11th WCRR 2016
World Congress on Railway Research
29th May – 2nd June
Milan - Italy

Statistical Process Control for Modern Switch Failure Detection

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Abstract

A highly available infrastructure is a premise for capable railway operation of high quality. Therefore maintenance is necessary to keep railway infrastructure elements available. Especially switches are critical because they connect different tracks and allow a train to change its moving direction without stopping. Their inspection, maintenance and repair have been identified as a cost driver. Especially switch failures are responsible for a comparable high number of failures and delay minutes. The reduction of failures would not only safe maintenance costs, but let more trains arrive on time and hence increase the attractiveness of the railway transport. Therefore, the Institute of Transportation Systems (TS) in cooperation with the German Railways (DB AG) is exploring ways to apply statistical process control to monitor the condition of switches and their degradation process to reduce failures and thus maintenance costs.

Currently, infrastructure managers use commercially available switch diagnostic systems. They are based on measuring the electrical power consumption of the switch engine and comparing it to a manually predefined threshold indicating the failure. But most of these systems do not reach a satisfying accuracy, because they miss too many failures or produce too many false alerts. TS has identified three main aspects to overcome these issues. 1) Instead of interpreting a single feature of the measured signals TS derives multiple statistical features from the signals each defining a different characteristic, so that more useful information is gained for more precise failure detection. 2) The features are used to develop a novel multidimensional correlation model which is robust to non-failure related changes in the original measurements. Therefore false alerts are reduced. 3) The manual adaption of any threshold is eliminated from the process via a new self-adapting algorithm based on clustering techniques. This safes maintenance staffs the effort for recalibrating thresholds when external parameters change, e.g. major temperature shifts with the change of seasons.

1. Introduction

Currently, infrastructure managers like Deutsche Bahn (DB AG), use commercially available switch diagnostic systems for remote condition monitoring. They are based on measuring the electrical power consumption of the switch engine and comparing it (or a single feature like the area under the curve) to a manually predefined threshold indicating the failure (see Figure 1). But most of these systems do not reach a satisfying accuracy [1], because they miss too many failures or produce too many false alerts [2]. TS has identified three main aspects to overcome these issues. 1) Instead of interpreting a single feature of the measured signals TS derives multiple statistical features from the signals. Each is defining a different characteristic, so that more useful information is retrieved for more precise failure detection. 2) The features are used to develop a novel multidimensional correlation model which is robust to non-failure related changes in the original measurements. Therefore false alerts are reduced. 3) The manual adaption of any threshold is eliminated from the process via a new self-adapting algorithm based on clustering techniques. This safes maintenance staffs the effort for recalibrating thresholds when external parameters change, e.g. major temperature shifts with the change of seasons.

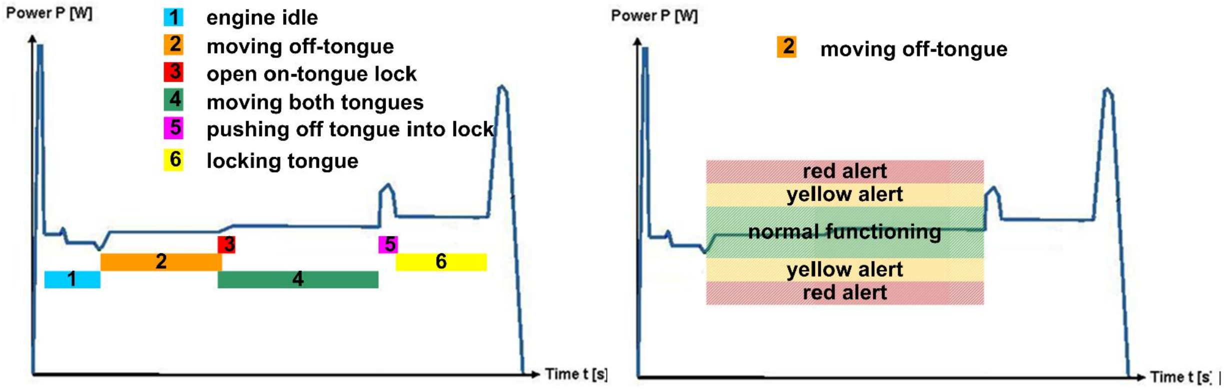

Figure 1: Pattern of effective power during repositioning of tongues within SIDIS W [3]

2. Feature Extraction

The utilisation of the raw measurement for failure detection is not recommendable in many cases. On the one hand is the length of the measurement vector variable, because it depends on the time for a repositioning (4 to 6 seconds) and on the sampling rate of the sensor. That makes it difficult to compare samples, e.g. using the common area under the curve, especially since the duration of each phase (see Figure 1 left) can vary. Therefore a set of features is extracted from the sample making it easy to keep track of the condition. These features can be statistical like minima, maxima, mode, median, standard deviation, skewness, or kurtosis. Also features can be extracted via transformation like Z-transformation, providing a frequency domain representation. Additional features are retrieved via time-frequency-transformation with Wavelets [4] or with the Angle-Measurement-Technique (AMT) [5]. Both take into account the localisation of certain properties of the sample. This is especially useful to the failure diagnosis since it is possible to tell whether the property is located in the beginning or the end of the repositioning, indicating a failure in the tongue movement or the locking respectively. The following example of the AMT will illustrate this. Sample points are extended with their scale range providing an additional dimension of information. The principle is shown in Figure 2. First a sample point is selected. It serves as the centre M of a circle with the given radius r. The intersection of the outer circle line gives two additional points L and R, one left of the centre and one right. Imagine two lines which connect L with M and R with M respectively. Now, the angle α between those two lines is used as the complexity information of the signal at this particular point. It tells how much the signal has changed at this point and at the given radius. The howl sample is analysed at different M with different α.

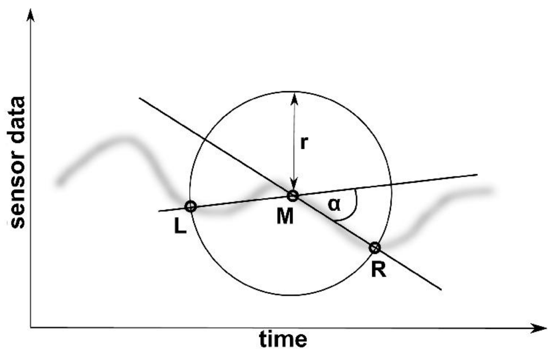

Figure 2: Principle of the Angle-Measurement-Technique (AMT)

All of the above mentioned features preserve some information of the original sample without the deceptiveness of different sampling length. Which features and their corresponding parameter are best suited for condition monitoring and failure detection is the result of an iterative process. It requires knowledge of the feature extraction techniques and of the asset maintenance (here the switch) in order to interpret results correctly.

The features represent different properties of a sample. Hence some features provide more information than others. The following example will demonstrate this. Figure 3 (a) shows three different samples of the motor current, a normal repositioning as a reference and two measurements with failures. Failure 1 is a juddering in the tongue movement due to a lack of slippage as result of dirty slide chairs. Failure 2 represents a difficulty to lock the tongue due to a misaligned lock. If the three samples are evaluated with the common feature of the area under the curve, they show no clear distinction (see Figure 4 left). As alternative the AMT is used as feature for evaluation. The scalograms in Figure 3 (b) to (d) show how different the characteristics of the samples are. If parameters M and α are well selected, the sum of the coefficients provides a feature which enables a clear diagnosis (see Figure 4 right). That makes AMT the much better feature in this case. However, other failure types will require different features. The example relies on well documented failures in order to use supervised learning methods for failure detection. But in many projects TS has experienced the opposite of that. Failure documentation was absent or the data quality did not allow supervised methods. Therefore an alternative had to be found. The following section will describe how to utilise many features and their combination to detect failures via an unsupervised method.

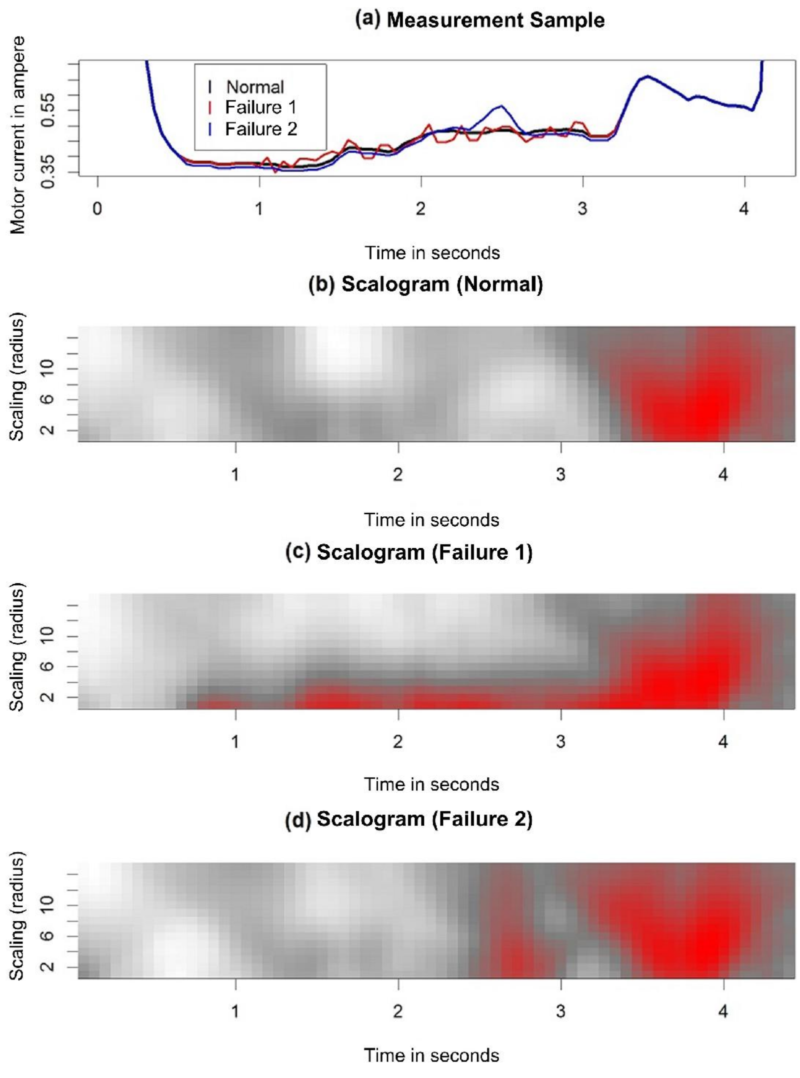

Figure 3: Current measurement samples (a) and the corresponding scalograms (b)-(d), red colour indicates high AMT values

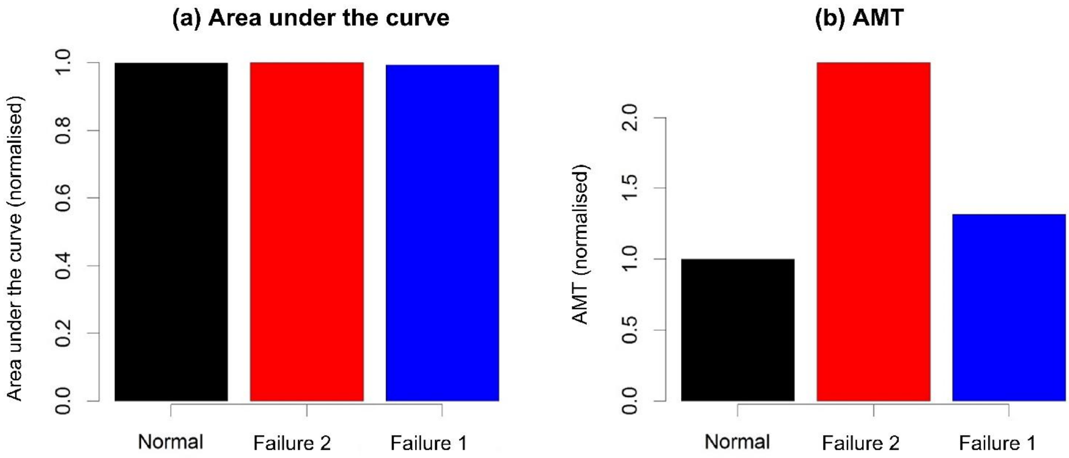

Figure 4: Comparison of area under the curve (left) with AMT (right) as features for failure diagnosis

3. Failure detection with multiple features

Considering a single feature of a measurement often means to leave out important information. Usually multiple features need to be used to detect failures. Additionally the correlation between features is an important aspect of automated condition monitoring. Because behaviour could appear to be well within normal range if the features of several measurements are evaluated separately. This is illustrated in Figure 5 where the two features don't exceed former measurements. But their correlation shows the opposite (Figure 5 lower part). In case of switches the electrical power consumption changes with the temperature [2]. The warmer it is within a certain temperature range the less power is required for moving the tongues. But if this relation is violated a failure might be present. (To describe the reason as well as the mechanical and physical limit to that relation would exceed this paper.)

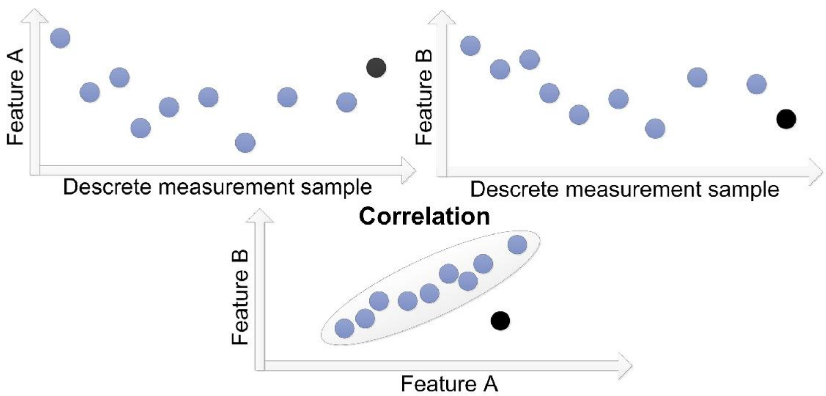

Figure 5: Normal variation in individual feature evaluation (upper part) against noticeable anomaly in correlated view (lower part)

In reality a multidimensional features space and its correlation has to be evaluated. Not only features of the measurements are taken into account but also environmental (e.g. temperature) and operational parameters (e.g. number of trains passing). This can be difficult in terms of interpretation, data storage and visualization. Techniques of dimension reduction such as Principle Component Analysis (PCA) can be used to overcome this [6]. PCA reduces dimensions while it makes use of correlations to minimise the loss of information. Though, the PCA reduces features to a reasonable minimum (five in this case) the goal for the robust failure detection is to use only two significant indicators in order to apply Statistical Process Control (SPC) as unsupervised method. SPC directly builds on multivariate data analysis and PCA. It explicitly uses only two indicators [7]. The first is derived from the most dominant component of the PCA and is called Hoteling-Parameter (T^2). The second, the Square Prediction Error (SPE) is derived from the remaining components. Feature changes which are abnormal will result in strong changes of SPE and are most likely a failure. If feature changes are significant but more or less in line with common changes, SPE will not react but T^2 will. This does not necessarily mean a failure. Moreover, it must be seen as a hint for the maintenance staff to further investigate the situation.

In order to automatically detect failures thresholds are defined for both parameters. The threshold definition is done statistically not manually and hence reflects the underlying multivariate characteristics. Confidence intervals are used for thresholds because they describe a probability p that the SPE or T^2 value is within normal behaviour. Therefore wide confidence intervals reflect a more failure critical change than narrow intervals. The example in Figure 6 uses the standard normal deviation of SPE and T^2 for thresholds. Values within the 1-Sigma interval ($p=0.68$) are considered as normal while the 3-Sigma interval ($p=0.99$) is treated as failure. TS applied SPC for switches. With its underlying multi feature model SPC is more robust to correlation related changes like temperature and different settings than existing systems. Additionally, changes of the sensor configurations (sample frequency, additional sensors, etc.) or of the feature number had been applied without changing the interpretation and visualization.

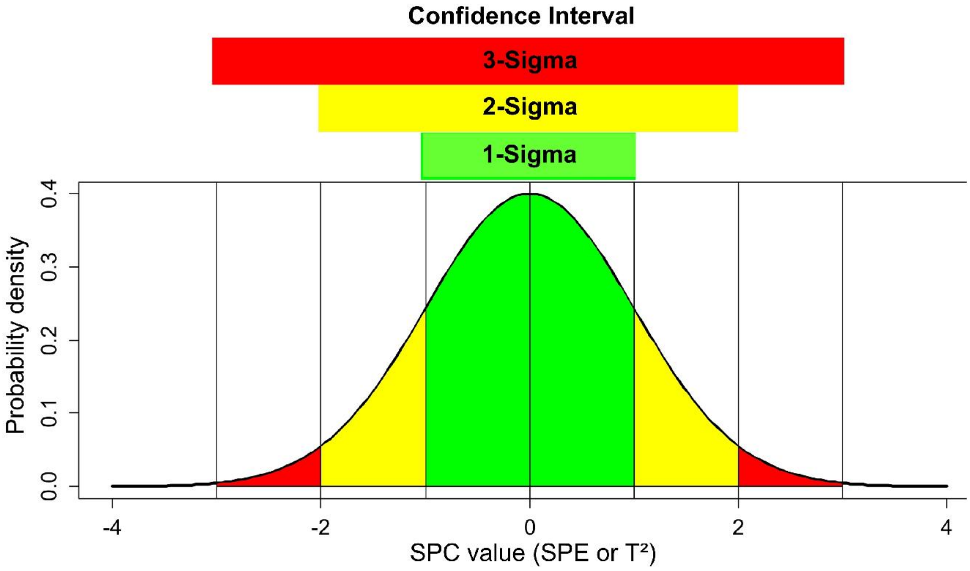

Figure 6: Visualisation of confidence intervals for SPC with standard normal deviation

4. Elimination of manual threshold adaption

The failure indicating thresholds of existing switch monitoring systems (see Figure 1 right) are set manually for each switch by defining a reference measure and precise deviation values. Hence the failure detection heavily depends on a good reference. The randomness of a single reference measure is one disadvantage. Another is the changing normal behaviour which happens over time because of wearout, etc. Here, the application of SPC provides additional benefit. Features are extracted from a great number of samples from recent past. Assuming that much more samples contain non failure switch repositionings than faulty ones, the most similar samples are combined via clustering. The biggest cluster is used to build the reference model for T^2 and SPE thresholds against which every new sample is evaluated. The cluster is updated automatically after a certain number of repositionings or days and can even be updated continuously. Only the initial selection of confidence interval remains to be done once a new switch type is in the field. This means a huge reduction in effort and costs.

5. Outlook

The approach presented in this paper uses multiple features of condition monitoring data samples to enable better failure diagnosis, to robustly detect failures with less false alerts and to eliminate manual threshold adaption. This implemented concept of statistical process control for modern switch failure is currently evaluated with DB AG. It will be further developed in the Shift2Rail Joint Undertaking, which will give the opportunity to expand the topic to different types of switches or railway infrastructure assets.

6. References

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