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Delft Center for Systems and Control  
Delft University of Technology  
Mekelweg 2, 2628 CD Delft  
The Netherlands  
phone: +31-15-278.51.19 (secretary)  
fax: +31-15-278.66.79  
URL: <http://www.dcsc.tudelft.nl>

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# Facilitating Maintenance Decisions on the Dutch Railways Using Big Data: The ABA Case Study

Alfredo Núñez, Jurjen Hendriks, Zili Li, Bart De Schutter, Rolf Dollevoet\*

**Abstract:** This paper discusses the applicability of Big Data techniques to facilitate maintenance decisions regarding railway tracks. Currently, in different countries, a huge amount of railway track condition-monitoring data is being collected from different sources. However, the data are not yet fully used because of the lack of suitable techniques to extract the relevant events and crucial historical information. Thus, valuable information is hidden behind a huge amount of terabytes from different sensors. In this paper, the conditions of the 5V's of Big Data (Volume, Velocity, Variety, Veracity and Value) in railway monitoring systems are discussed. Then, general methods that can be applied to facilitate the decision of efficient railway track maintenance are proposed for railway track condition monitoring. As a benchmark, axle box acceleration (ABA) measurements in the Dutch tracks are used, and generic reduction formulations to address new relevant information and handle failures are proposed.

**Keywords:** Big Data in Railway Engineering; Axle Box Acceleration Measurements; Railway Health Monitoring; Rolling Contact Fatigue.

## 1 Introduction

In recent years, rapid innovations in computer science have led to an increasing amount of available data. These data originate from many new sources that can be used in different sectors, including railway infrastructure. Contrary to the traditional data-collecting methods, where selected measurements are performed over specific assets, it is currently possible to collect a continuous load of information from many different sources for the entire railway infrastructure. Because of this increased amount of data, monitoring and maintaining railway tracks can be improved using almost real-time information about the track quality. To do so, there are several problems to overcome. There should be an efficient system to collect and store the data and more importantly, an efficient method to analyze the Big Data for decision making.

This requirement of new methods also holds for the Dutch railway network, which has the highest occupancy in the European Union. Track failures can lead to accumulative delays, that disturb railway traffic on many routes. Because of the high occupancy, scheduling maintenance work is a difficult task [1-7]. Track closures are planned in advance, but critical maintenance is sometimes required during operating hours, which causes huge delays for travelers. Thus, there is a high demand for efficient and reliable track maintenance methodologies based on frequent measurements of the track quality and quick analysis of the relevant historical information of the asset to determine the best maintenance action. To achieve this continuous data processing and high-quality decision making, the methods must handle a large amount of information about monitoring and maintenance of the track. Fixed-location-based monitoring solutions might provide a solution for some of the most fragile components

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\*Delft University of Technology, Delft, The Netherlands, email: {A.A.NunezVicencio, J.M.Hendriks, Z.Li, B.DeSchutter, R.P.B.J.Dollevoet}@Tudelft.nl

but cannot be used for the entire track because of the high costs. In this paper, a case study of a train-mounted monitoring solution is analyzed, involving ABA measurements, GPS, video/pictures of the track, and some open challenges for Big Data methodologies in railways are discussed.

## **2 Big data in railway condition monitoring**

### **2.1 Available systems**

Over the past decades, several systems have been introduced for railway condition monitoring, such as the ABA (axle box acceleration) system [8-13], measurements based on ultrasonic and eddy current for the detection of rail cracks [14] and video-based visual-inspection systems [15]. These systems are based on different techniques and methods of measuring.

The use of ABA in the Dutch railways to assess track condition was first tested in the 1980s [16]. Because of the lack of technology, the system could not cover the full network and detect notably high-frequency vibrations at that time. With the current use of the ABA system, track defects can be detected by analyzing their effect, which is transmitted to the axle when they are in contact with the wheels of the measuring train. In the literature, different ABA systems have been implemented [8-13], and their efficiency has been proven in detecting corrugation, welds, and other problems in the track. Railway infrastructure managers in different countries such as Poland, Italy, Japan, and South-Korea have used the technology in different settings. In the Netherlands, a system patented by Delft University of Technology [9] has been used for automatic detection of surface rail defects such as squats [10]. For current testing, the system is mounted on a hired measuring train, for which a slot on the track must be reserved. On the Dutch railways, with a usage of over 20.000 train km per track km per year, this requirement can be problematic. However, with the operating speeds of over 100 km/h at which the ABA system works, the system can potentially be installed on normal passenger trains to avoid reserving the track for measuring purposes. Further advantages of the ABA system are its low costs and easy maintenance.

Ultrasonic measurements use ultrasonic beams, which are sent into the rail [17]. By observing the reflection of the signals, the rail integrity can be analyzed. However, a big disadvantage of an ultrasonic system is that the reflections of shallow defects make it difficult to find severe cracks that are deeper in the track [18]. By combining ultrasonic measurement with an eddy-current system, which uses coils to induce eddy currents in the rail surface and measures the changes in these currents, the main disadvantage can partly be resolved, and a good overview of the track quality can be provided [14]. However, this system is limited to finding defects, that already developed cracks in the rail. Surface indentations, which can often lead to crack development, cannot be found using this measurement system. Moreover, when this system is used, the operating speeds are relatively low, which makes it expensive to obtain the measurements during normal operating hours.

Video imaging systems use cameras that are mounted below a train to take images of the track. This system has been proven to operate at speeds of up to 105 km/h [15], which is only slightly lower than the operational speed of the Dutch railroads. A problem with this system is the visibility of rail defects. Surface defects may be easily spotted, but deeper cracks, which are almost invisible at the track surface, are hardly noticeable with this system. Lastly, no available effective automatic algorithms can perform the complete visual inspection and assessment for the entire network. In the case of large cracks and insulated joints, they can be automatically found [15], but human analysis remains necessary for smaller defects, which is time-consuming and not effective.

Currently, all available railway-monitoring systems are implemented on a “run on demand” system, which implies that an integrated methodology to handle all information sources for the entire

system is not yet available. The measurements are implemented on separate trains and only sporadically provide data for locations. However, for good maintenance decisions, more detailed monitoring of the defect degradation is necessary, which requires a higher measurement frequency. Another problem with the current implementations is that all different systems are used separately from each other, and the huge amount of data from all sources are difficult for the technicians to process in an integrated method in order to draw conclusions.

## 2.2 5 V's for railway condition monitoring

Considering the available data for railway condition monitoring, particularly when an increased measurement frequency is suggested to optimize maintenance decisions, these datasets qualify as Big Data. Thus, the popular 5V's [19] for railway infrastructure are analyzed.

- **Volume:** Railway infrastructure is a distributed parameter system, which implies that the assessments should consider spatial and temporal dimensions. Monitoring the entire Dutch railway (more than 6500 km of tracks) with the ABA system only one time with different measurements provides a data volume of several terabytes. For example, when the system is implemented on commercial passenger trains to collect data all day, the data volume can exceed 100 terabyte a day because of the sampling speed of the required sensors (at least 25600 Hz for sampling and 16 sensors). A reduction/simplification of the specifications can compromise hit rates of defects and the quality of the high frequencies analysis.
- **Velocity:** With the requirement for early detection of problems and the desire to obtain good insight in the growth of defects, daily or weekly data acquisition is necessary. The main challenge with the current system is the processing time, which partly depends on human analysis of the data. Thus, the system update is currently a slow manual procedure. Moreover, when we collect data with an even higher frequency, this processing velocity is simply not feasible. Thus, computational intelligence is required to effectively process the available data, draw conclusions, and decide on the best maintenance action.
- **Variety:** In the railway infrastructure, different data-collecting systems are used, which leads into a wide variety of available data. In this paper, these data range from raw acceleration data of the wheels to images of the rail.
- **Veracity:** Different data sources have their own challenges when they are used to analyze railway track conditions. The results extracted from the ABA data can be different for the same defect in two runs, which depend on the wheel position on the track with respect to the defect. Although this problem is not present in the ultrasonic and eddy-current data, defects may go unnoticed because of reflections and other side effects of these techniques. For video imaging, only visible problems can be noticed. Deep cracks that do not penetrate the surface may be unobserved. Thus, the quality of each data source and the reliability of the conclusions drawn may differ.
- **Value:** Social aspects such as reduction of delays and the optimal track usage are the most evident benefits when the performance and availability of public transport services are improved. Collecting railway infrastructure data on a daily basis will provide valuable data to facilitate maintenance decisions and a valuable data source for further research on the causes and growth of rail defects.

In the next sections, the advantages and disadvantages of using big data for railway maintenance based on ABA measurements are discussed.

### **2.3 Curse of big data**

When one addresses Big Data problems, the difficulties lie in data capturing, storage, searching, sharing, analysis, and visualization. These difficulties also appear when one collects data from the different systems. The ABA system can theoretically be implemented on each train carriage in the Netherlands, which will result in over 100 terabyte of raw data per day. Although each carriage can collect and store the data of a single day's measurement, transferring this amount of data to a central location for processing will not be easy. When 100 terabytes of raw data are collected per day, storing the raw data for more than a few days will require large storage capacities. Considering the required processing for these data to draw conclusions, addressing all these data is clearly not yet feasible in this method. Online transferring can be an option, but trade-offs must be made to allow the collection, storage, processing, and analysis of the collected data.

### **2.4 Blessings of big data**

The financial benefits of using a train-mounted condition monitoring system based on big data on the Dutch railways are high. A case study in 2005-2008 showed that a cost reduction of 88% could be achieved on only grinding costs by actively monitoring the railway condition, which would be equal to an 80% reduction of the life cycle costs.

## **3 Case study for railway health monitoring**

Although the usage of big data shows a large potential in railway condition monitoring, it has not been generally deployed. New methodologies are required to make use of the full potential of these data. Hence, it is important to consider the potential of different implementations and a viable data-processing method.

### **3.1 What can be monitored**

With the currently used monitoring systems, different parts of the track can be monitored: from the quality of fixed parts such as insulated joints and welds to the development of surface defects (squats) and corrugation. The systems allow monitoring, and techniques have been developed for detection and decision making [10]. With the ABA system, over 85% of small squats and 100% larger squats are found (based on averaging data from 2 measurements). Current developments in the algorithms are expected to further increase these hit rates. Trials with the detection of corrugation from the ABA system used at Delft University of Technology have also shown good first results: they can detect severe corrugation on track and also less severe corrugation in some cases, which is consistent with the results from other studies.

### **3.2 How to set up the system in large scale**

To achieve a feasible system, it is important to distinguish which data can be collected at which rates. Currently, only the ABA system is completely ready for implementation on passenger trains and for daily measurements on track as the basis of the complete health-monitoring system.

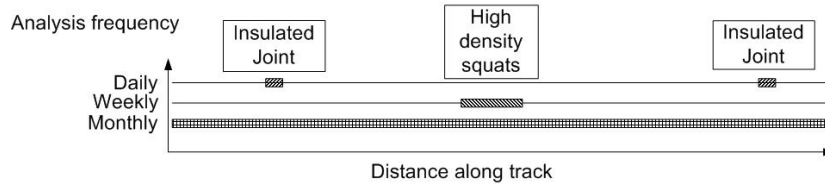


Figure 1: Data collection based on importance. Safety critical components are monitored with a high frequency, whereas slower processes are monitored with a slower frequency.

The possible amounts of data that can be generated using the ABA system when it is implemented on all available carriages are currently too large for processing as previously discussed and considering reasonable costs. Even when we invest in a huge amount of computing power, collecting and processing all data would require significant efforts. Therefore, to use the system in the near future, compromises must be made between the number of trains that contain the system and the measurement frequency over the defects.

Because of the characteristics of the measuring system and because the data processing gives the best results at speeds of approximately 100 km/h, the system can first be installed only on intercity trains. These trains have fewer stops and therefore provide more usable data for longer stretches of rail. The reason is the dependency on velocity of the signature tunes of defects from the ABA measurement. Some theoretical relations between ABA measurements and train speed have been obtained numerically [20], it is part of the further research to make the real system work under different speeds.

Furthermore, a minimum frequency can be established at which tracks should be measured. For surface defects on the rail, the defect degradation occurs on a timescale of months instead of days or hours. Thus, measuring a track once a day is sufficient for the current usage. For the main Dutch intercity lines the largest part of the tracks can be covered with approximately 10 trains per day. In addition, implementing the system on a single carriage per train should be sufficient for the data and reduce the data load to less than 1 terabyte a day.

In addition to the implementation of ABA measurements on a daily basis, any available data from ultrasonic and eddy-current measurements and video imaging should be collected. Later, data fusion and analysis from different sources can be done, keeping in mind that a good labeling for defects and also a good representation of the temporal dimension (date of the measurements) are considered for those different data sources.

### 3.3 General reduction method for Big Data processing in railways

Because degradation is a slow process for the largest part of the track, not all ABA data require direct processing every day. To further reduce the required processing power, intelligent processing can be used. Depending on the average number of trains that use a certain track, the processing interval for complete analysis can be adjusted. On average, monthly processing of each track can be sufficient. However, when certain locations prove to be problematic, more frequent analysis of these sections is required to obtain a better view of the degradation. This adjustment can be triggered using the train-positioning system (which is a combination of GPS and tacho data). With this strategy, the amount of data to be processed can be reduced by over 90%, but all important information remains collected. An example of the rate of data processing and analysis using this strategy can be found in Figure 1.

Insulated joints are safety critical components because they are the basis of the signaling system. If an insulated joint develops severe plastic deformation or the insulated material is damaged, they

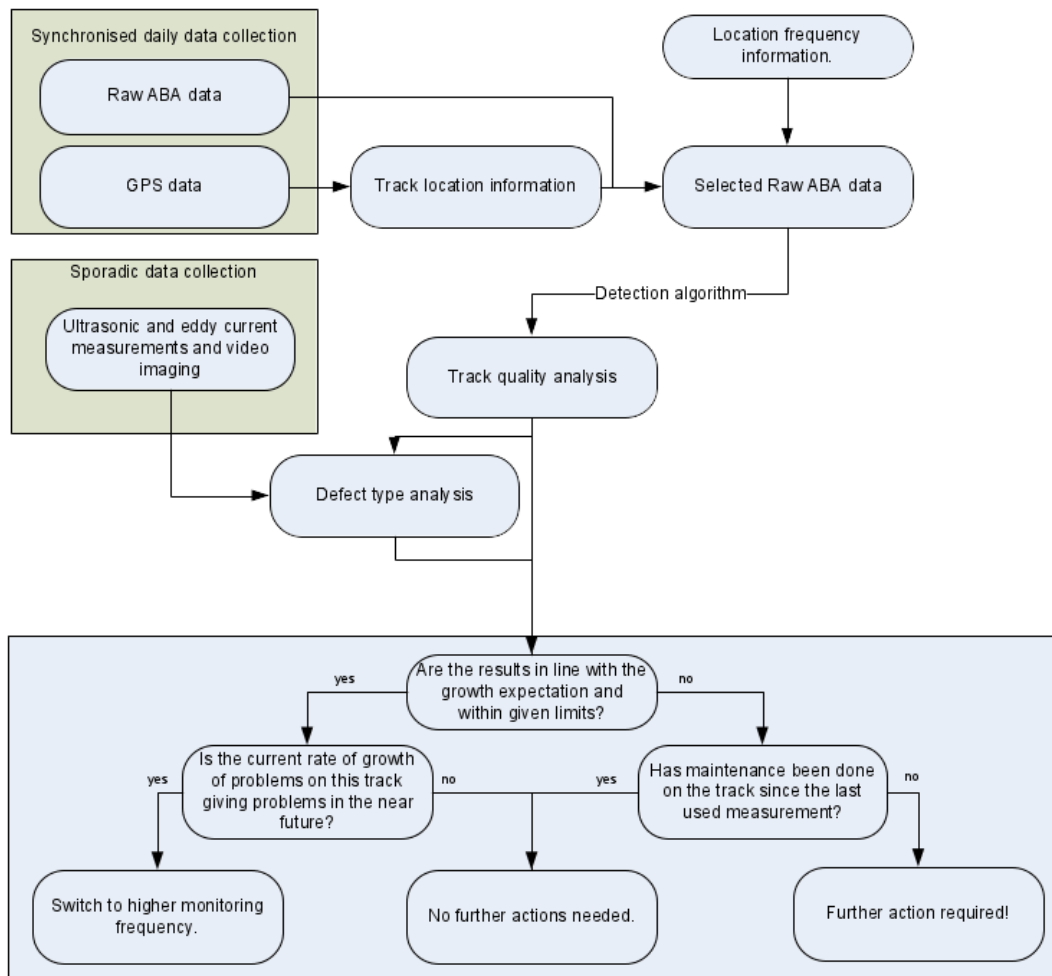


Figure 2: Diagram of the method to reduce/increase the monitoring frequency.

should be monitored daily to obtain real-time information about their performance and be able to take corrective measurements as soon as possible. For a high density of moderate squats, depending on the tonnage of the track, they may more rapidly evolve into severe squats. Thus, weekly monitoring of their condition can be a good solution. For the remainder of the track, only a monthly analysis is required.

The same method can be used to retrieve past data to analyze the track condition before a defect of a track component such as a switch. This reduction methodology is notably generic; the difficulty is to define the mechanisms that trigger the necessity of a higher or lower frequency of the analysis. Those mechanisms generally depend on the problems and the track.

Using this reduction method, the data are divided into many smaller sets. Then, by selecting different sections instead of processing the entire data sets, the system can easily be implemented either with parallel processing or on separate computers, which makes the data load feasible within the current processing limits.

The entire process to address these data can run without human intervention as shown in Figure 2. Only when the outcome shows that further action is required, human intervention is required to validate the results and to analyze which actions are advised to solve the problems in the track.

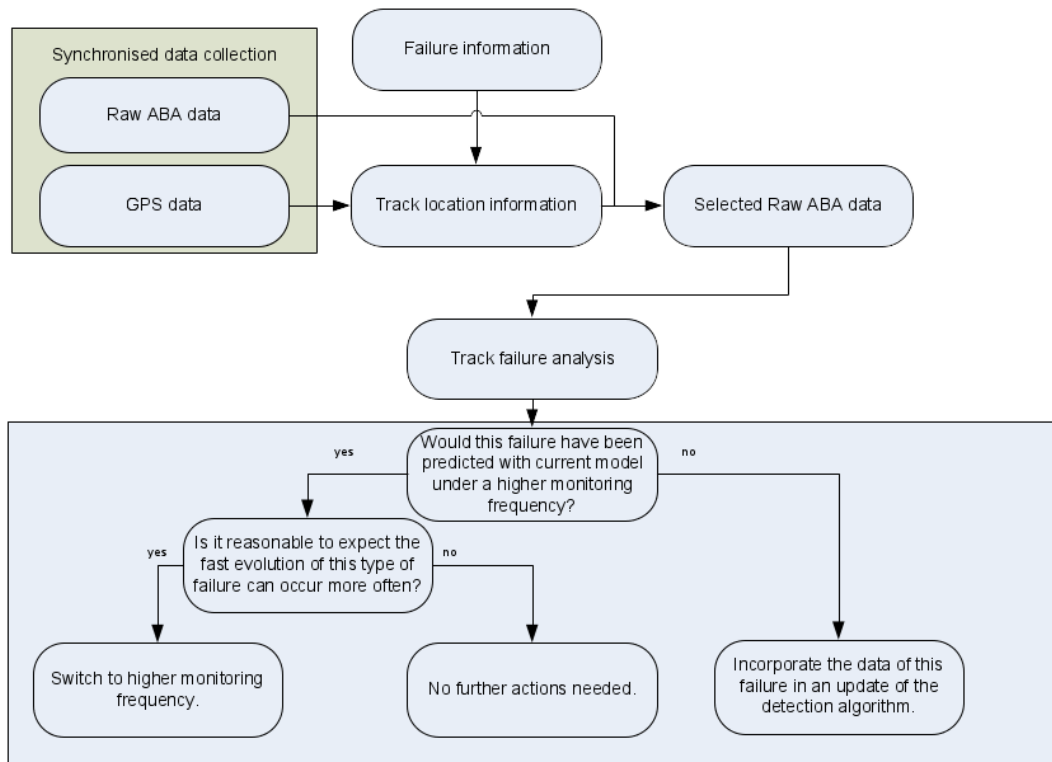


Figure 3: Diagram of the failure-handling procedure for Big Data in railways.

### 3.4 General failure handling procedure for Big Data in railways

For an unpredicted failure of a certain part of a track or unexpected fast growth of a defect, the information of these instances can be used to improve the model detection algorithms and growth predictions. The process that is followed in case of a failure is shown in Figure 3. Human intervention is required only when the data of the failure must be incorporated in the detection algorithm.

## 4 Examples with real data

Now an example of a dataset is considered to provide an overview of the method and an idea of the amount of data that must be processed. Because the system is not yet implemented to acquire data on a daily basis, a dataset is selected from one of the test runs of the ABA system. Images of the interesting locations are available but were acquired at a track visit instead of a measuring train. Ultrasonic and eddy-current data are not available for this location, and so they were not incorporated in this example. The chosen section is a 2 km track section of the track between Assen and Groningen in the Netherlands.

The energy values measured using the ABA system at this section are shown in Figure 4. As observed from Figure 4, there is a relatively constant noise band for all signals, and some clear energy peaks appear, which can be either single peaks or a group of closely spaced peaks. From this data, three details are taken as examples for the data processing.



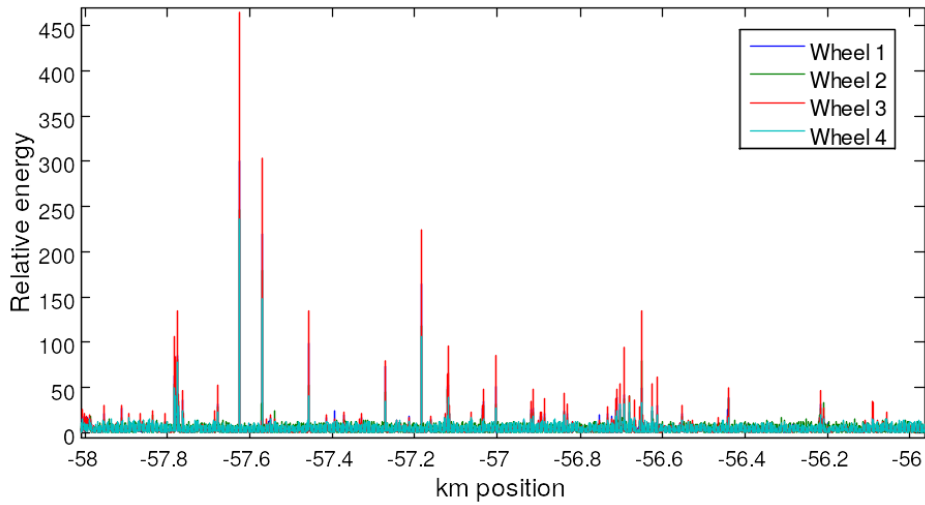


Figure 4: Processed data from 4 wheels using the ABA system in the vertical direction.

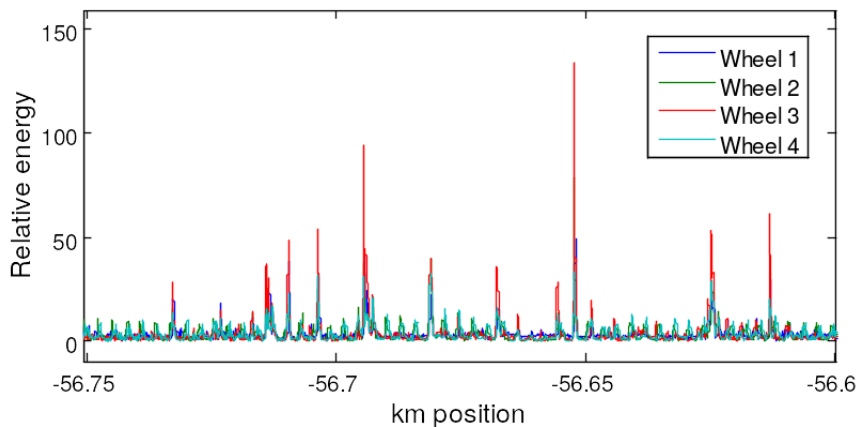


Figure 5: High density of events in a segment of track.

#### 4.1 Grouped peaks around km -56.650

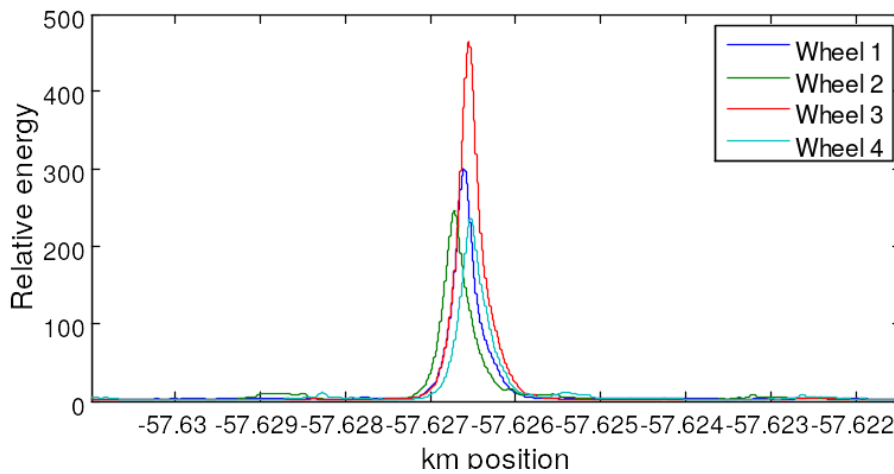
For this section around kilometer -56.650, a high density of trigger events was found in the data processing (Figure 5). Based on the density of these peaks (the number of nearby peaks), a trigger for a higher-frequency monitoring analysis on this track section can be activated.

#### 4.2 Isolated peak at km -57.627

The peak observed at kilometer position -57.627 is a clear example of an isolated peak (see Figure 6), which can be either a structure component or a local squat. Combining the ABA data with video data for this location (which was collected from a track visit in this case), this location is automatically classified as a squat. Now, we enter these data into the decision tree because the squat is larger than the currently used advised limit for maintenance, and no maintenance has been performed at this location in the last months; subsequently, this location will be outputted with the note: “Further action



(a) Picture of the defect



(b) Energy detected

Figure 6: A severe local defect.

required”. Then, human analysis can determine whether a replacement of this location on the track is required or grinding is sufficient.

### 4.3 Isolated peak at km -56.895

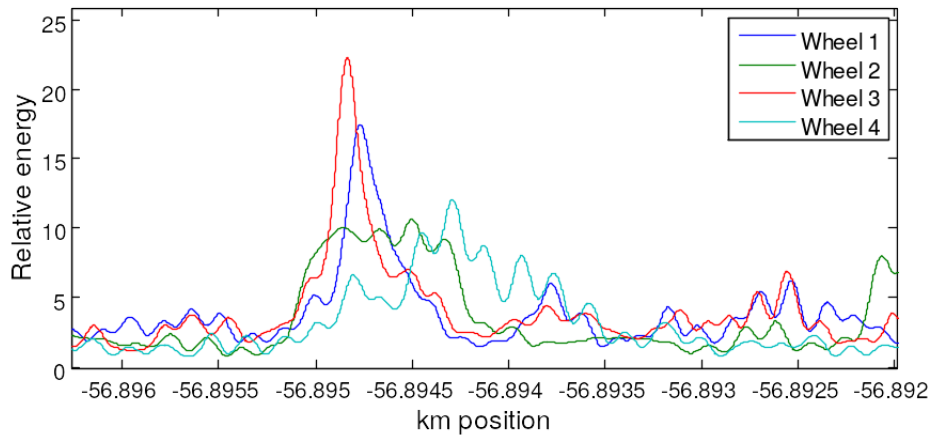
The peak at km -56.895 is relatively low; however because it triggers the ABA signal, it is entered into the data processing (Figure 7). With the available image for this location, it can be classified as a small visible defect. From previous records, nothing was found on this location, the growth is relatively slow, and the size is within the limits for maintenance. Although there has been growth, this rate of growth is not expected to make this location problematic within the next month. Therefore, no further actions are required at this location. The location will be stored in the database for comparison during the next data processing run.

### 4.4 Global results

For this entire section, the achieved processing results are as follows:



(a) Picture of the defect



(b) Energy detected

Figure 7: A small local defect.

- *Insulated joints:* A total of 3 insulated joints are located, for which the data are processed daily. Using the frequency-domain techniques and signal processing, it is possible to assess the degradation condition of those insulated joints to suggest preventive maintenance when necessary.
- *Severe defects:* From the detections, 8 defects that require further attention/maintenance were located.
- *Potential severe defects:* Three defects that can grow to a problematic size within the next few months were found. Subsequently, these defects will be processed weekly.
- *High-density sections:* One section is found with a high density of defects, which will be processed weekly.
- *Non-problematic defects:* Approximately 30 locations that show non-problematic surface defects on the track were found. For these locations, a monthly inspection is sufficient. Their data will be stored to make comparisons in the following month.

Because this track is not yet under constant inspection, the number of severe defects on this section is relatively high. The previous inspection on this track was approximately 1 year ago. Some of these defects are so severe that they require a replacement of a track section. When the new system of constant inspection is used, these defects would have been detected much earlier to enable more efficient maintenance.

## 5 Conclusions

There is a great potential for using Big Data to facilitate maintenance decisions on Dutch railways. First, the ABA system can be implemented on a selected number of passenger trains and combined with night data from separate runs of video imaging and other systems. This method results in the collection of approximately 1 terabyte of raw data per day for the ABA data. By using selective data processing, based on previous results and experience in the growth rate of defects, all parts of the track can be monitored with appropriate intervals while maintaining the processing load within feasible limits. By also incorporating the failure and maintenance information in the system, the system can be adaptive and self-learning. In addition to the significant reduction of maintenance costs, this system can prove to be highly valuable for research by providing unprecedented amounts of track degradation data. Further studies that include the analysis of computational intelligence methodologies [21] are considered.

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