c), which would however become relevant for a longer prediction horizon, which we will consider in a future study.

MAINTENANCE DECISION SUPPORT

In this study, we develop a model to reduce squat maintenance costs and prevent hazards in railway networks. Squats are detected by ABA measurement, which is a more reliable method than other detection methods for surface defects. After collecting the detection data for each track partition, the evolution of the squats are used to generate different possible scenarios. Figure 3 is a flowchart of the squat maintenance decision support methodology. Infrastructure managers can use the defined indicators to locate defects and monitor defect growth on the track.

Indicators based on three different scenarios are defined to assess the maintenance action decision that should be taken depending on the squat evolution behaviour. These indicators are used to determine whether an unhealthy rail should be repaired (using corrective grinding) or replaced. A nonlinear regression analysis based on the least squares method is used to determine the relation between the squat length of a squat and the time. The following functional is then minimised:

$$S = \sum_{i=1}^{p} r_i^2 \tag{1}$$

where the r_i (errors) can be defined as

$$r_i = y_i - f\left(x_i, \beta\right) \tag{2}$$

where p is the number of data points (x_1,y_1), (x_2,y_2),…, (x_p,y_p), and $y = f(x,\beta)$ is a nonlinear piecewise affine model with the set of parameters $\beta = (\beta_1, \beta_2, \ldots, \beta_n)$, which comprises the rates of growth and transitions. The data obtained from Figure 1.e is used to generate three different time predictions. In this study, only detected squats are analysed; in future studies, this model will be further developed to create scenarios generation of new seed squats over time.

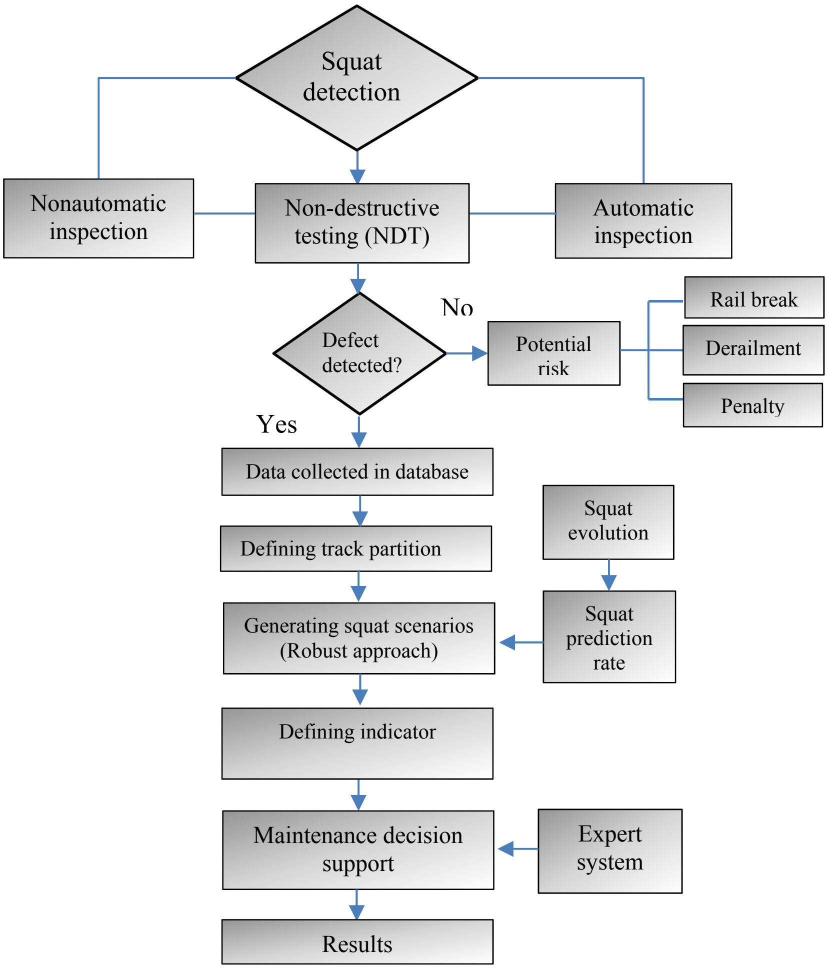


FIGURE 3: Flowchart of developed methodology

Squat number

Squat enumeration is a tool that an infrastructure manager can use to monitor the number of squats that are evolving in subsequent stages with time in each section *i*. The indicator $N_{s,i}^{d}(t)$ represents the number of A, B and C squats and the number of squats with potential risk (RC), i.e., the squats that are longer than 60 mm in length, that can be obtained at time *t* in section *i* using prediction scenario *s*. This key performance indicator is defined as

$$N_{s,i}^{d}(t) = \sum_{x \in [x_i, x_{i+1})} \delta_{s,i}^{d}(x,t) \tag{3}$$

where $d \in \{\mathrm{A}, \mathrm{BC}, \mathrm{RC}\}$, *t* is the time, and $\delta_{s,i}^{d}(x,t)$ is unity if the defect type *d* exists at position *x*, partition *i* and growth scenario *s* and is zero otherwise.

Squat density

The fourth indicator is the density of squats A, B and C. A window is defined for the position coordinates (in this study, the window is 50 m in length) to inform infrastructure managers of the number of squats per m that are on the tracks. A high density of B and C squats indicates a high potential risk to track safety, whereas a high density of A squats indicates that the area is suitable for grinding operations. The squat density indicator for scenario *s* at section *i* is defined as

$$y_{s,i}^{A}\left(t\right)=\sum_{x\in[x_i,x_{i+1})} d_{s,i}^{A}\left(x,t\right),\quad y_{s,i}^{BC}\left(t\right)=\sum_{x\in[x_i,x_{i+1})} d_{s,i}^{BC}\left(x,t\right) \tag{4}$$

where t is the time, $d_{s,i}^{A}\left(x,t\right)$ is the density of A squats, and $d_{s,i}^{BC}\left(x,t\right)$ is the density of B and C squats with respect to a window X_w that is defined around the position x.

Fuzzy global indicator

We assess the general track condition for each section by developing a fuzzy system that combines all of the developed key performance indicators. This fuzzy set of rules yields a score between zero and two to indicate the extent of deterioration of the track due to squats. Thus, corrective grinding and replacement decisions can be based on this global indicator. The rules are defined below.

$$\textit{If}\ \ N_{s,i}^{A}(t)\ \textit{is}\ A_1\ \textit{and}\ \ y_{s,i}^{A}\left(t\right)\ \textit{is}\ A_2\ \textit{and}\ N_{s,i}^{RC}(t)\ \textit{is}\ A_3\ \textit{and}\ y_{s,i}^{BC}\left(t\right)\ \textit{is}\ A_4\ \textit{then}\ U\ \textit{is}\ D$$

where $N_{s,i}^{A}(t)$ is the indicator for the number of A squats, $y_{s,i}^{A}\left(t\right)$ is the density of A squats, $N_{s,i}^{RC}(t)$ is the indicator for the number of potential risk points, and $y_{s,i}^{BC}\left(t\right)$ is the density of B and C squats. A_1, A_2, A_3, A_4 and C are the membership functions for the linguistic terms Very High (VH), High (H), Medium (M), Low (L) and Very Low (VL). VH or H indicate that an indicator is high, which corresponds to an unacceptable track condition; L and VL indicate that the indicator is low, which corresponds to a healthy track condition, and M is an intermediate condition between the high and low indicator values. The variable U denotes the condition of the health of the track, which takes the value Unhealthy when there are many severe squats (because many squats trigger track replacement), Average (which designates a mixture of replacement and grinding zones) and Healthy when the track is free of severe squats. The levels can be tuned by infrastructure managers to adjust to their needs (we just propose an example).

The linguistic terms of the fuzzy system are defined in Table 1. The fuzzy model is implemented using the Mamdani algorithm. The inputs and outputs are fuzzified with Gaussian membership functions. A total of 28 fuzzy if-then rules for assessing the health condition are generated. The crisp values in the last step of the inference system are determined using the centre of gravity method in the defuzzification process.

TABLE 1: Definition of fuzzy and crisp ratings

Factors	Linguistic term	Crisp rating	Fuzzy ratings	Universe of discourse (X)
$N_{s,i}^{A}$	Very high (VH)	5	$3.5 < y_A \leq 5$	$A_1 \in (1,5)$
	High (H)	4	$3 < y_A \leq 5$	
	Medium (M)	3	$2 < y_A \leq 4$	
	Low (L)	2	$1 < y_A \leq 3$	
	Very low (VL)	1	$1 < y_A \leq 2.5$	
$y_{s,i}^{A}$	Very high (VH)	5	$3.5 < d_A \leq 5$	$A_2 \in (1,5)$
	High (H)	4	$3 < d_A \leq 5$	
	Medium (M)	3	$2 < d_A \leq 4$	
	Low (L)	2	$1 < d_A \leq 3$	
	Very low (VL)	1	$1 < d_A \leq 2.5$	
$N_{s,i}^{RC}$	Very high (VH)	5	$3.5 < y_C \leq 5$	$A_3 \in (1,5)$
	High (H)	4	$3 < y_C \leq 5$	
	Medium (M)	3	$2 < y_C \leq 4$	
	Low (L)	2	$1 < y_C \leq 3$	
	Very low (VL)	1	$1 < y_C \leq 2.5$	
$y_{s,i}^{BC}$	Very high (VH)	5	$3.5 < d_{BC} \leq 5$	$A_4 \in (1,5)$
	High (H)	4	$3 < d_{BC} \leq 5$	
	Medium (M)	3	$2 < d_{BC} \leq 4$	
	Low (L)	2	$1 < d_{BC} \leq 3$	
	Very low (VL)	1	$1 < d_{BC} \leq 2.5$	
U	Unhealthy	2	$1.5 < U \leq 2$	$D \in [0,2]$
	Average	1	$0.5 < U \leq 1.5$	
	Healthy	0	$0 \leq U \leq 0.5$	

MEASUREMENTS AND SIMULATION RESULTS

In this section, we present the model predictions for squats on the entire left rail track between Groningen and Assen, which was measured beginning 2010. In this study, the track between Groningen and Assen is partitioned into five parts as shown in Figure 4.a. Table 2.a shows the number of predicted squats versus the month (T) for different growth scenarios, which are obtained based on the piecewise affine functions that are determined using equation (1), as shown in Figure 1.e. It is assumed that no maintenance is performed. Table 2.a shows the number of C squats for three predicted scenarios in the rail break risk zone (RC). Table 2.b shows the results of the fuzzy expert system for assessing the global condition of the track after 24 months when no track maintenance is performed.

TABLE 2.a : Predicted number of A, B and C squats and rail break risk squats (RC) over the entire track in the absence of maintenance

Evolution scenarios	Squat type	T=0	T=12	T=24	T=36	T=48	T=60
Slow growth	A	30	13	5	0	0	0
	B	19	28	29	29	21	10
	C	2	5	12	17	25	36
	RC	0	0	2	5	12	18
Average growth	A	30	9	2	0	0	0
	B	19	31	28	22	8	2
	C	2	6	16	24	38	44
	RC	0	1	5	12	19	32
Fast growth	A	30	8	0	0	0	0
	B	19	30	29	14	3	0
	C	2	8	17	32	43	46
	RC	0	1	5	16	29	41

TABLE 2.b: Definition of fuzzy global indicator after 12 and 24 months in the absence of maintenance

Evolution scenarios	Partition *i*	At the moment of the measurement		Fuzzy indicator after 12 months		Fuzzy indicator after 24 months	
Slow growth	1	1.39/2	Average	1.51/2	Unhealthy	1.59/2	Unhealthy
	2	0.86/2	Average	0.98/2	Average	0.99/2	Average
	3	0.95/2	Average	1.00/2	Average	1.10/2	Average
	4	0.87/2	Average	0.96/2	Average	1.00/2	Average
	5	1.44/2	Average	1.52/2	Unhealthy	1.60/2	Unhealthy
Average growth	1	1.39/2	Average	1.63/2	Unhealthy	1.70/2	Unhealthy
	2	0.86/2	Average	0.98/2	Average	0.99/2	Average
	3	0.95/2	Average	1.10/2	Average	1.20/2	Average
	4	0.87/2	Average	1.20/2	Average	1.30/2	Average
	5	1.44/2	Average	1.59/2	Unhealthy	1.60/2	Unhealthy
Fast growth	1	1.39/2	Average	1.64/2	Unhealthy	1.70/2	Unhealthy
	2	0.86/2	Average	1.18/2	Average	1.20/5	Average
	3	0.95/2	Average	1.15/2	Average	1.25/2	Average
	4	0.87/2	Average	1.35/2	Average	1.40/2	Average
	5	1.44/2	Average	1.70/2	Unhealthy	1.80/2	Unhealthy

Table 3.a shows the calculated costs for different maintenance strategies for each segment of the track. The no action option has a cost of zero Euros with the consequences that are listed in Tables 2.a and 2.b. The rail renewal cost and grinding cost per m are 100 Euros and three Euros, respectively. The cost for one rail replacement of six metres is 5000 Euros. Complete renewal is not a realistic strategy because squats are located everywhere, so this cost is shown in Table 3.a just as a higher bound of the maintenance costs. The disadvantage of cyclic grinding is that severe squats are not removed, and grinding healthy pieces of track is not efficient in the long-term. A conditioned-based maintenance strategy can substantially reduce all of these costs in terms of performance. This result is obtained because the relative importance of different defects is considered in this type of maintenance, and a mixed strategy that combines grinding and replacement can be performed locally without grinding tracks that are healthy and replacing tracks when necessary. Table 3.a shows an estimation of sporadic rail replacement costs, considering replacing pieces of tracks where squats B and C were detected, for left and right tracks.

To further exploit ABA system information, a condition-based methodology can be used to evaluate the best alternative for squat maintenance. Corrective grinding, unlike cyclic grinding, enables infrastructure managers to reduce maintenance costs and resources. Given the large number of A squats in the early stages of squat development, fuzzy c-mean clustering is used to group squats to facilitate the grinding operation. The clustering method groups squats that are sufficiently close to each other into the same cluster but groups squats that are sufficiently separated from each other into different clusters. Details on fuzzy C-means can be found in Babuška (1998). In this paper, we use the squats with at least 75% of membership degree to a given cluster. Those squats define the kilometres of track with a high number of defects near to each other; thus, good candidates kilometers to be grinded.

Table 3.b shows the number of A squats for corrective grinding for different numbers of clusters and the positions of the cluster centre. The estimated costs of this strategy are included in the last column of Table 3.a. The negative position values in Table 3.b are related to the travel direction: for track B of Groningen-Assen, the starting

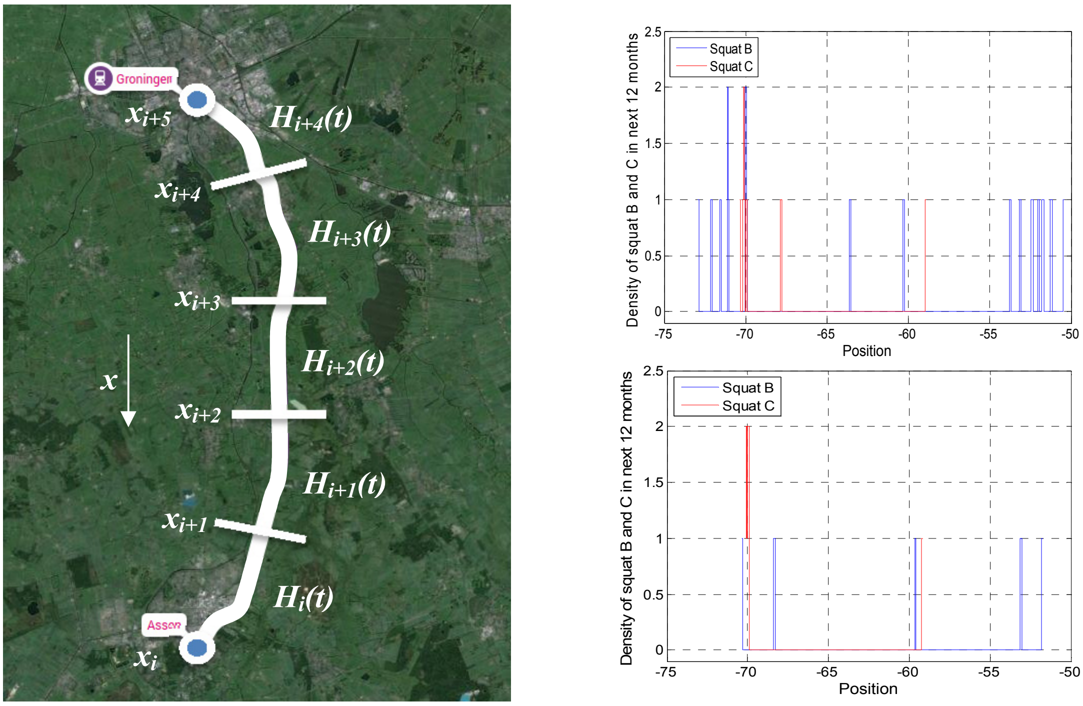
location is in Groningen and the remaining locations have negative position values. The developed model shows that the densities of the B and C squats should be considered to determine if the track should be replaced. The highlighted zones in Figure 4.b for the entire track (the left and right rails) correspond to the locations that should be replaced over the next 12 months. The relative importance of the indicators is considered in the developed model to determine the most inexpensive decision that combines sporadic rail replacement and grinding.

TABLE 3.a: Maintenance costs of different decisions

	Cost do nothing decision (1000 euro)	Complete rail renewal decision (1000 euro)	Full cyclic grinding decision (1000 euro)	Sporadic rail replacement, left rail (1000 euro)	Sporadic rail replacement, right rail (1000 euro)	Corrective grinding (1000 euro)
Partition 1	0	500000	15.0	423.33	128.78	4.04
Partition 2	0	500000	15.0	55.22	110.45	2.12
Partition 3	0	500000	15.0	202.41	55.22	2.60
Partition 4	0	500000	15.0	73.63	36.73	1.65
Partition 5	0	251709.2	7.56	533.61	331.28	1.80

TABLE 3.b: Three different fuzzy partitions for corrective grinding, t=0

No. of clusters	Centers of clusters (km)	No. of treated squat A	Grinded interval (km)	No. of squat A (not treated)	Intervals not grinded using fuzzy clustering (km)
2	-52.4499	37	-53.6510 to -50.1950	18	-61.3789 to -57.7783 -72.5170 to -70.8834
	-66.7307	17	-70.8835 to -62.6731		
3	-51.7411	37	-53.6510 to -50.1950	11	-67.1838 to -63.6713 -58.3440 to -57.7783
	-60.9880	12	-63.1587to -58.7025		
	-70.4759	12	-72.5171 to -67.9765		
4	-51.6954	37	-53.6510 to -50.1950	2	-67.9764 to -67.1838
	-59.2416	13	-61.3789 to -57.7783		
	-63.8745	9	-64.9760 to -62.6731		
	-70.8966	11	-72.5171 to -68.9199		
5	-51.6919	34	-53.1677 to -50.1950	4	-62.6730 to -60.6123 -53.6510 to -53.5224
	-59.1877	12	-60.6123 to -57.7783		
	-63.5923	9	-64.9760 to -62.6731		
	-68.0267	3	-68.9199 to -67.1838		
	-71.3246	10	-72.5471 to -69.9791		



(a) (b)

FIGURE 4: (a) Schematic of track partitioning between two stations, Groningen and Assen, (*i* is the counter for different partitions), (b) Decision zones for track replacement for the left rail and the right rail

CONCLUSION

In this study, we develop a methodology for modelling the squat maintenance process in railway infrastructure. This methodology is used to formulate a fuzzy-based methodology for making maintenance decisions. Six indicators based on the prediction of squat evolution are defined. These maintenance indicators can enable an infrastructure manager to easily manipulate information on squats. For squats that are detected at an early stage of growth (A squats), corrective grinding can be planned over cluster of squats. For dangerous squats on a track, an accurate estimate of the positions for rail replacement can enable the problem to be resolved, thereby averting dangerous consequences, such as rail breakage and derailment. In future studies, we will develop a multi-objective optimisation framework to analytically reduce life cycle costs and develop key performance indicators for different partners (the infrastructure manager, the operator and the contractor).

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