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Turning data driven condition now- and forecasting for railway switches into maintenance actions

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Abstract

Railway switches are crucial for normal operation and during disruptions of the railroad system since they allow trains to use alternative routes. Switches moving parts are subject to high deterioration and prone to malfunctioning, representing a potential safety hazard. Thus frequent inspection, maintenance and renewal are required. Models to optimize the railroad system operation and reduce costs are possible on the basis of inspections vehicles, online condition monitoring, inspection standardization and data-based models. This paper presents a switch condition now- and forecasting model based on continuous monitored data (switch engine current during blades movement). The model is capable of identifying unusual behavior due to emerging failures without the need of manually set switch-specific thresholds. In this approach no labelled training data set of historic switch failures is required for training the model. Its output combined with maintenance information and the switch functional model sheds light on switch degradation modes, helping to optimize maintenance actions.

Keywords: Sensors, Data Acquisition and Management; ITS and Traffic Management.

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1 Introduction

Train punctuality depends on correct train operation, which in turn partly depends on the ability to guide the trains to the correct track or platform. If a switch fails to move the switch-blades the train cannot change tracks and get into the right position, often leading to delays and, in the worst case, causing a chain reaction affecting many following trains. Switches as complex electro-mechanical systems are prone to failure, thus there is a high interest in developing reliable monitoring systems capable of anticipating malfunctions with sufficient time in advance. Such a system would lead to a decrease in maintenance expenses and an increased quality of service (Rama and Andrews, 2013), making the railway transport more attractive.

A common approach to monitor switches driven by electric engines is to measure the engine current with a sensor while the switch-blades are moving (García et al., 2010). Assuming that the current is proportional to the engine's power consumption (Stoll and Bollrath, 2002), variations in it are detectable through the measured current curves, which enable to identify e.g. degradation or irregularities in the switch movement. Automated switch status forecasting systems based on continuous switch current consumption (or other comparable measurements such as from a force sensor at the switch-blades) are not yet seen in 24/7 operation. (Camci et al., 2016) provides a comprehensive overview of existing significant efforts at research institutions and companies to develop forecasting models. The main challenge that such systems face is the numerous failure types, which can occur simultaneously, and that are inherent to railway switches as complex electro-mechanical systems. Even under well controlled laboratory conditions with simulated failure development physical models show poor performance (Camci et al., 2016). Therefore recent developments have focused on data-driven models based on historic data e. g. by (Eker et al., 2010) and (Letot et al., 2015). Several studies have applied a wide range of sophisticated empirical statistical models and supervised machine learning approaches. The main advantage of data-driven methods (especially of supervised machine learning approaches) is that models with good apparent prediction performance can be derived from example data sets. Main remaining challenges are over-fitting, the creation of complete (containing all relevant types of switch failures) training data sets with correct labelling, and the generalization of derived models for a large amount of switches.

1.1 State of the art switch monitoring

Failures originate due to various causes. Not all failure types can be monitored through electric power consumption or by the latest technology. To detect potential failures several commercial switch or point engine diagnosis systems are used (Böhm, 2013); one of them is POSS® by Strukton Rail (SR), which monitors about 2000 switches in the Netherlands. Approximately 80% of these switches have an engine similar to the one considered here[†]. POSS® monitors the condition of the point engine by analyzing the power it consumes (via the measured current curve) while the position of the switch-blades changes. 25% to 50% of all switch failures, depending on various factors, are detected with POSS®. Many failures can be prevented based on the alerts the system provides[‡].

POSS® monitors the power consumed during the different phases of the switch blade movement and generates alerts when these exceed the corresponding thresholds. Each phase of the current graph is associated to a different step/part of the functional switch model (FM). For the switch considered here these are: inrush current to start the motor, blades unlocking, blades movement, blades locking. The thresholds are manually set for every switch individually by an engineer based on experience and the latest observed switch behavior. Some of the thresholds are set to exceed the reference graph by up to 45% in order to reduce the number of false alerts. The reference graphs representing 'normal' switch movement are manually chosen by maintenance engineers for each switch and each direction from available historic measurements. Most switches have per direction a reference graph associated to 'normal' behavior in the summer and another one in the winter (per switch four reference graphs need to be set and maintained), given that temperature plays a decisive role on the power consumed by the motor during the movement[§]. Defining the thresholds heavily depends on a good reference, which is not an automatic process and is thus a limiting factor for the precise detection of problems. POSS® raises an alarm when it detects abnormal behavior of a measured current curve with respect to the reference curve, i.e. when any of the thresholds is exceeded. **Figure 1**a shows a current curve whose shape is typically

[†] http://www.struktonrail.com/smart-maintenance-services/measure-monitor/
[‡] Success completely depends on the company which operates POSS® and the way the system is being used in their process
[§] The relationship between power consumption and temperature is unique for each switch.

associated to a failure in the blades locking part. This movement triggered an alarm because it exceeded the total power consumption threshold set based on the reference graph. We refer the reader to (Dutschk et al., 2017) for further details of POSS®. A process flow diagram (**Figure 1**b) shows schematically the decaying quality of an asset, i.e. its functional capability; typically POSS® detects odd engine current curves and generates an alarm when the condition can compromise the functionality. In case of alarm a maintenance engineer determines the necessary repair/maintenance actions. It is challenging to determine the urgency of these actions, given that the time evolution of the condition curve is not well understood and depends on the failure type as well as on external factors. POSS® preventive maintenance approach, described in the next section, ideally consists of detecting possible problems and providing alerts with sufficient time in advance such that the problem can be solved before the failure occurs.

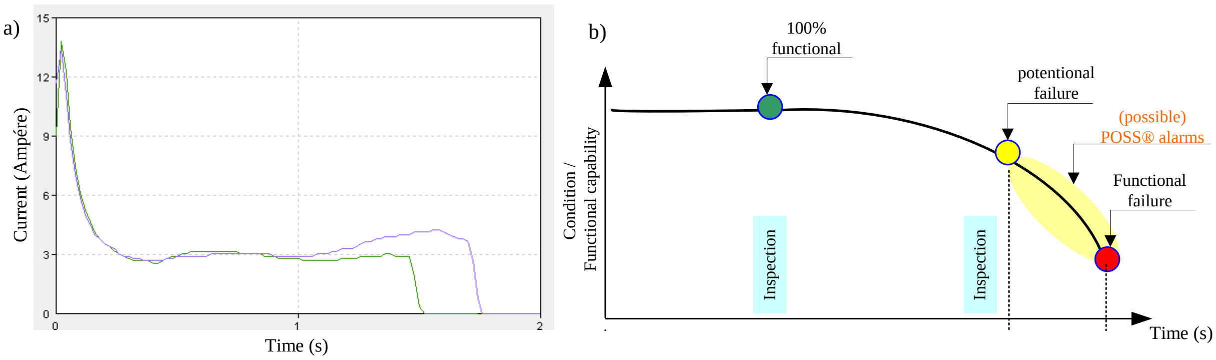

Figure 1 (a) Current graph (blue) triggered an alert due to 24% more power consumption with respect to the reference curve (green); (b) process flow diagram showing a classic preventive maintenance process and the time when POSS® alarms are usually triggered

1.2 Data-driven switch failure detection and forecasting tools

POSS® has provided insight into switch behavior under different circumstances, and into the switch functional states (degradation behavior), enriching the domain knowledge significantly. However it is desirable to incorporate forecasting tools into switch monitoring systems (POSS® in particular) to detect developing failures and provide a switch condition forecast. For this purpose statistical, data-driven (supervised/unsupervised methods) and model-based approaches are currently being exploited (Vileiniskis et al., 2014).

The approach presented in this paper consists of a data-driven unsupervised machine learning approach in combination with the switch FM. They are expected to jointly provide information to identify both patterns associated to asset failures and their cause, leading to failure forecast and current asset technical status. In practice the shift from (current) preventive to predictive maintenance implies developing algorithms that:

- set dynamical thresholds (adapted to environmental information),
- detect abnormal switch behavior in an early stage,
- forecast failures,
- recognize the failure origin and allocate the corresponding switch component,
- provide insight into unique asset behavior

Here a switch failure detection model concept is described, which builds on the existing domain knowledge formalized in a FM (see section 2) and an unsupervised data-driven approach, namely the statistical process control (SPC) model. The SPC model is presented through a case study showing its ability to detect the development of failures, see (Böhm et al., 2016). The SPC model is trained with available current curves during 'normal' functioning of a given switch. The link between the FM and the SPC model will be further explored in two directions. First, the FM will be used to extend the heuristically selected features (see section 0) such that they are directly related to switch units and their functions (see **Figure 2**). Second, based on these specialized features the SPC model will identify abnormal switch behavior and relate it to potentially affected units and/or functions, see (Yue and Qin, 2001). In this way, the detections provided by the SPC failure detection model will be enriched with diagnostic information to improve the asset now- and forecasted status.

This paper is based on work package (WP) 9 in conjunction with WP6 of the In2Rail project. It represents an interim step towards the development of automated repair switches. To reach this longer-term goal these work packages are being developed in parallel with - and will be integrated to – work currently carried out in WP2, which focuses on new locking mechanisms with integrated switch motion system and embedded sensors that enable self-diagnosis and remote condition monitoring. In this paper we focus on asset status now- and forecasting for legacy switch types utilizing data of existing systems to monitor the point machine power consumption. The approach presented here is beyond the state of the art as unsupervised data analysis techniques are applied to detect emerging failures in an early stage without the need for switch type-specific labelled training data sets of historic failures.

2 Functional model

There are different switch types and manufacturers, and local circumstances such as load and weather conditions may differ significantly. As a consequence, the maintenance/repair costs analysis is done mostly at individual switches. To compare the performance of similar switches and evaluate and improve maintenance concepts, more insight into the degeneration process of switches and their components or units is needed. For this purpose it is of advantage to look at switches from a more generic point of view. In the FM a switch is represented by its main- and sub-functions (see **Figure 2**) with the purpose of linking these, independent of switch type and/or manufacturer, to costs, criticality, malfunctions, usage, maintenance activities, etc. Through the FM, new insight can be gained and used as a decision support tool, as previously explained.

Domain knowledge and the availability of data are key for the implementation and daily operation of the FM. SR brings in knowledge and experience on maintenance and reliability engineering (consisting of the Failure Mode, Effect and Criticality Analysis (FMECA)) as well as access to data from its maintenance contracts in order to analyze the failure and maintenance costs and determine the cost-drivers and performance killers. The outcome of FMECA is a long term risk-based maintenance plan (under continuous improvement) that considers a given (sub-) function and the effects of failures per maintainable unit. Combining risk data with the FM gives a good indication where most failure modes are, which sub-function is most critical and further optimizes maintenance concepts. Several common failures/anomalies are associated to specific switch components and might be forecasted by the SPC model; this information will be incorporated into the FM to generate a predictive maintenance plan that pinpoints the root-cause of the problem, reduces the probability of failure and optimizes maintenance.

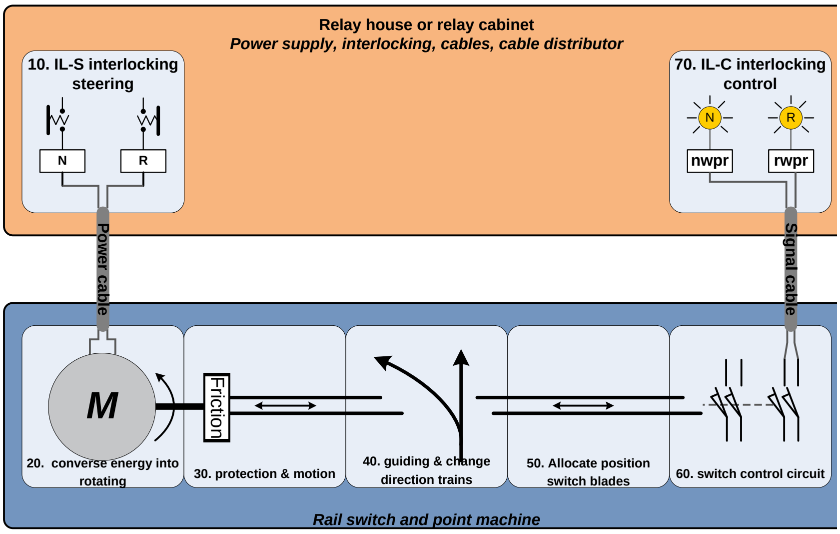

Figure 2 Graphical representation of the switch functional model. The functions of each unit are indicated, the units are: 10) interlocking output, 20) electromotor, 30) clutch and drive bars, 40) switch blades, 50) detection bars, 60) detection circuit, 70) interlocking input

3 Input data

For the case study 12’674 switch blade movements measured at a given switch between 01-January-2013 and 31-December-2015 are considered. During this period twelve failures were reported by network operators; they were then treated and documented by the maintenance operators. It is possible that during this period temporary malfunctions occurred, which emerged and vanished within a short period of time without a maintenance or repair action taking place (e.g. blades blocked by snow or an obstacle), and were thus not reported by the operators to SR. The main input for the data-driven model is the engine current curves acquired by POSS® with a frequency of 50 Hz during each switch movement. The input data is complemented by ambient temperature measurements at the relay house (about 1 km away from the switch) at the time of each switch movement. Available information about maintenance (scheduled) and repair (due to a reported failure) actions performed on the switch are useful for identifying sudden changes in the power consumption and the general asset behavior. Maintenance actions are either performed every 24 months and include several activities and repairs, or are follow-up actions from inspections done every 3 months. These actions (of mechanical or signaling/electronic nature) can influence the switch behavior with different degrees (small or large). The switch movements that raised an alarm in POSS® are used here to verify the performance of the SPC model. The alarms provide four different messages: power too high, power too low, current too high and time too long.

3.1 Feature extraction

The performance of the SPC model for failure or anomaly detection depends on the capability of the features extracted from the current curves to represent them. The heuristic feature selection for this study case combines data science and asset maintenance domain knowledge as well an explorative data analysis, see (Dutschk et al., 2017). The feature set consists of 1) area under the current curve, 2) maximum current, 3) median current, 4) current kurtosis, 5) current skewness, 6) movement duration, 7) mean current value during switch blade movement, and 8) current standard deviation during switch-blade movement. The values in feature sets typically vary in range, e.g. maximum values of current curves vary between 14 and 16 A, while the current standard deviation during switch movement is usually below 0.5 A. As most data-driven approaches the SPC model is sensitive to the different feature ranges and requires the normalization of each feature such that each scaled feature has zero mean and standard deviation equal to one; this transformation is also known as centering and scaling, see (Kuhn and Johnson, 2016). Additionally the features present systematic temperature dependence, e.g. the total power consumption decreases when temperature increases due to changes in the switch-blades length caused by thermal expansion. In order to account for the temperature dependence of the features, the centering and scaling transformation is separately applied to feature values belonging to current curves, which were measured at approximately the same temperature (within 1 K temperature bins). By scaling the features in this way, the temperature dependence is removed. In what follows we refer to the scaled features as features.

4 Statistical Process Control model

A SPC model (Böhm et al., 2016) is built for each blade moving direction (identified by 0 and 1); features from a selection of current curves for each direction are used to train the model. The selected current curves were acquired in a time frame (July 1st 2014 - July 1st 2015) with no reported failures, thus it is assumed that the selected curves represent normal switch behavior. Further selection criteria are applied as there are a few current graphs in this time frame showing significant unusual behavior (which did not lead to switch malfunctioning), such as outstanding large total duration and/or total power. The selection criteria thresholds are derived automatically from the statistics of the training set. Once the training data set is selected a data compression technique (basically a change of basis) named Principal Component Analysis (PCA) (Jackson and Mudholkar, 1979), (Sotiris and Pecht, 2017) is applied to the features extracted from this set. By applying PCA the redundancy (or correlation) among the features describing the observations is minimized, thus information is summarized into fewer representative dimensions, the so-called Principal Components (PCs). The higher the correlation, the less PCs are required. PCA assumes the dynamics of interest exist along the orthogonal PCs with the largest variance. PCA builds a model subspace retaining (in our case chosen) 90% of the PCs variance of the training set and a complementary orthogonal residual subspace. PCA transforms features of a current curve into the new basis; the projection into the model and residual subspaces results in statistical indexes Hotelling's Parameter (T^2) and Square Prediction Error (SPE), respectively. That is, T^2 is derived from the most dominant components of the PCA, and SPE from the residual components. The parameters T^2 and SPE obtained for the training set follow a chi-square probability distribution, which allows defining confidence intervals (based on probability quantiles) for normal switch behavior. Confidence intervals are used as thresholds as they describe a probability that the SPE or T^2 value is within normal behavior. If the features significantly change but remain in line with the prevailing relations among all features under normal behavior, this will be reflected in T^2. Feature changes which are abnormal with respect to the prevailing relations affect the SPE parameter. Finally the SPC concepts (Böhm et al., 2016) are applied to the statistical indexes T^2 and SPE, and remain valid as long as the model maintains its structure through time.

5 SPC model verification and analysis

The models (for each direction) based on the training data set are applied to other current curves measured between January 1st 2013 and June 30th 2014, and from July 2nd 2015 to December 31st 2015. For each current curve not belonging to the training data set T^2 and SPE parameter values are obtained. The T^2 and SPE confidence intervals are used to identify outliers associated to abnormal current curves. The failure, maintenance and alarms available information is used to verify the models and shed light on the switch behavior e.g. after a major maintenance action.

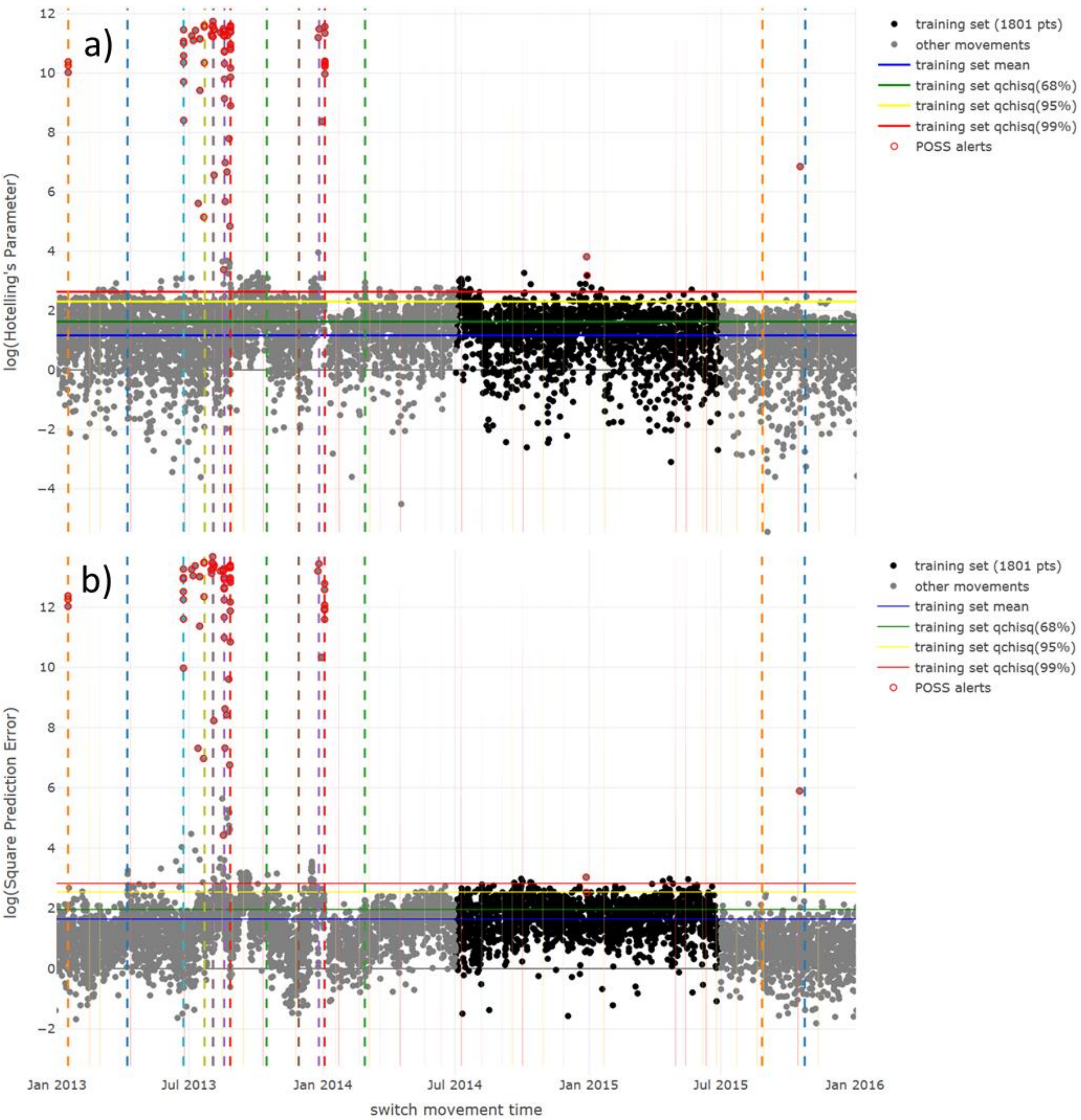

Figure 3 Logarithm of parameters (a) T^2 and (b) SPE of switch movements in direction 1

The parameters T^2 and SPE for switch movement in direction 1 are shown in Figure 3 (direction 0 presents fewer alarms, due to this and space constriction the results are not included). Each dot represents a measured current curve. Black points belong to the training set; grey dots are current curves outside the training set, thus denoted as "other movements". Horizontal lines indicate the mean value of the training set (blue), the 68.2% (green), 95.4% (yellow) and 99.7 % (red) confidence intervals. The data points of the training set mostly lay within the 99.7% confidence interval. Thin solid vertical lines in light red and yellow indicate maintenance actions with expected large and small possible implications, respectively. The red open circles correspond to switch movements that raised an alarm in POSS®. All are well beyond the 99.7% confidence interval, except for one in Figure 3b. Fifteen dashed vertical lines (two nearly overlap, thus only fourteen can visually be identified) indicate reported switch failures (note there is none in the training set), e.g. due to snow on the switch. Most data points outside the 99.7% confidence interval are close to several of the failure incidents maintenance actions.

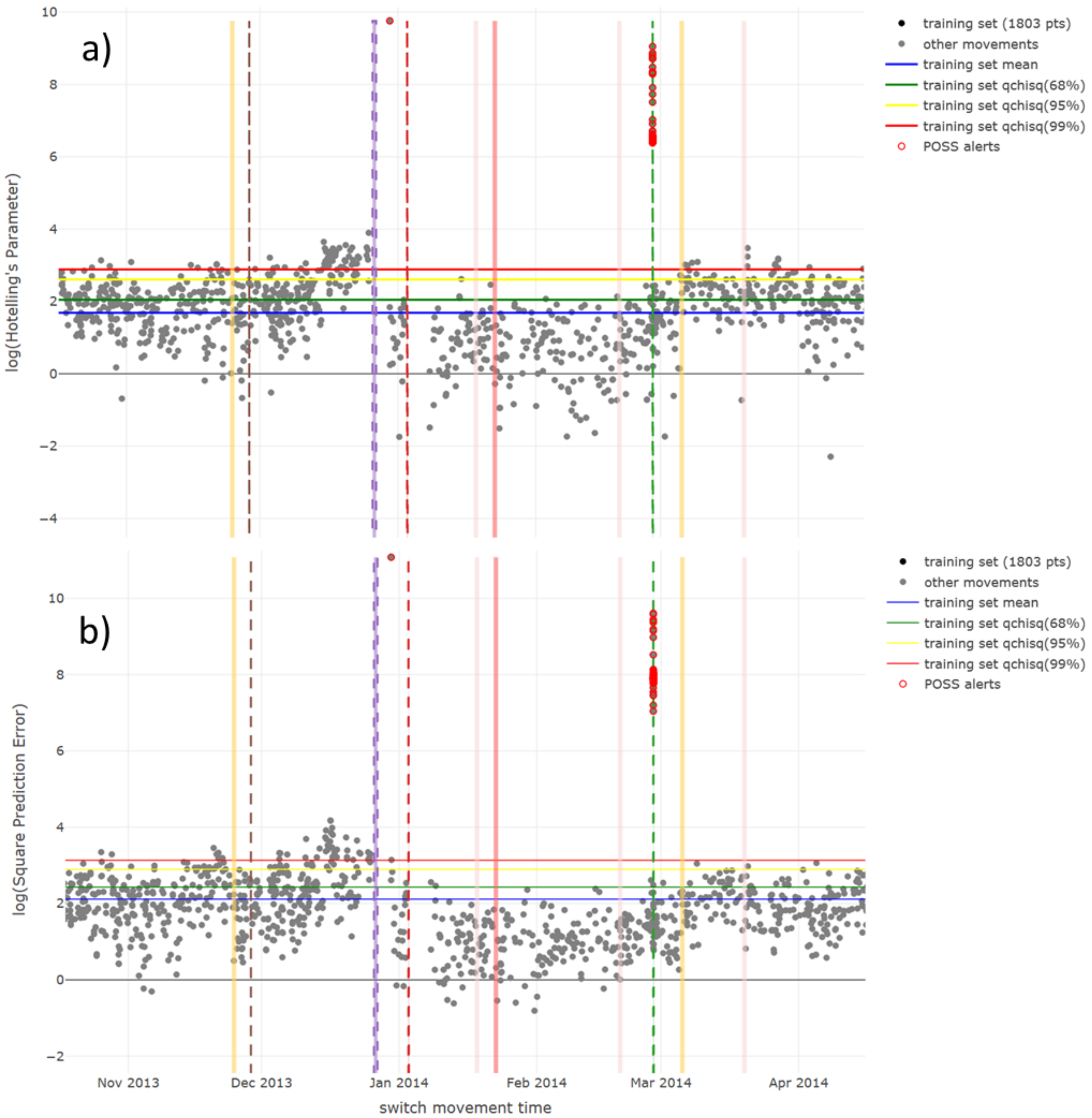

Figure 4 Logarithm of parameters (a) T^2 and (b) SPE in movement direction 0 of movements between mid-October 2013 and mid-April 2014

In order to link the reported failure incidents as well as the maintenance actions with the results of the SPC model, a closer look into single incidents is necessary (see Figure 4). The time between a switch malfunction being reported and being repaired corresponds to the width of the dashed bars representing reported failures: reported on December 26th 2013 and repair time of about 19 hours (purple); reported on January 3rd 2014 and repair time of 2 hours and 10 minutes (red); reported on February 27th 2014 and repair time of 2 hours and 15 minutes (green). Maintenance duration takes at most a few hours and is carried out either the night before the reported date or the night after, however this specific information is not available. Therefore the width of the shaded areas is set to 24 hours. The failure reported on December 26th 2013 (in purple) was due to water leaking into the engine-case over a longer time causing degradation and rusting of the gear box. Based on the SPC model results, first alerts could have been raised days before the malfunction occurred. That is, in the 0-direction the T^2 and SPE values cross and exceed the 99.7% confidence interval for the first time since the previous big-mechanical maintenance action (on October 10th) on December 5th. In the 1-direction (not shown here due to the lack of space) there are about a dozen T^2 and SPE outliers, the first one on December 15th, found after October 10th and before the failure, however the trend among those outliers is not as clear. The systematic increase is especially evident in the T^2 evolution in both directions. This trend reflects the steady increasing power consumption due to the degrading gear box. The model calculates extremely high T^2 and SPE values in direction 1 one hour before the malfunction was reported, which also raised the "time too long" alarm in POSS®. Clearly all these indications (outliers, systematic trends followed by extreme outliers as well as alarms) can be exploited to implement statistical rules for failure forecast. After the 26th December reported malfunction (purple) and its consecutive repair, the switch performed no movements during three consecutive days. During this time the rust accumulated and caused the switchgear to jam, which prevented the engine from moving the switch-blades. The next movement after the repair (of the purple failure) in both directions raised the "power too high" alarm and is detected as extreme outlier in both directions by the SPC model. From the movements that followed and that took place before the next reported failure on January 3rd (in red), one is detected as outlier by the model in the direction 0 and raised an alarm. This could indicate that the repair actions conducted for the December 26th malfunction (purple) did not fully solve all the mechanical/signalling problems that initiated in December. On January 3rd a malfunction (in red) was reported, indicating the necessity to replace the point-machine. Afterwards the switch was not used during four days, until the switch engine was exchanged on January 8th. There was additional maintenance given on January 18th and 22nd. After these maintenance actions, the switch resumed normal operation. On February 27th another malfunction (in green) was reported; previous to it no outliers are detected in either direction or parameters. Nevertheless in direction 0 the model detects the failure through extreme outliers, which are linked to alarms of types "time too long" and "power too high". This indicates that some types of failures, like the one that occurred on February 27th (green) caused by a burned electrical contact in the switch control part (not of mechanical nature), might not be able to be forecasted by condition monitoring based on current curve measurements; however they are detected right when they occur, as done by POSS®.

Maintenance and repairs can reset the normal behavior of a switch, as exemplified in Figure 5. The April 7th 2013 reported failure (dark blue) was repaired 3 hours and 45 minutes later. The actions performed on the switch led to a step change in the SPE parameters in direction 0. This failure was not preceded by outliers in direction 0 and only by a few T^2 ones (with no systematic trend) in direction 1. After this failure the switch operated normally until the next failure (light blue) on June 23rd, which was repaired within 1.5 hours. This failure was preceded by a few isolated outliers for both parameters in both directions 0. Nevertheless the SPC model in direction 0 detected several outliers as the failure occurred, which were missed by POSS®, i.e. no alarm was raised. In direction 1 several extreme outliers detected by the SPC model during the failure raised the "time too long" alarm. It is expected that certain maintenance/repair actions trigger changes in the normal functioning behavior of the switch, and that this can be reflected in both parameters.

6 Forecasting strategies

The forecasting approach presented here consists of applying SPC concepts to both output parameters and confidence intervals derived from the training set to detect switch failure through outlier identification and, whenever possible (e. g. through systematic trends) to create a short- to mid-term (several days to a few weeks) forecast of emerging switch failures together with automatic alerts (Atienza et al., 1997). In this approach no historic failure data set, as well as no a-priori knowledge of switch failures together with their typical degradation behaviour (in the form of a labelled training set) are necessary since failures are detected through SPC outliers. Furthermore given that the SPC model is built by utilizing data of normal operation (with failures explicitly excluded from the training set before modelling), it can be trained within a short time after installation or maintenance, which, as shown, can have an effect on the normal switch operation.

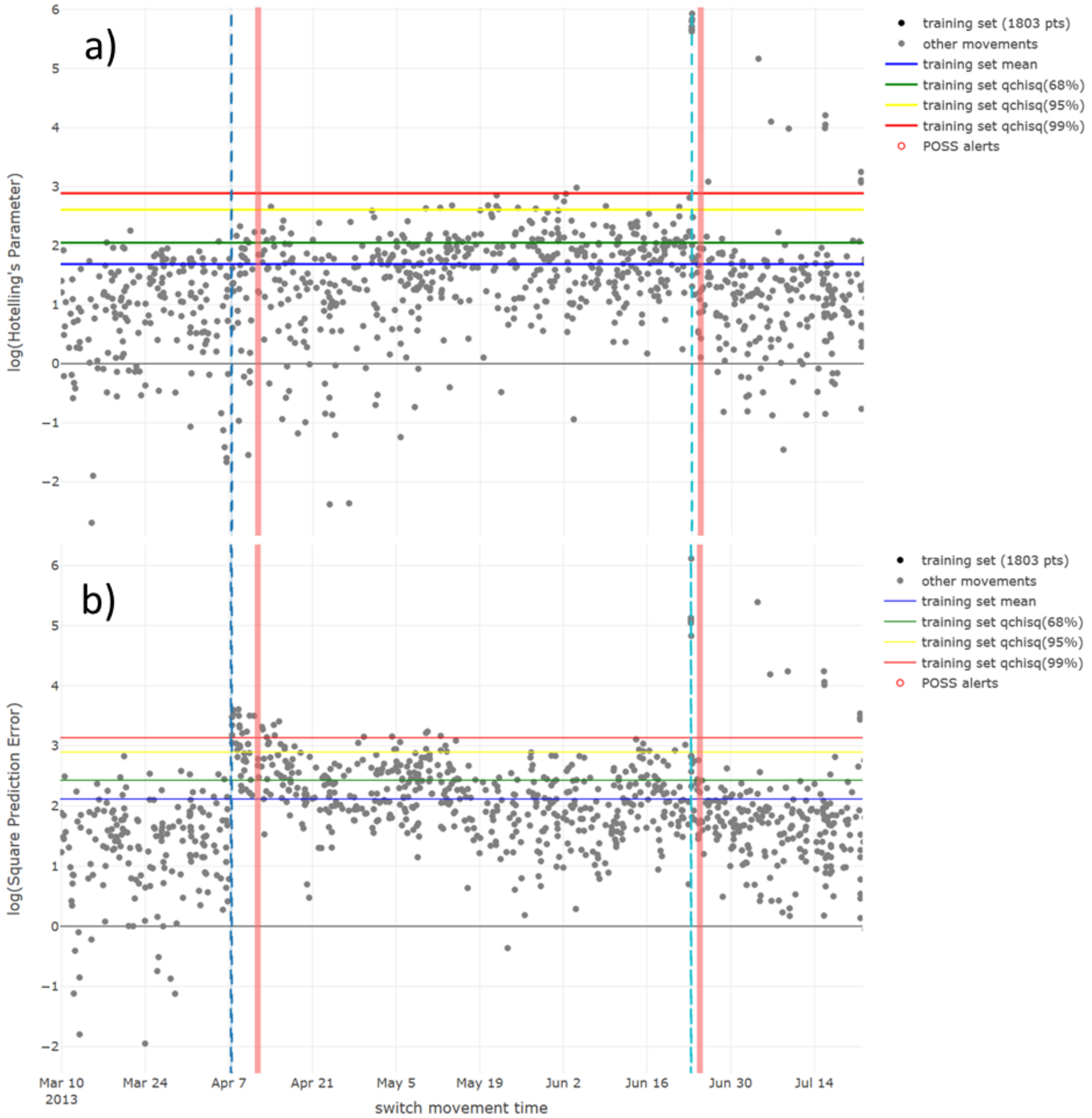

Figure 5 Logarithm of parameters (a) T2 and (b) SPE of switch movements in direction 0 between mid-March and mid-July 2013

7 Conclusions and outlook

The approach presented in this paper consists of training the SPC model with features of condition monitoring data. The model can robustly detect failures and be used to automatically raise alarms, eliminating frequent manually selected thresholds necessary in POSS®. Based on a study case the forecasting capabilities of the model are discussed in terms of failures that present systematic trends in time. Not all failures can be foreseen, this depends on the nature of the failure and (not monitored) environmental conditions. Nevertheless most reported failures and virtually all POSS® alarms are detected by the model. The performance of the SPC model heavily relies on the quality and completeness of the used feature set. At this stage more research is necessary in order to optimize the feature set; for this purpose the FM will be exploited. The quality of the features used in the case study was shown to be good enough to capture failures and alarms, however a higher sampling frequency of the engine current would increase feature precision, for example through a better resolved maximum current curve value. Relevant influences such as weather conditions (including rain, solar radiation, etc.), maintenance (scheduled and reactive) and train operations need to be included into the automated data analysis to further improve now- and forecasting for switches. The detection approach can be taken one step further by developing models trained on specific (sub) feature sets to generate specialized detection and diagnostic information of a specific failure type. To validate the model, larger data sets from more switches need to be included.

In Figure 6 a flow diagram shows the interaction, yet to be implemented, between the different models presented in this paper. Together they provide switch failure information to generate a maintenance plan that shall be optimized based on FMECA analysis. The SPC model transfers information about nowcasted and forecasted failures into the functional model. The functional model links this input to the functions and maintainable units of the switch possibly affected by the detected (emerging) failure. The FMECA analysis considers the different failure modes and necessary interventions and determines which maintenance actions are required in the longer term. The costs implicated can be asses based on risk analysis. Feedback concerning the effects that failures and repairs had on the switch is provided for continuous improvement of the whole process.

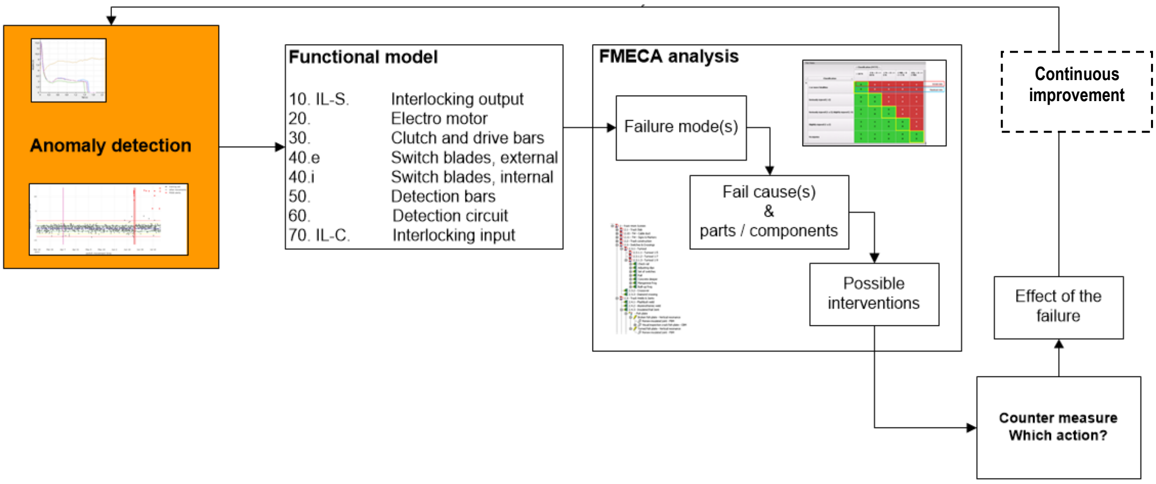

Figure 6 Interaction between parts of the switch detection and forecasting model yet to be implemented that shall enable early failure detection and an optimized maintenance plan

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