Health Assessment of Railway Turnouts: A Case Study

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ABSTRACT

Within railway infrastructure, railway point systems are among the most critical equipment, not only due to accidents and delays caused by their failures but also due to maintenance costs. The detection of early signs of degradation and the ability to identify the maintenance actions required to prevent a failure are key aspects of a successful and advantageous health assessment strategy. While studies focusing on the detection and prognostics of railway point systems exist, few or none address the correlation between environment, field layout and the point system behavior. This paper aims to consider the interaction between these factors and the point system behavior, and compare a fleet-based approach to an asset-based approach for the point systems health assessment, highlighting the influence of the field configuration on the effectiveness of the two methods. The proposed methods exploit Self-Organizing Maps (SOMs) to construct a health indicator for both the detection and the diagnosis of railway point systems. The approaches are applied to a case study for the on-line health assessment of 20 electro-mechanical point systems operating on a main line over the course of 6 months. The results show how an asset-based monitoring system is necessary in order to maintain a level of information which enables to achieve an efficient detection of anomalies and a correct identification of degradation mechanisms. In addition, fleet-based health assessment leads to a higher percentage of missed alarms, due to the intrinsic hypothesis of considering all point systems as operating in the same context and mission profile.

1. INTRODUCTION

Railway point systems are devices which enable trains to be directed from one track to another, by mechanically moving a section of railroad track. They are composed of a motor which generates power, which is used in turn to move sections of track to the desired position.

Railway point systems are a crucial component of the railway infrastructure as their operation directly affects the service, safety and the maintenance cost. The failure of a point system strongly impacts the quality of the service, as it causes delays and can limit train circulation. For instance, the Network Rail annual report for 2014 indicates that the total delay of passenger trains amounts to 433,400 minutes a year due to point systems failures (Network Rail, 2014). However, the failure of a point system does not only impact the quality of the service, but it may sometimes also affect safety as it can cause the derailment of a train, such as in the 2002 Potters Barn accident in the UK, where 7 persons lost their lives (Tobias, Marquez and Roberts, 2010). In order to ensure a high quality of service and to minimize the risks involved, operators resort to stringent maintenance policies, which result in excessive costs: for example in the UK, point system maintenance resulted in 3.4 million GBP every year for 1000 km of rails (Marquez, Lewis, Tobias and Roberts, 2008). To reduce the frequency of inspections and the unnecessary maintenance tasks whilst ensuring a high dependability, the railway point systems would benefit from the development of a condition-based maintenance [CBM] system. CBM would allow to improve the availability of the point system, by preventing failures and therefore reducing the corrective maintenance actions which lead to down time, and to trigger specific maintenance action only when required, reducing the maintenance costs (Gupta & Lawsirirat, 2006).

The topic of proposing a health monitoring system for point systems has been often addressed in literature. Eker, Camci, Guclu, Yilboga, Sevkli, and Baskan (2010), propose a Simple State Based model and compare the results to a Hidden Markov Model approach to identify the health state of 10 turnouts, with very promising results. However, they note the difficulty in obtaining real-life data, and proceed to simulate a lack of lubrication over the course of 13 maneuvers for each of the turnouts. Marquez, Weston and Roberts (2007) apply a moving average filter on data from simulated faults in a laboratory setting on a single point system, and are able to detect faults. Asada, Roberts and Koseki (2013) propose a Support Vector Machine model to detect and diagnose misalignments on railway point systems, and the method is applied to a series of data collected from a single point system in a laboratory set up. Letot, Dersin, Pugnaloni, Dehombreux, Fleurquin, Douziech and La-Cascia (2015) propose a data-driven approach for the development of a degradation law for point systems, and tested the method on simulated degradations in a laboratory set-up of a single point system. While the study relied solely on experimental data, the method was able to obtain a satisfactory evaluation of the Remaining Useful Life of the component. Vileiniskis, Remenyte-Prescott and Rama, (2015) develop a support vector machine for classifying the behavior of several machines from on field application. Finally, McHutchon, Staszewski and Schmid (2005) define a signal processing method using wavelet transforms, statistical parameters and principal component analysis on a single point-system in a laboratory set-up, where faults were simulated.

While all methods proposed seem to produce results which are very promising and in line with the expectation to produce a health assessment of point machines, very few focus on real data from the field, acquired over a period of time, or from a series of different assets. This paper will focus on addressing the issue of monitoring not a single point system, but rather a fleet of 20 machines in a real field layout, with differences in the positioning in the field and the environment over the course of 6 months. The method proposed to assess the health of the point system consists of three steps: first, the data are processed in order to extract the relevant features from the acquired data, then Self-Organizing Maps (SOMs) are used to define a nominal and healthy state-space of data during the training and, finally, the health assessment of each new maneuver is done by the SOM. A comparison between a fleet-based approach and an asset-based approach on the SOM is proposed, to evaluate whether parameters such as environment and field positioning affect the behavior of the machines on an asset-level. The remaining part of the paper is structured as follows: Section 2 describes the railway point system operation and the details of the case study; Section 3 illustrates the methods proposed and the necessary pre-processing; Section 4 discusses and compares the application of the two approaches on the case study; Section 5 recalls the concluding remarks and results.

2. RAILWAY POINT SYSTEM

Railway point systems, also known as turnouts, consist of a device which generates the motion of the switch rails between two positions, allowing the train to travel in one of two directions. The switch rails can be moved laterally by a force generated within the point machine and passed onto the switch rails through the movement rods. The motor uses a clutch and gear mechanism to move the movement rods. Depending on the direction of rotation of the point machine motor, either the near or far switch rails close. The movement can be initiated remotely, and once the stroke is completed, the switch rails are locked into position and allow for a safe journey. The switch rails have two rest positions, designated as 'normal' ('N') and 'reverse' ('R'). Figure 1 illustrates a point system and its parts. Indeed, the point system is comprehensive not only of the point machine, but also of the rails and the rods. The point machine contains the electric motor, which transmits the power to the movement rods. These are connected to the switch rails and move them from one position to the other, while the stock rails remain still.

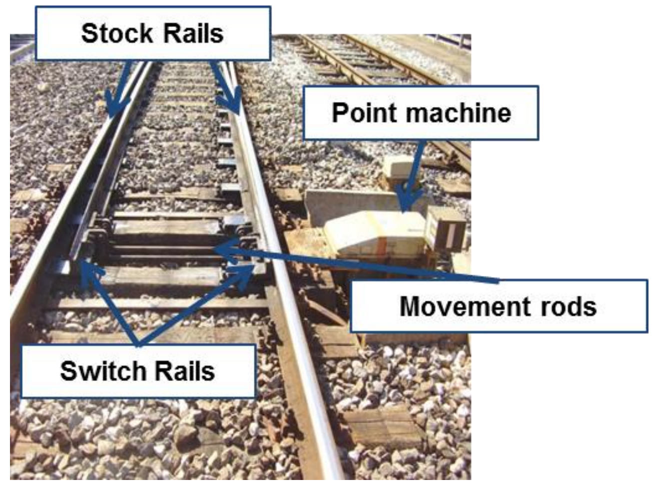

Figure 1: Illustration of a point system and its parts

There exist a variety of different machines depending on the working principle to transfer the electric motor power to the rods movement, such as hydraulic, electro-mechanic and pneumatic. This paper focuses on electro-mechanic point machines.

While the description of a point system can be limited to its component and functioning, fundamental aspects which are often overlooked are the environment, the field layout and the mission profile of the point system. The influence of the environment and context on the point system is due to factors such as temperature, saline air and climate, which can influence the behavior of any electro-mechanical component. The field layout refers to the position in the field of the point system, which can be influenced by a series of parameters, mainly the cant of the rails, the curvature of the track, and the position of the machine. These can be seen in Figure 2.

The direction of the movement influences the behavior of the machine as the efforts to push or pull the maneuver rods by the motor are not symmetric. The cant of the rails influences the maneuver as the movement uphill, and thus against gravity, involves different forces. The curvature of the track influences the effort necessary to bend the switch rail (the switch rail movement is done through the switch rail bending). All of these factors influence the behavior of the machine, and their effects on the values of the signals acquired is not easily identifiable.

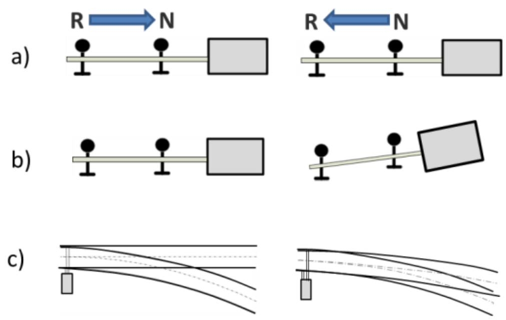

Figure 2: Visual representation of the differences on the direction of the maneuver (a), the cant of the rails (b) and the curvature of the track (c)

While the lack of correlation between these factors and the rate of degradation of the point system has been extensively studied by Zwanenburg (2006), the effects of these on the nominal behavior of the machine have not been accounted for. Most studies evaluate the behavior of a single machine, without thought of how to extend the solution to multiple point systems (Marquez et al., 2007; Asada et al., 2013; McHutchon et al., 2005; Letot et al., 2015). When more than one point system is available, most studies proceed with the analysis of the single point system without regarding these factors and assimilate the behavior of a single asset to that of the fleet (Eker et al., 2010). Of the reviewed studies, only one has noted that the single machine has singular properties and as a single asset not entirely representable by the fleet (Vileiniskis et al. 2015). In order to evaluate whether it should be necessary to take the environment and field positioning into account, two methods for the health assessment are proposed and compared: an asset-based approach and a fleet-based approach.

2.1. Case Study

The case presented involves a set of 20 point systems in an en-route station on a trafficked line in the Italian railway infrastructure, over the course of 6 months. The operation of these point systems is vital to the circulation of both passenger and freight trains, as it is one of the main arteries for north-south rail traffic. The failure of one of these point systems will cause the system to have to re-route several trains and delays will easily accumulate. For these reasons, maintenance inspections are carried out every month. The point systems considered in this work were installed between 7 and 10 years ago. The mission profiles of the point systems are very diverse: some point systems are operated up to 15 times a day whilst others merely once a day.

The data collected in this case study consist of the (direct) current and the voltage of the electric motor during a maneuver, as well as a series of contextual information, such as the direction of movement and the final position achieved. An example of the typical DC current and voltage acquired from a single point system during a maneuver can be seen in Figure 3.

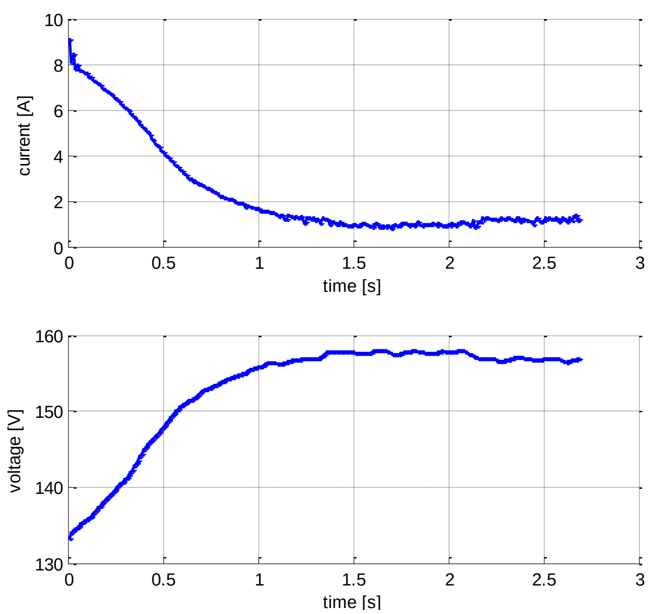

Figure 3: Typical acquisition signal from a point system with current (above) and voltage (below) of the maneuver

The point system maneuver consists of the unlocking of the switch rails, their movement into the correct position and the locking. The maneuver is controlled and completed entirely by the electric motor, therefore it is possible to consider that the signals acquired during each maneuver contains data which are highly informative about the behavior of the point system, and, consequently, its health state. The acquired signals from the point systems in degraded and nominal conditions are very similar in shape, form and values. In fact, they are so alike that it is necessary to resort to a method which involves the extraction of relevant features and a model, such as the one proposed, as a simple threshold on the signals would not serve its purpose.

Due to the frequent nature of maintenance inspections and actions on the field, the data of the case study contain very few failures. The failures and reported problems include the presence of an obstacle between the switch and stock rail, the shape of the switch rail changing over time and the loss of tolerance. The loss of tolerance refers to the event where the switch rail and stock rail do not perfectly adhere and there is a gap between the two: the point system in this case study is designed to tolerate a gap of 3 millimeters at most. The method will therefore try to assess whether a point system is deviating from the expected nominal behavior and if this could result in a loss of tolerance. Over the course of six months, we have reported once the presence of an obstacle in the field, and five machines have lost tolerance.

3. METHOD

In this Section, the methods proposed for comparison are described. The procedure for the extraction of relevant information from the data is presented in Section 3.1, the SOM concepts and the two different approaches are presented in Section 3.2, the procedure for the health assessment is presented in Section 3.3, and the criteria for the comparison of the two methods are discussed in Section 3.4.

3.1. Feature Extraction

In order to obtain the information which is significant for the health assessment from the data acquired from the point system, presented in Figure 3, a feature extraction procedure is necessary. Several features can be computed from the current and voltage signature of each maneuver: mean value, root mean square value, standard deviation, slope, maximum value and minimum value (Letot et al., 2015). These, coupled with information relative to the maneuver as a whole (e.g. duration of the maneuver, area under the current curve, total power consumed, etc.) make up 16 variables that characterize the maneuver as a whole. This reduces the data from a time-series to 16 features, thus diminishing the computational time as well as the storage space needed. This vector is representative of a maneuver, and therefore of the health state of the point system during that maneuver. The 16-dimensional vector, containing characterizing information of the maneuver, will now be referred to as the feature vector of the maneuver.

3.2. Self-Organizing Maps: Fleet-based approach and Asset-based approach

SOMs have first been introduced in Kohonen (1995), and are a type of Artificial Neural Network (ANN) which use a supervised training to identify a topological map which summarizes and clusters the various behaviors present in the training data. The map is made up of a series of units or neurons, where each neuron identifies a behavior and is associated to a vector of the same dimensionality as the original training data, known as weight vector. The neurons of the SOM are connected to each other through a relationship function, known as neighborhood function.

To construct a SOM map, the training consists of three steps:

1) A training vector from the training set is randomly selected;
2) The neuron with weight vector most similar to the selected training vector is identified, which becomes the Best Matching Unit (BMU);
3) The weight vector of the BMU and its neighbor neurons are updated to more closely resemble the training vector.

At the end of the training the data are now captured and described by the topology of the SOM, in a visually simple and easily comprehensible 2-dimensional representation. For more information on the theory of SOMs please refer to Kohonen (1995).

For this application, a set of 40 maneuvers for each point system is selected, based on expert knowledge, to represent the nominal and healthy behavior of each asset. Of these 40, half represent maneuvers in one direction and the other half belong to maneuvers in the opposite direction. This will be referred to as the training data. The remaining maneuvers from the 6-month period will be referred to as the testing data. The SOM will be trained using the feature-vector of these maneuvers, thus, the weight vectors of the neurons will be 16-dimensional as well.

The fleet-based approach relies on the assumption that, given the fact that all 20 point systems are of the same manufacturer, in the same station and of similar age, they can be assimilated to a uniform fleet: therefore, a single SOM for the whole fleet characterizes the fleet nominal behavior. In this approach, all the training data from the point systems are merged together to create a data set of 800 feature vectors, 40 feature vectors from each of the 20 point systems, which will be the fleet training data. The SOM resulting from the fleet training data will be made up of feature vectors from all the point systems in the field.

The asset-based approach relies on the assumption that the environment, field layout and positioning influence the behavior of the point system to an extent that, despite all the similarities in manufacturing, age and location, each point system must be treated as a single asset: therefore a dedicated SOM for each asset will be trained to characterize the nominal behavior of the specific asset in a specific direction. In this approach, the training data consisting of the 20 feature vectors for each point system for a given direction will be used singularly to train a unique SOM. Therefore, there will be 40 SOMs, each representing the nominal behavior of a single point system maneuver, in a given direction. The decision to train two different SOMs for each point system depending on the direction of maneuver reflects the ideas presented in Section 2.2 where the direction of the maneuver is hypothesized to influence the behavior. In order to assess the health of a maneuver, and to not confuse the effects of the direction with the effects of degradation, the asset-based approach is designed to render the assessment independent of the effects of the direction of maneuver.

3.3. Health Assessment

In order to assess the health of a point system which is being monitored, the feature vectors of the testing data will be used, and the health of each of these vectors will be assessed through the SOM model. New unknown data will be evaluated by the SOM without altering the structure of the neurons during the testing phase. Several types of information can be given as output by the SOM on this test vector, such as the cluster to which it most likely belongs, the error in association or the most similar original training data. One of the most common outputs is the Quantization Error (QE), which is the Euclidean distance between the new data being tested and the weight vector of the neuron which most closely resembles the new data, as shown in Eq. 1.

$$QE(y^{PS,test}) = \sqrt{\left(y_1^{PS,test} - w_1^{BMU}\right)^2 + \ldots + \left(y_{16}^{PS,test} - w_{16}^{BMU}\right)^2} \quad (1)$$

Where $y^{PS,test}$ is the feature vector y, belonging to the testing data of the point system PS, w^{BMU} is the weight vector of the BMU, and for both these vectors the pedicle indicates the component of the vector from 1 to 16. The QE represents the error in Euclidean distance of associating the testing data to the same cluster as the original SOM training data. High values indicate testing data which are very different from the original training data, whilst low values indicate similar behaviors. For this reason, a high value of QE will result in a point system which is degrading or behaving abnormally, whilst low values will indicate a point system which is operating consistently with our definition of healthy behavior.

For both approaches, the testing data from the point systems being monitored are given as input to the SOM model, and the QE for each data is obtained as output. In the fleet-based approach, the same SOM evaluates the testing data for all point systems, while for the asset-based approach the testing data will only be tested on the SOM trained with the same point system, in the direction of the testing data.

3.4. Comparison of Approaches

In order to evaluate the two different approaches, it is necessary to evaluate the health assessment made by each in similar situations. The best method will be the one which:

i) Identifies a variation in the health state of the point systems which are known to lose tolerance in the week preceding the failure, i.e., correctly identifies this failure;

ii) Identifies variation in the health state before the failure of the point system in the month preceding the loss of tolerance, i.e., correctly identifies precursor behaviors of this failure;

iii) Identifies the presence of an obstacle in the field;

iv) Identifies a steady, non-variant health for the point systems which do not fail.

These four parameters will be evaluated for each method, and each will be assigned a score on the basis of the fraction of correctly identified instances. The evaluation is done through a visual inspection of the QE obtained from each approach. For example, as we have 5 machines which have lost tolerance, for the first two parameters the score will be the number of machines correctly identified out of 5. The best method will be the one which has higher total score for all the parameters.

4. APPLICATION AND RESULTS

To evaluate the outcome of the health assessment for both approaches, we will first assess the outcome on machines which lost tolerance, then on the machine which had an obstacle, and finally, on the healthy machines.

For ease of illustration, the results of the two approaches on the machines which lost tolerance are compared in Figure 4, where the failure event is marked with a vertical red line.

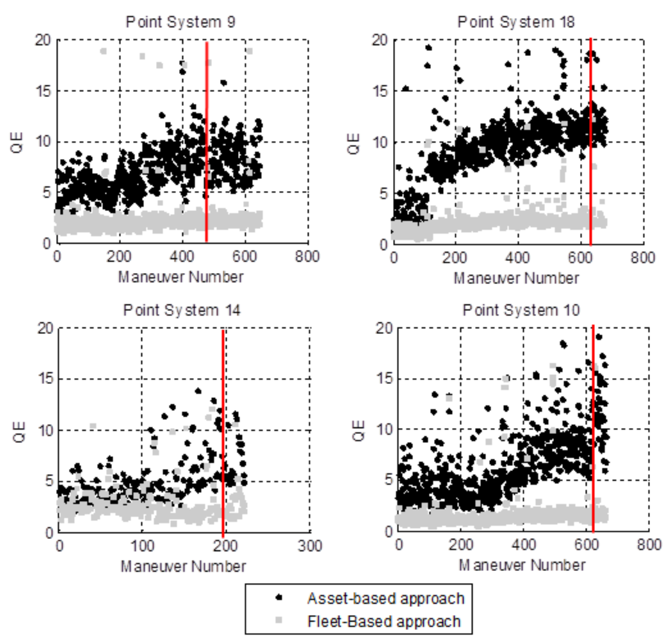

Figure 4: Result of asset-based approach (in black circles) and fleet-based approach (in grey squares) on four point systems which failed at different times, with the failure marked by a red vertical line

In Figure 4, it is evident that the health assessment done by the asset-based approach highlights the ongoing degradation in the point system beforehand. In all four cases, the QE from the asset-based approach increases about 2 months before the event. In comparison, the fleet-based approach evaluated a QE which is remarkably stable, with a single indication of a slight change in point system 18, as shown in Figure 4 top right corner. The QE from the fleet-based does detect a slight shift in behavior, but it does not appear to substantially increase over time. Additionally, for point system 14, bottom left corner of Figure 4, the fleet-based QE seems to decrease over time, indicating that the health of the system is improving, which is a severe error. The QE for the fifth and final point system which failed increases for the asset-based approach whilst remaining constant for the fleet-based.

Overall, the asset-based approach was able to identify all five failures out of five, and it was able to detect this change beforehand for all five. On the other hand, the fleet-based approach was able to merely detect the failure and the shift for one machine out of five. This result indicates that the assumption that all point systems have the same behavior leads to some gross overestimations of their health. When looking at the whole fleet, the effects of the environment and field positioning on the behavior of a point system may be very similar to the effects of a failure mechanism on a different point system.

An obstacle between the switch and stock rail occurred on point system 10, on maneuver 257, visible in Figure 5 .

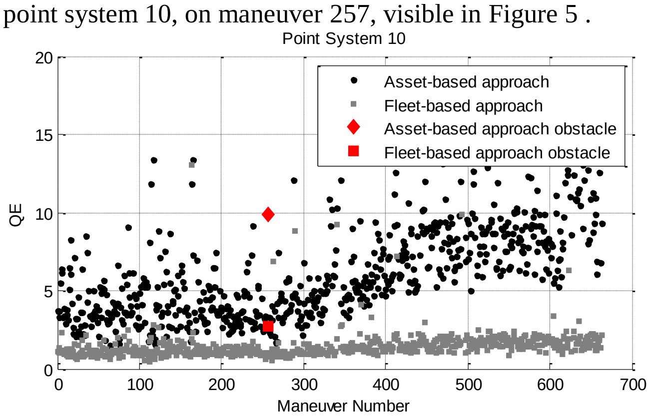

Figure 5: Result of asset-based and fleet-based approaches on the point system which encountered an obstacle, the obstacle maneuver is marked in red

For both the fleet-based and asset-based approach in Figure 5, the maneuver which encountered an obstacle has a much higher QE value than the maneuvers just before and just after. Unfortunately, many other maneuvers have high QEs with respect to the near-by measurements. This indicates that the QE alone is not sufficient to isolate the presence of an obstacle in the field, but it does reveal itself as a maneuver with abnormal behavior. Both approaches fail this identification.

With regards to the other 15 machines which do not result in any failure on-field, a specimen of four cases has been selected for show, in Figure 6.

For most cases, such as the top row of Figure **6**, the results from both approaches on non-faulty point systems yielded the same results, with no significant variation in trend. For two cases, one of which is point system 18 in the bottom left corner of Figure 6, the results were identical for the two approaches even if incorrect: the point system QE resulted with an increasing trend, signifying a change and an anomaly.

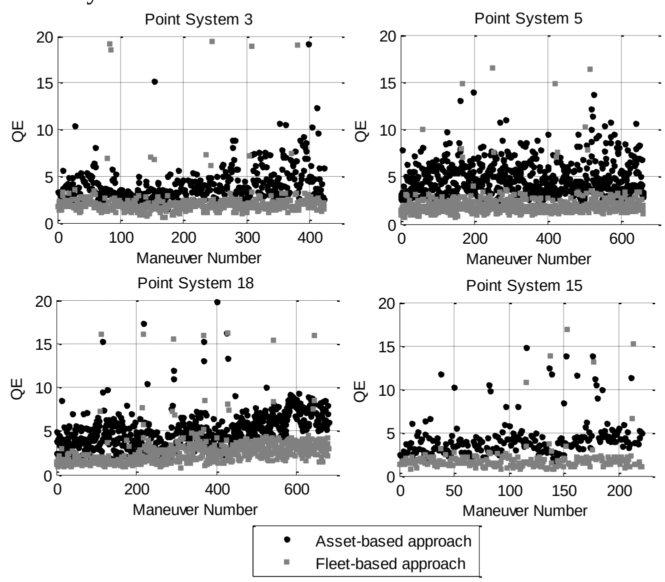

Figure 6: Results of the asset-based and fleet-based approach to four point systems which did not fail over the course of the six-month investigation

This, although counting as an error in identification, indicates that the point system is varying its behavior in time according to both approaches, though the reason for this variation is not yet identified. In three cases, one of which is illustrated in bottom right corner of Figure 6 for point system 15, the fleet-based approach resulted in an increased QE, therefore an erroneous health assessment. However, for these cases the increase occurs at the very end of the six-month trial which is right-censored, not allowing us knowledge as to whether the machines actually lost tolerance in the coming months. These will be considered as incorrect identifications, but this decision remains inconclusive, as only the data from the following months could confirm this claim. Overall, the asset-based approach correctly identified 10 out of 15 point systems as stable and the fleet-based correctly identified 13 out of 15 as stable.

A review of the results of the two approaches can be found in Table 1, with reference to the parameters for the comparison outlined in Section 3.4. From Table 1 it can be seen that the fleet-based approach misses almost all of the failure events with respect to the asset-based approach. However, the fleet-based approach obtains less false alarms than the asset-based approach. This is because the fleet-based approach over fits the problem, and regards a lot of the variations in behavior as acceptable with respect to the fleet, and is more unlikely to report these as anomalies.

Table 1: Comparison of the two approaches

Parameter	Fraction of Cases Identified correctly by the Fleet-based approach	Fraction of Cases Identified correctly by the Asset-based approach
i) variation in the health state of the point systems which lose tolerance	$\frac{1}{5}$	$\frac{5}{5}$
ii) variation in the health state of the point systems which lose tolerance at least a month before	$\frac{1}{5}$	$\frac{5}{5}$
iii) presence of an obstacle in the field	$\frac{0}{1}$	$\frac{0}{1}$
iv) steady, non-variant health for the point systems which do not fail	$\frac{13}{15}$	$\frac{10}{15}$

5. CONCLUSION AND FUTURE WORK

The necessity to introduce a CBM system to point systems is becoming ever more a reality, due to the criticality of point systems in the railway infrastructure. The signals from the case study were not adequate for a simple threshold to detect failures and abnormal behaviors, as healthy signals were very similar to degraded ones. For this reason, this work resorted to a method which involves the extraction of relevant features and a model for the health assessment of the point systems.

This works aims to compare the results of a point system health assessment of using a fleet-based approach and an asset-based approach on a six-month case study on 20 point systems in a field setting. While the asset-based approach was computationally more expensive and required a greater memory for storage, it ensured that no failures would go unpredicted, whilst the fleet-based approach missed 4 failures out of 5. Neither the fleet-based nor the asset-based approach alone were sufficient to identify the presence of an obstacle on the field. However, during the study it was evaluated that other information collected from the data acquisition, when joined to the QE, does allow for detection of an obstacle in the field. This is true for both approaches. Finally, the fleet-based approach did grant 3 fewer false alarms than the asset-based approach. However, these were considered as a mistake for the purpose of the case study, but the consensus as to whether these are actually false-alarms or early detections cannot be reached: the data of the following months is unavailable to confirm or deny this claim.

The reduction of the dataset from a time series to a 16-dimensional vector may have affected the results, as these rely on the feature vector of the maneuver to be complete. This specific feature vector is the result of a long and extensive study and the authors believe that it extracts the most pertinent information from the original raw data. In addition, this paper aims to compare a fleet-based approach and an asset-based approach, and uses the same data to do so. For this reason, if the quality of the results has been negatively affected by the dimensionality reduction, this is true for both approaches and the comparison of the two is still possible.

In conclusion, the fleet-based approach contains a series of assumptions about the general behavior of the point system which do not confront with the reality: a variation in a point system behavior is often similar to the nominal behavior of another point system, resulting in a lack of detection of the anomalous behavior. Furthermore, adopting a fleet-based approach removes the context information from the health assessment, and it misses more failures than advisable.

Future work will be focused on the possibility of joining the outputs of these two approaches in a weighted ensemble, which could lead to an optimum output. Furthermore, in order to improve the fault detection, additional data might be necessary in order to characterize the behavior of the point system more comprehensively. Sensors such as rod displacement, vibration of the point machine motor and pushing force could bring valuable information to the method overall.

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BIOGRAPHIES

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