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APPLICATION OF A BOTTOM-UP APPROACH FOR THE ANALYSIS OF ROLLING CONTACT FATIGUE ON THE DUTCH HIGH SPEED TRACK

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ABSTRACT

This paper describes the use of big data analytics for understanding the Rolling Contact Fatigue (RCF) phenomena at the High Speed Line (HSL Zuid) in The Netherlands. The authors developed a data model to investigate the impacting parameters in train-track interaction. This has been done to gain more insight about the circumstances under which RCF occurs and to conclude why some track sections are severely affected and others not.

To evaluate the worst affected areas by RCF, the methodology proposes a bottom-up approach. By focusing on the worst affected sections with RCF, a set of characteristic parameter values are defined to describe different types of hotspots. Then, a comparison between the hotspots is performed. The methodology has been applied using real-life data of the Dutch High-speed line, where certain sections had been heavily affected by RCF. Findings concluded that slow running traffic through curves on a high-speed line is likely to contribute to the appearance of RCF.

INTRODUCTION

Data analytics are a common way to study relationships between one or more data parameters. In the case of rail infra managers, data analytics can be used to gain insight about the connections between all sort of different train-track parameters in order to understand much better the infrastructure and to support decision making. In this paper, data analytics is used to study the cause of Rolling Contact Fatigue (RCF) at the Dutch High-Speed track (HSL-Zuid).

RCF is an issue affecting the integrity of the rails. It is the result of the stress cycle between wheels rolling over the rails (Dollevoet, 2010). This stress cycle eventually leads to material fatigue in the rails which can result into various types of defects. Squats, head checks and various forms of corrugations are typical examples of defects, all of them with different complex initiation and growth mechanisms. These defects affect the integrity of the rails, hereby also affecting the track availability and safety. Therefore it is valuable to know if some train-track parameters are more recurrent in rail sections affected by RCF, to be able to address their cause and improve the overall railway infrastructure performance.

The HSL-Zuid has been used in (Schalk, 2016) to test two approaches to study the causes of RCF. The approaches are ‘bottom-up-’ and ‘top-down approach’, which can be used separately or together to study the cause of RCF. In this paper, the bottom-up approach is further described and the results from its application at HSL-Zuid are discussed.

HSL-ZUID

The HSL-Zuid is the only high-speed track in The Netherlands. The construction of the HSL-Zuid was intended to connect the Netherlands with the European high-speed rail network, establishing a high-speed connection between Schiphol Amsterdam Airport, Rotterdam, Breda and Belgium. Its construction started in 2001 and was finished in 2006, the track was opened for commercial traffic in 2009.

The HSL-Zuid consists of two main sections: the North Track running from Hoofddorp to Rotterdam and the South Track running from Barendrecht to the Belgian border with turnouts halfway from- and to Breda. At Hoofddorp, Rotterdam and Breda the HSL-Zuid connects to the Dutch conventional track. Both sections consist of about 45km, double track.

The HSL-Zuid has been designed for speeds of up to 300km/h, the curves at the maximum speed sections have been designed for a speed range of 220-300km/h. The track is constructed in Rheda2000 slab track with transition zones to Ballast 160 and Ballast 300 (Belgian Border). Among these transition zones also voltage locks are installed whereas among the HSL-Zuid 25kV AC is the electrification. The regular Dutch tracks are powered by 1500kV DC. The 60E1 rail profile has been installed with 60E2 among the high rails throughout the curves, which has been chosen with an anti-headcheck profile. These profiles have either a regular 260 rail grade or a 350HT rail grade (curves). Several special assets have also been constructed like tunnels, viaducts, a bridge, among others.

The HSL-Zuid has been designed for high-speed traffic. Two types of rolling stock were intended to use the tracks commercially. The first was a Thalys PBKA/PBA with a maximum speed of 300km/h and second the Fyra V250 by AnsaldoBreda with a maximum speed of 250km/h. However, the second type was initially delayed and temporary replaced by Bombardier TRAXX locomotives with conventional ICR carriages with a maximum speed of 160km/h. But, when the Fyra was finally scheduled after a long period of delays in December 2012, it was again cancelled in January 2013 due to technical difficulties. This caused the TRAXX to be used since then. The Thalys has two locs, one in the front and one in the back, each having four powered axles. The TRAXX was up to 2015 using a single pulling loc and since 2015 used a so-called sandwich configuration. The TRAXX has between 2009 and 2016 been scheduled more frequently than the Thalys, 33 times against 14 times a day (each direction). However, both trains are not using the same track sections, the TRAXX is scheduled domestically, between Breda and Amsterdam Schiphol Airport, whereas the Thalys is scheduled internationally, between the Belgian Border and Amsterdam Schiphol Airport.

ROLLING CONTACT FATIGUE AT THE HSL-ZUID

In November 2014, during a visual inspection along the tracks of the HSL-Zuid, unexpected severe damages were found. These unexpected damages were not detected during the regular measuring campaigns. The regular measurements included eddy current, gauge corner and ultrasonic measurements, also visual and video inspections have been deployed. Following these findings the whole track was inspected. This procedure resulted in the finding of five other major affected areas, so-called hotspots.

Fig. 1 (a) and Fig 1 (b) show examples of the damage among one of these hotspots typically in the transition zone to ballasted sections.

(a) (b)

Fig. 1 (a) RCF damage at one of the hotspots at Hoofddorp, in a ballast track transition zone. (b) close up at the same hotspot, damage is located at the rail head.

Characteristic to the RCF found at the HSL-Zuid is their location on top of the rail head. Therefore, a new measurement method was introduced: the Sperry eddy current walking stick. Using this new tool the whole track was measured between July and October 2015. Using the walking stick the cracks were measured. An examined piece of rail with the damage is shown in Fig. 2 (a). Fig 2 (b) shows the mismatch between the original measuring campaign for the smallest cracks by eddy current. Eddy current measures cracks up to 5.00 mm of depth.

(a) (b)

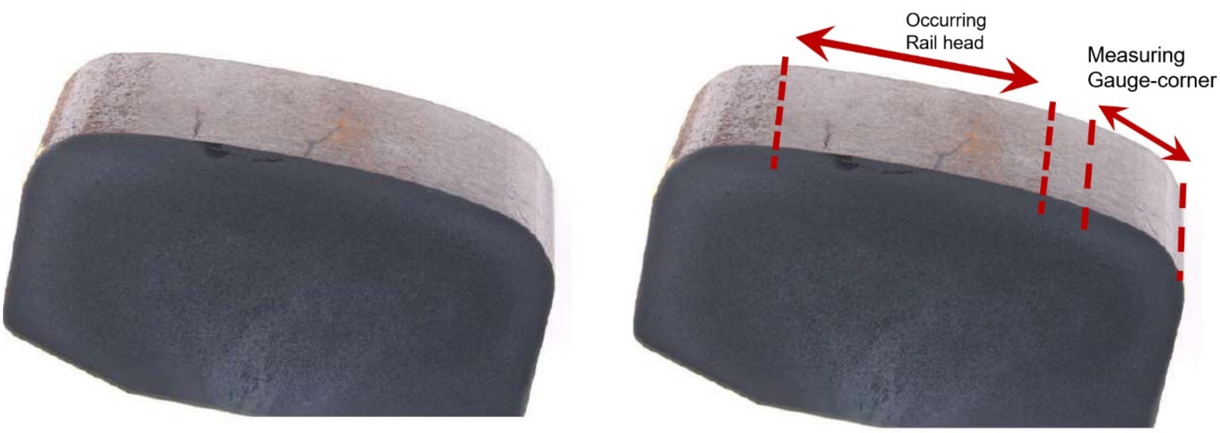


Fig. 2 (a) Examined rail with damage on top of rail. (b) Same rail showing the mismatch in the measuring campaign.

The damages found occurred in hotspots ranging in lengths from 700m up to 5km. Material investigation showed the rails were according specifications and free of irregularities. The damages show most similarities with ‘studs’ or ‘spalling defects’, they don’t meet the ‘lung-shape’ and the depression among the surface of squats. They show similarities with the studs described in (S.L. Grassie, 2012), (S.L. Grassie, 2015) and (Stuart L Grassie, Fletcher, Hernandez, & Summers, 2011) in particular: the occurrence on top of the rail and growing across the rail towards the field side. Also striking is the occurrence of the damages only in the open areas and occurrence in only heat treated rail sections among the HSL-Zuid. Also, the RCF at the HSL-Zuid occurred only after 17MGT at the least loaded sections and 30MGT at the most loaded. Other observations indicate that the defects might somehow be related to squats/spalling defects. As much further research is required for the proper classification of the defects, in this study the defects are called RCF for the sake of generality.

METHODOLOGY

Parameters

In order to find the causes for the RCF at the HSL-Zuid an approach called the ‘bottom up’ (B-U) approach has been developed. It relies on the use of eddy current measurements, design data in reports, alignment data, maintenance data and rolling stock data. Thus, an important number for the variety of the sources. In this approach the rail condition, whether its affected by RCF or not- and in what extend, was approached by the interaction of track, rolling stock and maintenance parameters (Fig. 1).

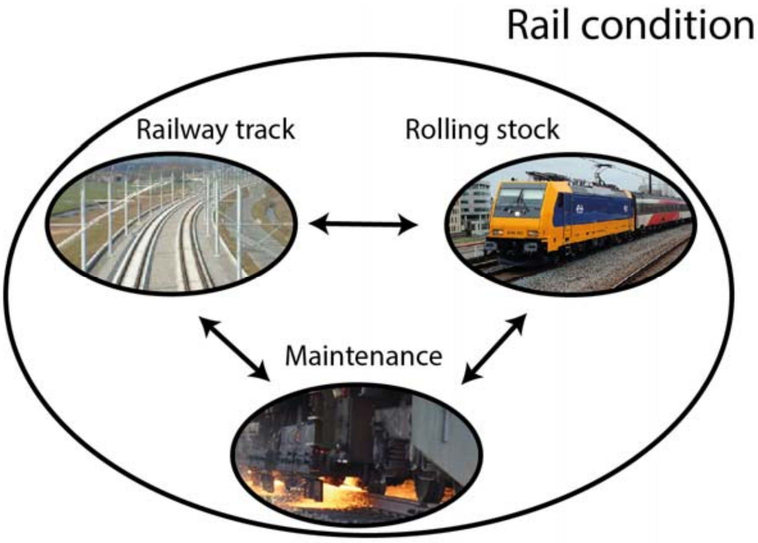


Fig. 1 Visual representation of the rail condition approached as the interaction between groups of track-, rolling stock- and maintenance parameters.

Using this approach the following parameters with their respective variables have been used, which are shown in Table 1.

Table 1 Overview of the parameters used and their variables

Category	Track	Rolling stock	Maintenance	Damage
Parameter	Superstructure (type)	Speed (km/h)	Grinding type (type)	Damage depth (mm)
	Rail grade (type)	Traction (% of max)	Grinding depth (mm)	
	Rail profile (type)	Tonnage cumulative (MGT)	Grinding date (d/m/y)	
	Assets (type)	Tonnage per vehicle (MGT)		
	Design speed (km/h)	Cant deficiency (mm)		
	Curve radius (m)			
	Curve cant (mm)			
	Height difference (m)			

The parameters have been chosen according the possible influence they can have on the appearance of RCF. No direct data from the trains regarding forces on the track nor wheel maintenance was available for this study. Regarding the rolling stock, for both types of train the average tractive effort per axle and the average speed profiles were available.

Intensity

To study the condition of the rail, a new parameter was introduced to represent both the depth of the defects and the amount of defects in a track partition. This has been done using eddy current measurements. The introduced parameter has been named ‘intensity’ and functions as a KPI for rail condition. Regarding railway operations KPI’s govern the way maintenance operations are governed KPI’s in railways have been reported in (Åhrén & Parida, 2009), (Parida & Chattopadhyay, 2007), (Stenström, Parida, Lundberg, & Kumar, 2015) and (Stenström, Norrbin, Parida, & Kumar, 2016).

Connecting measurements with a KPI, using ABA, defining robust and predictive KPI’s which consider the stochasticities of the defects and predicting over maintenance time horizons has been reported in (Jamshidi, Núñez, Li & Dollevoet, 2015), (Jamshidi et al., 2016) and (Jamshidi, Núñez, Dollevoet & Li, 2017). For this study, only one round of eddy current measurements was available. The intensity has been calculated for each leg separately. Threshold values have been introduced for each mm of depth. Cracks smaller than 0,1 have been filtered out due to the accuracy of the measurements. For the calculation of intensity at a track partition the following formula has been introduced:

$$I_X(t) = \sum_{c=1}^{5} \lambda_c * n_{c,X}\,(t)$$

where I_X is the intensity at rail partition X, X is the interval position; km x to x+500m, t is the time of measurement, c is the category, λ_c is the category coefficient, and $n_{c,X}(t)$ is the number of defects in category c at partition X at time t.

Partitioning

With the introduction of the intensity parameter the track can be modelled dividing it in a number of partitions. Each of these partitions will be characterized by its respective parameter values. The smaller the partitions the more accurate the results. The bigger the partitions, the more aggregate the results will be. The partitioning is proposed to be done for each leg separately in order to evaluate the respective values throughout curves. The partitioning process ca be visualized in Fig. 2.

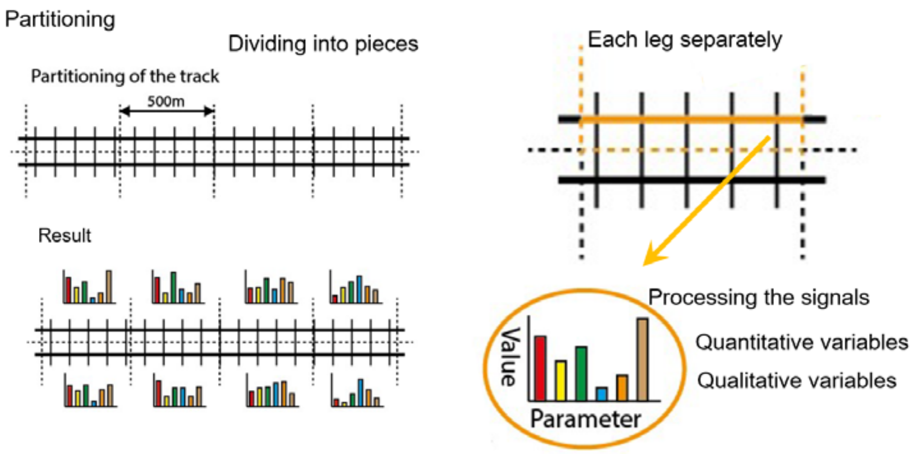


Fig. 2 Visualization of the partitioning process

Processing parameters

Using the modelled track divided in partitions and with the introduction of the intensity parameter, the identification of the hotspots is the next step. The aim of this approach is to find influencing parameters regarding the rail condition (intensity). The hotspots can be identified as the partitions with the highest intensity values, given a threshold value. In order to increase the veracity of the big data processing, it is recommended to also have visual evidence of an inspection to support the measurements, to guarantee the noise and false positive detection are reduced.

As both quantitative and qualitative variables are being processed these signals should be treated differently. For the qualitative variables a 'mixed' variable has been introduced for when a transition point is present among the partition. The method for partitioning is thus non-homogenous, where different signals regarding parameter values are to be found in a single partition. An example regarding rail grade is mathematically formulated as:

$$\delta_X^{rail}(k) = \begin{cases} 260 \; if \; \delta^{rail}(x,k) = 260 \; for \; all \; x \in X \\ 350HT \; if \; \delta^{rail}(x,k) = 350HT \; for \; all \; x \in X \\ mix \; if \; \delta^{rail}(x_1,k) = 260, \delta^{rail}(x_2,k) = 350HT, x_1 \neq x_2 \in X \end{cases}$$

where $\delta_X^{rail}(k)$ is the value of the parameter at moment of measurement k, X is the partition, k is the moment of the measurement, and x a location.

For the quantitative variables (speed, radius, cant, etc.), the non-homogenous partitioning results in different number of data points for the calculation of the average values of the different signals within the 500m partition. Quantitative variables are formulated as in the the example of the speed of the TRAXX as:

$$\delta_X^{VTRAXX}(k) = \frac{1}{N_X^{VTRAXX}(k)} \sum_{x \in X} \delta^{VTRAXX}(x,k), \qquad for \; \delta^{VTRAXX}(x,k) \neq null$$

where $\delta^{VTRAXX}(k)$ is the value of the parameter speed TRAXX at moment of measurement k, x is location, k the moment of measurement, X the partition, and $N_X(k)$ the number of signals within partition X at moment of measurement k.

Similarity

The next step of the process is to find similarities among the hotspots. The parameter values among the different hotspots are compared to each other. This in order to be able to pinpoint the parameters which should be investigated more closely. Another argument would also to be able to exclude a number of parameters as the cause for the damages at the hotspots. For quantitative variables we search for hotspots with the same values, and for quantitative variables a similar value.

The similarity function to describe how close is the value of one parameter at the two hotspots is:

$$V\left(\delta_{X_{h1}}(k), \delta_{X_{h2}}(k)\right) = \left\|\delta_{X_{h1}}(k) - \delta_{X_{h2}}(k)\right\|^2$$

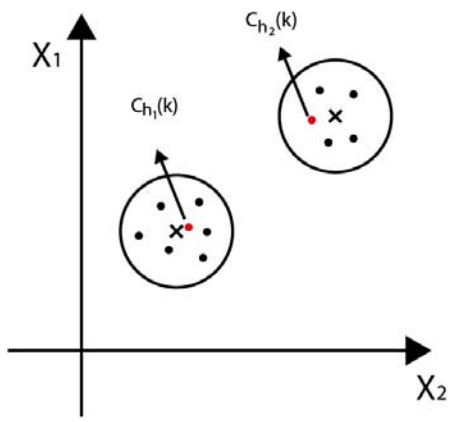
in which V is the similarity function, δ the parameter, X_h the partition of hotspot h, and k is the moment of measurement.

The condition for similarity will be described according a threshold ε_δ:

If: $V(\delta_{X_{h1}}(k), \delta_{X_{h2}}(k)) \leq \varepsilon_\delta$ we will say: $\delta_{X_{h1}}(k) \approx \delta_{X_{h2}}(k)$, thus similar.

Clustering
One of the possible outcomes is that not all the hotspots among a track are affected by the same cause for RCF. In order to distinguish possible influencing factors, clustering is introduced to group characteristic parameter values for each type of hotspot. Clustering is a measure of classification, more specifically 'unsupervised classification' which aims at discovering groups in data (Govaert, 2009).

Regarding the clusters, they are required to be homogenous and well separated (Hansen & Jaumard, 1997). The data for the clustering will be the set of parameters from the hotspots which have been found earlier. The clusters will consist of sets of characteristic similar parameters for a certain hotspot type according the formulas and Fig. 5:



$$\overline{C_{h_1}}(k) = \begin{bmatrix} \delta_{h_1}^{1} \\ . \\ . \\ . \\ \delta_{h_1}^{m} \end{bmatrix}$$

$$\overline{C_{h_2}}(k) = \begin{bmatrix} \delta_{h_2}^{1} \\ . \\ . \\ . \\ \delta_{h_2}^{m} \end{bmatrix}$$

Fig. 3 How the proposed clustering is set up according two types of hotspots.

$$C_i(k) \in C_{h_1} \text{if } \mathrm{V}(\overline{C_{h_1}}(k), C_i(k)) \leq \varepsilon_c$$

For example, when there are five hotspots evaluated, the output can for instance be that two characteristic hotspots types are found which divide the five hotspots, which can be described mathematically as:

$$C_{h_1} = \{C_2(k), C_3(k)\}$$

$$C_{h_2} = \{C_1(k), C_4(k), C_5(k)\}$$

where $C_{h_1}(k)$ is the selection of characteristic parameter values which are similar for a certain hotspot type h_1 at moment of measurement k. The hotspot types are thus described as a vector of a set of parameter values (center of clusters).

Hypothesis
The bottom-up approach results in a set of characteristic parameter values for each hotspot type. These values are linked (or not) to the RCF among these hotspots setting a hypothesis for each type of hotspot regarding the most likely cause of RCF.

However, this set of characteristic parameter values for each hotspot can also be used checking the hypothesis, testing it against the rest of the track to identify other areas which share the same characteristic parameter values.

A flow chart is introduced to help checking the set of characteristic parameter values, as shown in Fig. 4.

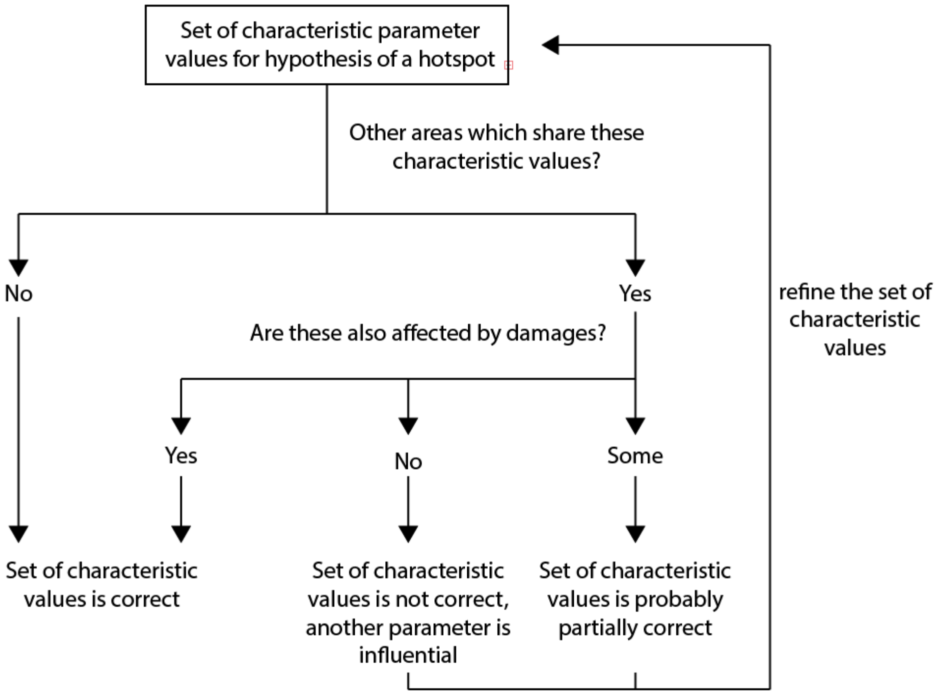


Fig. 4 Flow chart regarding the checking of the hypothesis for the hotspots

RESULTS

The application of the B-U approach resulted in some unexpected findings for the HSL-Zuid. Partitioning values of 500m have been used, resulting in over 700 partitions. Intensity has been introduced with two additional thresholds to identify hotspots, filtering cracks larger than 1.00mm and 3.00. Results from this application are shown in Fig. 7 (a) & (b).

(a) (b)

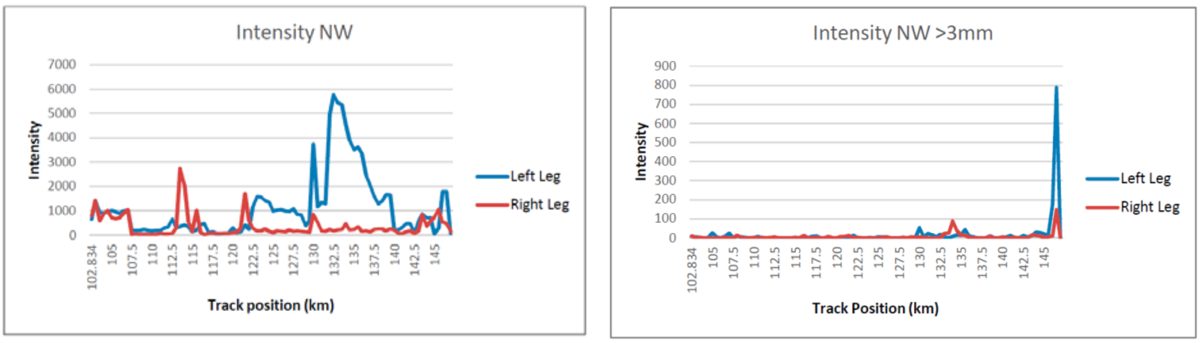


Fig. 7(a) Intensity of the North-West track for all cracks. (b) Intensity for cracks larger than 3.00mm, example of one single peak which is the hotspot near Hoofddorp.

Similarities among all the hotspots were that they occurred only among sections where the 350HT rail grade was installed – thus among curves. These curves had cant of at least 75mm. Dominant load by vehicles came from the TRAXX with the conventional ICR carriages. One of the hotspots occurs on a section where only the TRAXX is scheduled, near Breda. There are no hotspots at the tracks where only the Thalys is scheduled. Also, there are no hotspots among the tunnel sections.

Clustering resulted in the identification of two types of hotspots. Which can be best differentiated among their respective locations among the ‘open track’, where the design speed is at maximum and among the ‘entry zones’ where the trains enter the HSL-Zuid. The characteristic parameter values of these two hotspot types are presented in Table 2.

Table 2 Overview of the characteristic parameter values for both types of hotspots

Open track hotspots		**Entry zone Hotspots**	
Parameter	**Value**	**Parameter**	**Value**
Superstructure	Rheda 2000	Asset	Voltage lock
Rail grade	350HT	Superstructure	Ballast 160
Rail profile	60E2 upper leg	Rail grade	350HT
Design speed	300	Rail profile	60E2 upper leg
Average speed Thalys	300	Vertical curves	yes
Average speed TRAXX	160	Design speed	160 km/h
Cant excess TRAXX	>50	Cant Excess TRAXX	Theoretical canting ~0
Dominant load	TRAXX	Dominant load	TRAXX
Traction TRAXX	Yes	Traction TRAXX	No
Traction Thalys	Yes	Traction Thalys	No

The dynamic effects through curves are much different from the Thalys among both areas. At both areas the TRAXX drives below design speed, resulting in undesired effects through the curves. For instance, having different steering moments through the curves and other vertical loading on the rails. At the open track hotspots this results in large cant excess of up to 100mm. Whereas, at the entry zone hotspots this results in zero cant excess/deficiency. The latter, causing theoretically, the train having no leading leg through the curve, thus unpredictable dynamic effects. It is expected to see the differentiations between both hotspot types in which leg throughout is affected mostly in the open track hotspots. Among the open track hotspots, at all, the lower leg was affected by RCF and in 2 out of 4 only the lower leg was affected.

Regarding checking of the hypothesis, among the entry zones there were only the two initially identified hotspots. The other entry zones didn’t meet the same characteristic parameter values. One of the entry zones was at the Belgian border, where no TRAXX types are scheduled and it lies in the maximum speed area. The two other entry zones are located in tunnels, thus not meeting the criteria (and show no high intensity values).

Whereas for the open track characteristic parameter values. Additional thirteen partitions in curves were found which met the characteristic cant excess value of at least 50mm for the TRAXX. Two of these curves had a 260 rail grade installed, these showed no RCF. One of these curves was located along a voltage lock where both trains do not have any tractive efforts, these rails were also unaffected. For three curves, only the TRAXX is giving tractive efforts, these showed very small intensities. At two curves only the Thalys gives tractive efforts these showed very small intensities. Four out of the remaining five showed larger damage concentrations, here all the characteristic parameter values were met.

CONCLUSIONS

Regarding the application of this approach; processing big data in this way, is not so much 'big' in the sense of the volume of the data. The 700 processed partitions and their respective parameters required a refined approach to identify influencing factors. Initially the veracity of the data was a problem; the eddy current, video and ultrasonic equipment were not able to identify the cracks at the rails of the HSL. The variety of the data available is large, gps signals, photos, measurements etc., the bottom-up approach processes these so they can be combined to find causes. The velocity of the processing is dependent on the availability of new data; regular measurement campaigns provide new data, once the measurements have been processed. The visualization of the RCF problems was easy to interpret plotting the intensity along the partitions, this provided an effective application supporting maintenance.

The proposed KPI intensity could locate all the hotspots of RCF among the HSL-Zuid. Also, two types of hotpots have been identified using the methodology consisting of very different parameter values. For the HSL-South further study should focus on the rail grades and the wheel-rail interaction of both types of rolling stock through curves. Also, the introduction of more maintenance related-parameters can open new perspectives upon the appearance of RCF.

Proposed further application of data analytics is applying a top-down approach with regard to the intensity to be able to locate new hotspots. Proposed is using the intensity for statistical applications like correlation or regression analysis with regard to other parameters. Another consideration is the introduction of homogenous partitioning instead of non-homogenous partitioning using fixed partition lengths, this will reduce the number of samples but will remove the 'mixed values' which can provide more accurate results. Also, introducing more eddy current measurements is expected to give better results as growth rates among different partitions can be monitored and linked to possible causes of RCF and eventually improve the performance of the rails.

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