On-site Online Condition Monitoring of Medium-Voltage Switchgear Units

Christina Nicolaou
Robert Bosch GmbH, Germany
University of Siegen, Germany
christina.nicolaou2@de.bosch.com

Ahmad Mansour
Robert Bosch GmbH
Renningen, Germany
ahmad.mansour@de.bosch.com

Kristof Van Laerhoven
University of Siegen
Siegen, Germany
kvl@uni-siegen.de

ABSTRACT

Our electricity networks highly rely on switchgear to control and safeguard electrical power infrastructure. It is therefore not surprising that distributed monitoring of switchgear through local sensors, signal processing and analysis in real-time, has emerged as a promising research field. Of particular interest are the non-invasive detection of switching operations, their differentiation and aging, which can be monitored by tracking acoustic emissions generated during a switching operation using small microelectromechanical system (MEMS) based sensors. This paper presents a novel and computationally efficient method that allows on-site feature selection and online classification of switchgear actions. Process- and design-specific features can be learned locally on the sensor system without the need of prior offline training. This avoids the high effort associated with adapting the model for other use cases offsite (e.g., analysis, feature selection, implementation). Besides, it offers the possibility to re-train the model, which may be required due to changes in the structure of the concerned application (e.g., replacement of components, ageing or changes in sensor position). Furthermore, the method is independent of the application, thus making it generic to other application areas. We evaluate our method as well as the MEMS sensors (acoustic and vibration) using datasets of switchgear measurements to differentiate between different switching operations. We furthermore show that the features selected by our method can be used to track changes in switching processes due to aging effects.

CCS CONCEPTS

• **Hardware** → **Smart grid**; • **Theory of computation** → **Online learning algorithms**; • **Computing methodologies** → *Feature selection*; • **Computer systems organization** → Embedded systems.

KEYWORDS

Signal Processing and Analytics in IoT Pilots, Condition Monitoring, Smart Grid, Feature Selection, Online Learning, Vibration Analysis, Acoustic Emission, Mechanical Fault Diagnosis, Medium-Voltage Switchgear

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1 INTRODUCTION

Improved power quality, reduction of power outages as well as higher safety and environmental standards are just a few examples for the ever growing demand on our electrical power grids [19]. To meet such requirements, power system transparency is taking on an increasingly important role in the transformation from classical to smart grids. With the help of Internet-of-Things sensor units, utility companies not only get the ability to remotely monitor power flow but also to assess the health condition of their equipment in much greater detail than was previously possible. Particular critical systems are the electrical substations used for all voltage conversions throughout the grid as shown in Fig. 1. In most (extra)-high voltage grids (primary substations), complex monitoring systems in combination with extensive measurement technology and diagnostic procedures are already in use. In contrast, this is not the case for most transformer substations at the lower voltage levels of the distribution grid (secondary substations). Here, cost-intensive monitoring solutions are not reasonable, as they are at the same price level as the examined equipment [3]. Only few low-cost systems, mainly focusing on transformer monitoring and ambient temperature, are available on the market [12] [18]. A more holistic approach for an interconnected, modular condition monitoring system for substations is presented in [13].

Beside the monitoring of transformers, the supervision of switchgear (e.g. circuit breaker, disconnect/ earthing switch) plays a major role in these substations (Fig. 1). In its basic function, the switchgear works like classic switches for switching electrical circuits on and off, but it is designed for higher voltages where arcs must be quenched for load or fault currents. By protecting and de-energizing critical equipment in failure cases, switchgear guarantees a continuous, reliable and resilient power grid. Safe and continuous operations over decades despite the onset of ageing and wear effects is therefore essential. While cost-intensive monitoring solutions for high-voltage switchgear are vast, including the recording of opening and closing times, drive motor current, insulation condition or electrical parameters [19], usually not even the switching operation itself is detected on the medium-voltage level [14]. However, this, in addition to the switching frequency and the switched current, significantly determines the wear and aging which are the cause of 42.3 % of major failures [16]. As installed switchgear units normally contain several load break switches (also called disconnector

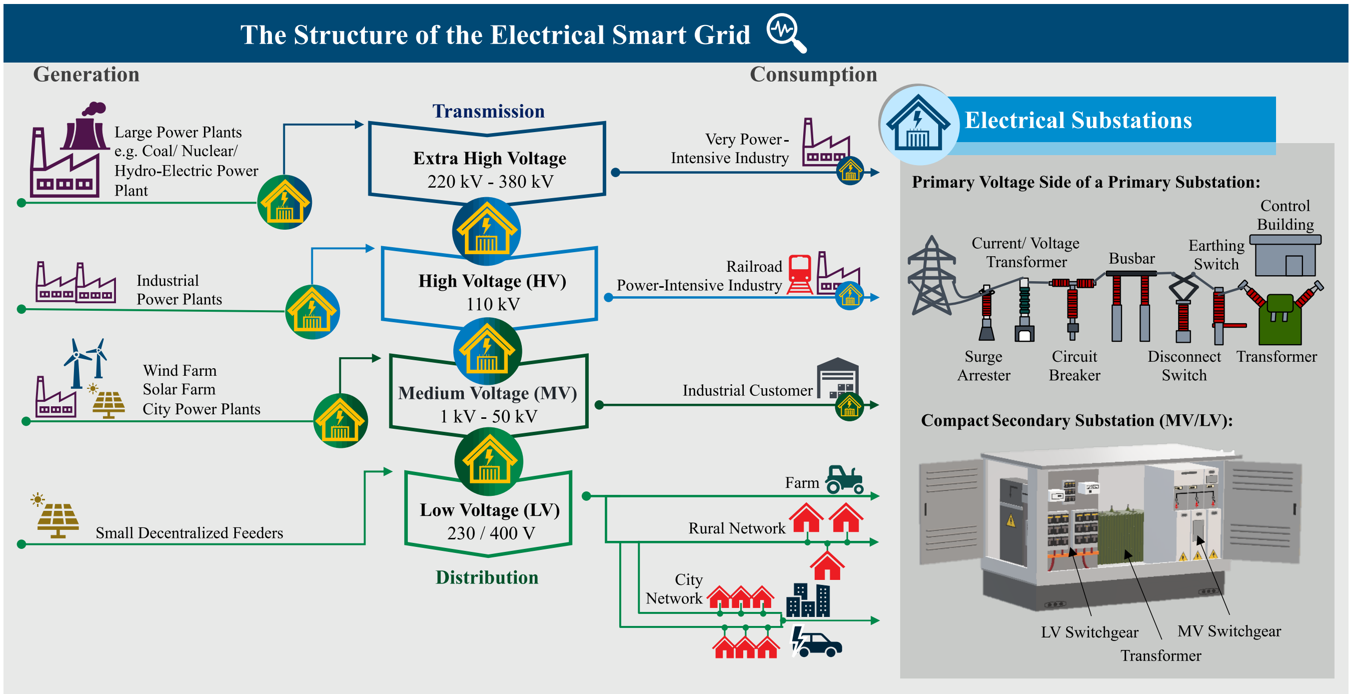


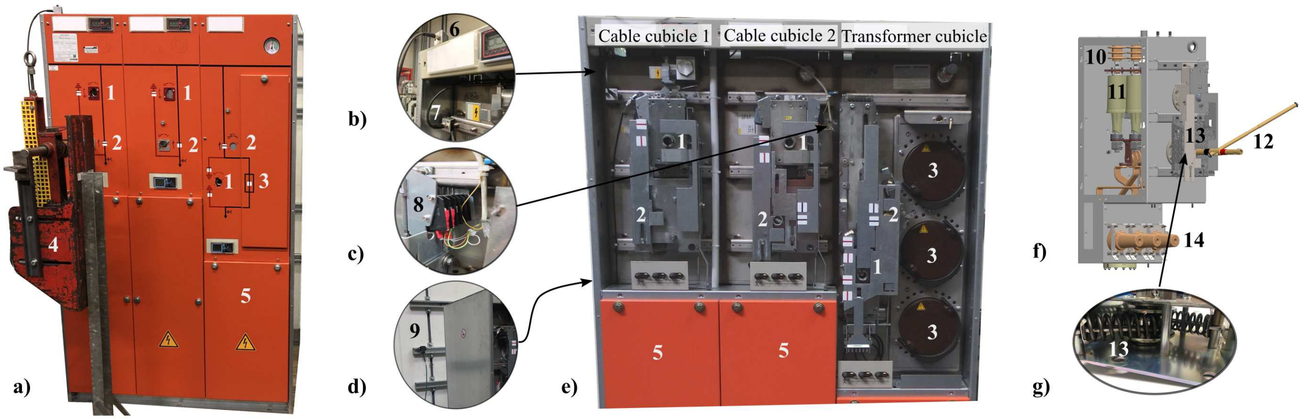
Figure 1: The structure of the electrical grid, with substations for voltage transformation between all voltage levels. Each substation is protected by switchgear on at least one side as shown for the primary voltage side of a primary substation (top right). Classically secondary substations (bottom right) are equipped with fuses on the LV side and MV switchgear.

switches) and/or circuit breakers (as shown in Fig. 2 a) for a triple cubicle MV switchgear unit), it is important to track all activities of the individual switches to evaluate the overall condition of a unit. To recognize a switch operation, existing solutions rely on signal switches at each breaker (Fig. 2 c) to extract the current position of the shaft or on the monitoring of electrical parameters by checking if the circuit is opened or closed. Yet, those solutions require a high amount of installation and cabling effort inside the unit to monitor the individual switches.

In contrast, we investigate the use of a single sensor system to monitor the complete switchgear unit. To achieve this, we take advantage of the fact that switches are equipped with springs within the gear mechanism. Those are preloaded (e.g., by a drive motor or manually with the switching crank, Fig. 2 f-g) to ensure safe switching operations. If the drive is rotated beyond a certain position, the energy of the springs is released abruptly, which guarantees that every operation is performed in the same way, independent of the operational speed of the drive. The released energy of the springs and the opening/closing of the contacts in the arcing chamber cause vibrations and acoustic emissions in the switchgear, which can be perceived as a loud blast. In a first step towards a single sensor system, we show that cost-effective microelectromechanical system (MEMS)-based acoustic and vibration sensors in combination with intelligent data analysis can be used for basic condition monitoring tasks such as the detection of switching operations, the differentiation of processes (switching-on and -off) for different breaker types and the tracking of mechanical ageing effects.

For the use as a retro-fit solution, the system has to be able to cope with the high diversity of switchgear types and manufactures installed in the field. For this reason, generalizable data models, which can be used independently of the switch type and installation position, are needed for the signal processing. In comparison, standard models are formed by collecting recorded data and extracting application-relevant features offline (e.g. on computationally powerful CPUs) for the best possible differentiation of classes in the feature domain. Afterwards, the design-specific model is implemented on-site e.g. on a gateway or microcontroller. This offline learning cycle has to be repeated for each type of switchgear, which leads to a considerable high effort. Therefore, we propose a configuration concept for automated online classification of switching processes for different breaker types without inference of a user. For the single learning phase, only a few labeled training data are needed to extract a relatively small number of informative features for classification using an adapted Silhouette Score. This enables on-site deployment with limited computing power without offline training in the back-end. Furthermore, we show that the selected features can be used for online assessment of the switchgear condition. Besides the use for switchgear process classification, the proposed method can also be configured for the use in other applications of the machine condition monitoring domain.

In the following, a short overview of existing monitoring solutions for switchgear will be given, followed by introducing our proposed method and the evaluation on seven datasets of switchgear measurements in a proof-of-concept study.



1 Earthing switch
2 Load break switch
3 Fuse
4 Pneumatic switching device
5 Cable connection compartment
6 Outside vibration sensor system
7 Inside vibration sensor system
8 Signal switch unit
9 Microphone
10 Switchgear compartment
11 Arcing chamber
12 Switching crank
13 Spring-driven mechanism
14 Bushings

Figure 2: Example of sensors installed in a triple cubicle switchgear unit from Driescher Wegberg: (a) Two vibration sensor systems, (b) a signal switch unit (c) and one microphone (d) as well as the view into the interior structure of two feed-in cable cubicles and an outgoing transformer cubicle (e) and the switchgear compartment (f) with spring-driven mechanism (g).

2 RELATED WORK

The development towards a smart electrical grid is leading to a shift from time-based to condition-based maintenance, driving the progression of online condition monitoring (CM) methods. This also applies to switchgear whose condition is classically tested by personnel who inspect manually on-site (offline) at fixed time intervals. In recent years, a variety of offline and online CM methods have evolved, including monitoring of insulation condition, detection of partial discharge, thermal measurements for hot-spot identification, supervision of the operating mechanism and tracking of the contact positions [1, 15, 19]. Nevertheless, the main area of research focuses on vibration and acoustic monitoring for the detection of mechanical faults which have been reported as the origin of 52.6 % of major failures [1, 6, 16, 20, 22, 23].

The main difficulty for sensor data analysis follows from the complexity of the signals. They can be characterized by a damping system with a trumpet-shaped envelope that is wide in the frequency domain and very short in the time domain due to the short switching time. Furthermore, the signals are subject to strong non-linearity, non-stationarity, distortion by noise and a dependence on the switchgear type [1, 8, 23]. The entire data processing is further complicated by the fact that the switching operation is only performed few times a year for maintenance reasons. To distinguish fault conditions (known and unknown ones) from natural variations in the signals, two main research directions were investigated: extraction and selection of distinctive features to determine slight changes between faulty and healthy condition measurements and appropriate classifications of those states. So far, mainly high-voltage circuit breakers have been considered [1, 11, 20, 23].

For the feature extraction and selection, especially, frequency-related features were considered due to the short switching duration and their potential relation to various failures. Apart from traditional spectral analysis using Fourier transform [22] methods for extracting local time-frequency information in better resolution were investigated. Thereby, the non-stationary and non-linear signals were decomposed into several non-inferences modes using, among others, empirical mode or wavelet decomposition, wavelet packet transform or variational mode decomposition [11, 23]. The presented methods, however, are among others subject to modal aliasing, energy losses and adaptability. Moreover, they suffer from the randomness of the decomposition level, which affects the reliability of the analysis, and most importantly, from the high computational complexity, which hinders online monitoring [1]. Following the feature extraction and selection, methods for classification between healthy and faulty condition were studied, including fuzzy based methods, back propagation neural networks, support vector machines, random forest or decision trees [11, 20]. Although these methods are properly trained to detect defined mechanical faults (such as for example poor lubrication, spring fatigue, or contact damage), they are highly dependent on the training set and on the sensor location, and they lack robustness for unknown faults and noisy data. They also have been shown to need a long time for training and have limited generalizability given the diversity of switchgear types [1]. The high manual effort and expert knowledge required for adaption of this methods and the necessary precise sensors with high bandwidth are not justified at MV level. Furthermore, the switching operations are not detected using the acoustic emission but signal switches. For these reasons, the usability of operation and condition monitoring for MV switchgear using acoustic and vibration signals is still an open research topic [8, 14].

In the following sections of this paper, the use of cost-effective MEMS-based sensors as well as a more generalizable classification method on their data using self-learning algorithms are examined.

3 APPROACH

The proposed method is designed to simplify the use of the monitoring sensor system in the field as much as possible. The basic idea is to be able to install the system within a short period of time and then learn to distinguish different switching processes directly on-site without interference from the user. The proposed algorithm is summarized in Fig. 3 under the caption "Intelligent Online Feature Selection & Classification". For better accuracy of process classification, it is assumed that a few labeled data can be recorded on-site at a given sensor position and switchgear type. As for standard methods, the algorithm is provided with these labeled training data on the classes (processes/scenarios) to be distinguished in the first step. In the next step, in contrast to existing methods, the model is also learned on-site such that the recorded data can be processed directly. For representing the time series data, extracted features have to be defined to map the data in the feature space, where the characteristics of different processes are better distinguishable. The specification of the implemented features by the user in advance provides the possibility to incorporate expert as well as physical knowledge. Furthermore, there are no restrictions on the kind and number of features. Either standard features from the time and frequency domains can be used (e.g. [2]) or suitable features can be extracted using more complicated methods such as decomposition methods, the use of non-linear kernel functions or autoencoders, depending on the available computing power installed on-site and the number of labeled time series data. Packages extracting a high amount of different features exist in Python (tsfresh [4], 794 extracted features) and MATLAB (hctsa [7], 7700 extracted features). Those packages also use highly parallelized feature selection algorithms that are based on statistical hypothesis tests, which require high computational power and are therefore not suitable for our use case.

For classification or clustering problems, the generalizability beyond the training set is a major concern, which is why the significance of extracted features is of high relevance and the selection of too many irrelevant features needs to be avoided. Furthermore, feature selection optimizes the performance of the algorithm by reducing its complexity as well as the needed computation time, which in turn enables online or even real-time monitoring for IoT solutions. Often, a multi-dimensional feature space is created to distribute the features in space for a better separability. However, with the increase of dimensions, the number of needed training data also increases exponentially (curse of dimensionality). This is critical as only few labeled training data can be provided for practical reasons. For this reason, a combination of clustering and classification is used to identify the relevant features that lead to a high information gain in the one-dimensional feature space. To achieve this, the training data labels are compared with the clustering quality, which is determined using a modified Silhouette analysis. The Silhouette Score $S_i = \frac{b_i - a_i}{\max(a_i, b_i)}$ is a measure on how similar a feature point i is to points of its own cluster (cohesion) compared to points of other clusters (separation) [9]. For the similarity, the average intra-cluster distance a_i and inter-cluster distance b_i are calculated, defining the cluster compactness. Traditionally, the Silhouette Score is one of the most popular cluster validity indices used to determine the optimal number of clusters in a very effective way e.g. for cluster

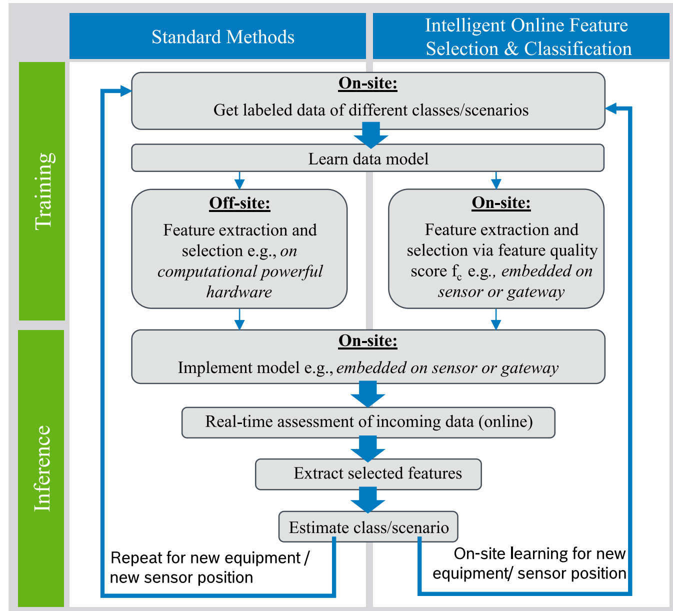


Figure 3: Compared to standard methods, our approach enables the deployment of a monitoring system in one appointment by first installing the sensors, followed by recording few labeled training data, which are directly processed to select appropriate features on-site for classification.

algorithms like k-means [5, 17]. Here, we adapt the method to find features that classify our labeled data most accurately. The only disadvantage of the Silhouette Score is the high computational effort for calculating the pairwise distances a_i and b_i between all points, which scales with the size of training data (number of features and number of samples). Our adaption instead calculates a feature quality score (fc) out of the distance between the features and their own cluster center c_i and the nearest cluster center c_k (similar to [21]) as follows:

$$fc = \frac{1}{N} \sum_{i=1}^{N} \frac{d_{ik} - d_{ii}}{\max(d_{ik}, d_{ii})}, \tag{1}$$

whereby N is the number of different clusters, d_{ii} is the average distance of feature values of one cluster to its own cluster center c_i and d_{ik} is the average distance of those features to the nearest cluster center c_k (Fig. 4). A good clustering is given for a feature quality score near 1, while a score of -1 corresponds to a bad clustering. Wang et al. showed that the simplified Silhouette Score leads to similar results as the original one [21]. In comparison to other methods, the mapping into a joint-feature space is not necessary, which leads to an easier interpretability, lower computational costs, and an increased robustness against overfitting.

In the inference phase, the data are continuously collected and then automatically analysed. If a switch operation is detected, the selected features are calculated for the measurement. Based on the distance of the features to the center a model based classification probability is calculated, as shown in Fig. 4, to evaluate the detected process. Point i is assigned to scenario/process 1 with a probability

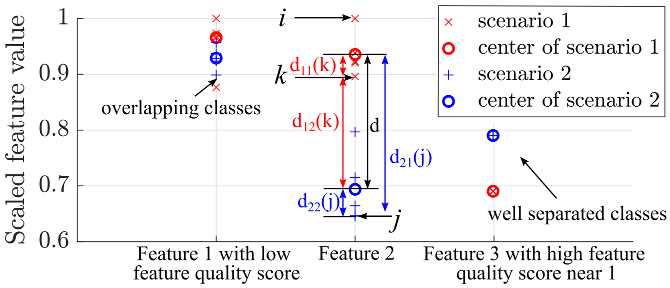


Figure 4: Example of three scaled features and illustration of the distances for exemplary point used for the feature quality score calculation.

of 100 %, and point j correspondingly to scenario 2. Point k, laying between the clusters, is assigned to scenario 1 with a probability of $P = 1 - \frac{d_{11}}{d}$ with d being the distance between the centers.

4 PROOF-OF-CONCEPT-STUDY

The benefits of our approach are studied in this section for the differentiation of switching processes on seven datasets that were recorded for a medium voltage (MV) switchgear unit.

4.1 System Setup and Data

This study's data were recorded at encapsulated (SF6- and vacuum-isolated) medium-voltage switchgear, which is manufactured according to a modular principle from individual metal-encapsulated cubicles (e.g. feed-in cable and transformer outgoing feeder cubicles) consisting of circuit breakers, fuses and switches as shown in Fig. 2. Load-break switches are used to (dis)connect single assets or entire units at rated current, while circuit breakers can also switch in a disturbed case (e.g. at short circuit). In contrast, earthing switches are used to ground the assets. Measurements were taken on all three switch types to show that the method can be used to distinguish switching processes and thus track the number of operations. For the measurements, two different sensor systems were tested on their suitability for non-invasive monitoring. The first one is a MEMS-based stereo microphone (*MBSM*) with a sampling frequency of 48 kHz, an SNR of 66 dB, a sensitivity tolerance of -38 dB ± 1 dB and a flat frequency response from 50 Hz to 14 kHz, which is integrated in an MM5 housing with a USB connection (Fig. 2 d). The second system is a MEMS vibration sensor system (*VSS*) consisting of two accelerometers, which are packaged in an industrial suited housing together with a microcontroller for possible pre-processing tasks (Fig. 2 b). The two accelerometers are used to cover a high bandwidth as well as a good resolution in the low frequency range. The first accelerometer (*A*1) has a single degree of freedom, a sampling rate of 62.5 kHz, a measurement range of several 10s of g and a sensitivity of few LSB/g. The second one (*A*2) is a three-axis sensor for consumer applications with a sampling rate of 2 kHz, a resolution of 0.98 mg, a sensitivity of 1024 LSB/g, a programmable measurement range between 2-16 g and a non-linearity of ± 0.5 %. The microphone was installed in a distance of approximately two meters behind the switchgear unit, while two of the vibration sensor systems were tested on two different positions for evaluating the mounting position influence. One vibration sensor (*VSS1*) was screwed inside the cubicle next to the spring-drive mechanism, whereas the second system (*VSS2*) was mounted on top of the corresponding cubicle (see Fig. 2 b, d). All sensor systems feature integrated A/D conversion, amplification and correction factors, thus providing processed digital values. For this study, all three systems were connected via USB to an industrial Raspberry Pi which controls the data recording using a trigger circuit, saves the data on a USB device or transfers it via LTE for remote monitoring. The data recording was triggered by limit switches, which were turned after each opening and closing operation (Fig. 2 c), whereby the switching operations were performed automatically with the help of a pneumatic switching device (Fig. 2 a). Details of the recorded datasets DS1 to DS7 are listed in Table 1. As the limit switches tend to bounce, the number of measurement files in one dataset is not consistent over all sensors.

4.2 Actuation Detection

Compared to literature, which described the switching duration for circuit breakers in the range of 10s milliseconds [8] and thus did not consider features in the time domain, the measured signals at

Table 1: Datasets and parameter variations per sensor (vibration sensors VSS1 and VSS2, stereo microphone MBSM)

Dataset	Switchgear type	Sensor	Records
DS1	load break switch in cable cubicle	VSS1	585
		VSS2	948
		MBSM	1118
DS2	load break switch in cable cubicle	VSS1	306
		VSS2	27
		MBSM	279
DS3	load break switch in transformer cubicle	VSS1	3295
		VSS2	3299
		MBSM	3187
DS4	vacuum circuit breaker	VSS1	3830
		VSS2	533
		MBSM	3831
DS5	load break switch in cable cubicle	VSS1	4000
		VSS2	4000
		MBSM	4000
DS6	earthing switch in cable cubicle	VSS1	3750
		VSS2	3823
		MBSM	3942
DS7	load break switch with SEA-drive in transformer cubicle	VSS1	2170
		VSS2	4351
		MBSM	4163

the MV switchgear have an average switching duration of several 100s milliseconds and last up to one second with fully recorded decay. An example can be found in Fig. 5. If measurements are taken directly at the switchgear or in close proximity, a signal-to-noise ratio (SNR) of around 20 dB is achieved due to the high released energy. Therefore, the switching operation can be very well distinguished from the background.

To detect switchgear operations for further classification of different processes, a threshold recognition is implemented. In order to reduce the amount of data and increase the robustness against outliers, the raw data are compressed by computing the sum of power spectral density (PSD) estimates in intervals of equal lengths (Fig. 6). From the average and standard deviation of the PSD values of training data, the detection threshold is calculated. When switching a circuit breaker as in Fig. 6, a spring is pre-tensioned to guarantee that the switch-off process can be carried out safely. When this spring snaps into place, a second peak is detected. To ensure that only one process is identified, new start points within the average switching time of the training data are discarded. For DS1-DS7, this leads to a detection accuracy of > 99% for all sensors, whereby the

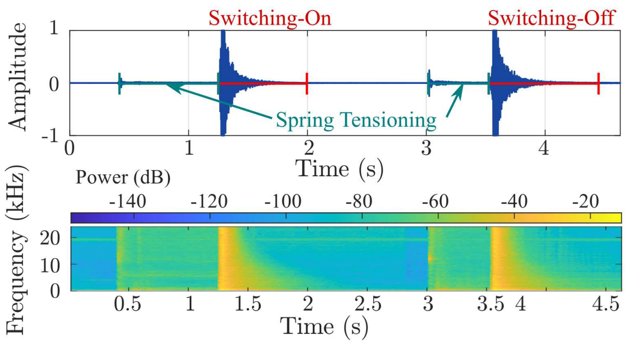


Figure 5: Example of a switching-on and -off process as recorded by the MEMS microphone (MSBS, top timeseries plot) and its corresponding spectrogram (below).

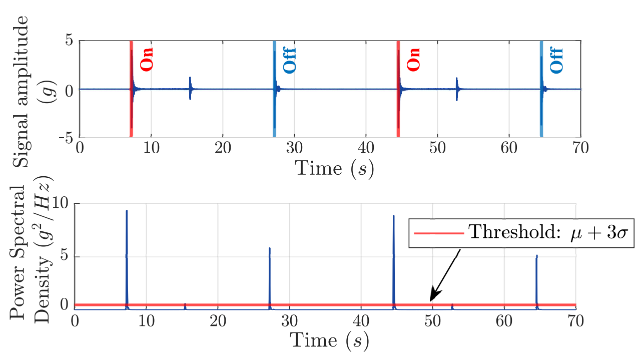


Figure 6: Vibration signal from DS3 (above) and its power spectral density computed over intervals of 33 ms (below). A switchgear operation is detected when the threshold on the power spectral density is exceeded.

method is robust against usual background noises (e.g. speaking, loud coughing) that were captured during the measurements.

4.3 Online Feature Selection and Classification

In addition to the basic detection, the determination of the number and frequency of switching is of great interest. When having more than one switch installed, the simple counting of detected operations is no longer sufficient and a signal-based differentiation of processes (e.g. on/off, switchgear types) becomes necessary. For the first step, the sensor is installed in its final position and the different processes that need to be classified are executed several times. For a realistic practicability, five recurrences for each process have been selected. It is assumed that, as the switching operation through the spring mechanism is always carried out in the same way, five recurrences are sufficient to distinguish discriminative features. Differentiable processes can be the switching of different breaker types, new and old switchgear, as well as switching-on and -off, which is the focus here. For this use case, the labeling of the training data is done automatically by first detecting the actuations with the above algorithm and then alternately labeling it with "on" and "off" (Fig. 6). In a second step, the training data are low pass filtered with different cut-off frequencies as especially during the decay process a lot of information lies in the low-frequency range (<10 kHz [10], Fig. 5). Feature calculation is executed for each of the filtered signals. In this study, 21 features listed in Table 2 were extracted and afterwards rescaled (e.g. z-score) for data normalization. Thereby, as mentioned above, also features in the time domain were considered. For the study, the best five discriminative features were selected with the proposed method and used for the inference.

4.4 Results and Discussion

The average accuracy per sensor over all selected features and axes is shown in Table 3 (*Selected features*). For the differentiation between switching-on and -off, the microphone leads to the best results over all datasets with an accuracy of 93.4 %. Care must be taken not to place the sensors too close to the unit under test to ensure that the sensors do not exceed their defined measuring range and begin to clip. This also leads to artifacts in the measurements which can be seen in the results of the two vibration sensor systems. The outside installed system *VSS2* leads to a better detection with an average accuracy of 89.3 % compared to the sensors installed near the switchgear drive with 85 %. This shows that a non-invasive wired power supply is possible without modifying the unit. As the

Table 2: Time and Frequency Domain Features

Domain	Features
Frequency & Time	mean, variance, skewness, kurtosis, power, flatness
Time	root mean square, absolute mean, maximum, minimum, dynamic range, crest factor
Frequency	spectral centroid, median frequency, dominant frequency

measurements show a damped oscillation frequency, features from the frequency domain are primarily selected. The most selected feature is the dominant frequency with extracted values mostly located below 1 kHz. This supports the approach of filtering the signal before extracting the features and also explains why the accelerometers *A2* with a greater resolution in the low frequency range perform better (90.6 %) compared to *A1* (87.9 %) in *VSS2*. In contrast to the selected features, the axis orientation of *A2* plays a minor role for the accuracy. Trigger problems and therefore inconsistent truncated measurements result in a lower accuracy in DS2. To reduce the dependency on individual features for the scenario estimation, a majority vote of the result from the five extracted features is implemented. Three different versions (equally weighted, weighted with feature quality score, weighted with scenario estimation probability) are tested, which all lead to a similar accuracy (0.5% deviation). Table 3 (*Majority vote*) shows the equally weighted feature results, which, in most cases, improves the overall accuracy compared to the first column. A further increase in the number of features (up to 15) for the vote was tested for 2000 operations of DS5, increasing only the accuracy of *VSS1 A2* and *VSS2 A1* by 2%-5% per additional two features. An increase of training measurement (up to 20) did not improve the overall accuracy significantly. Learned features from DS1 were also tested on the inference data of DS2, which led to worse results (3 % overall accuracy loss). This shows that even features learned for the same switch type with similar sensor location cannot easily be transferred since the signal characteristics differ if the setup changes. This results in the the necessity of our approach to give an opportunity for on-site learning.

4.5 Trend Detection for Ageing Effects

For DS5, the load break switch was switched beyond its specified end of life. As the contacts and spring deteriorate, the characteristics of the data distribution change over time, resulting in decreasing detection accuracy. However, this property can be exploited to map aging processes with the help of the selected features. At the end of the measurements of DS1, there was a failure of the spring-based switching mechanism of the load switch. Figure 7 shows the change in one of the selected features for *VSS2 A2*. As data from broken switches are not always available, the above method cannot always be used to differentiate between new and used switchgear to track changes. An alternative is the change tracking of the already selected features by continuously updating the calculated cluster centers to track their development. The update is done with the exponential weighted moving average (EWMA)

$$c_{ij} = \alpha * f_{ij} + (1 - \alpha) * c_{ij-1}, \tag{2}$$

whereby c_{ij} describes the center of a scenario i at time j, f_{ij} is the corresponding feature and $\alpha \in [0, 1]$ is a weighting factor to determine how much influence the new feature f_{ij} has on the old center c_{ij-1} . In our implementation, only features in the $\mu \pm 3\sigma$-range of the center were considered for the calculation and $\alpha = 0.05$ was used. This approach leads to an improvement of the accuracy as shown in *Updated centers* of Table 3. The change between the current value of the center and the beginning one is a good indicator for the aging of switchgear. By using defined alarm thresholds (e.g., 20 % deviation from original center), an alarm or a relearning can be triggered in case of a major change (Fig. 7).

Table 3: Obtained accuracy figures for the Online Feature Selection per sensor modality and across all datasets DS1-DS7

Dataset	Sensor	Accuracy in [%]		
		Selected features	Majority vote	Updated centers
DS1	VSS1 A1	70.8	75.5	91.4
	VSS1 A2	81.7	89.1	96.9
	VSS2 A1	85.9	85.9	85.9
	VSS2 A2	89.0	95.3	99.8
	MBSM	98.7	98.9	99.1
DS2	VSS1 A1	57.1	57.1	57.1
	VSS1 A2	66.0	68.4	65.7
	VSS2 A1	78.6	78.6	78.6
	VSS2 A2	76.7	85.4	85.4
	MBSM	89.0	93.6	94.4
DS3	VSS1 A1	98.5	98.5	98.6
	VSS1 A2	99.0	99.3	99.3
	VSS2 A1	100	100	99.9
	VSS2 A2	96.1	97.6	97.6
	MBSM	94.8	94.8	99.7
DS4	VSS1 A1	93.8	95.2	100
	VSS1 A2	91.6	98.0	100
	VSS2 A1	97.8	97.9	99.8
	VSS2 A2	97.8	98.1	98.1
	MBSM	97.1	98.9	98.8
DS5	VSS1 A1	76.0	79.7	96.8
	VSS1 A2	60.8	58.5	64.3
	VSS2 A1	54.8	57.2	59.0
	VSS2 A2	78.8	82.0	100
	MBSM	74.0	72.1	97.3
DS6	VSS1 A1	100	100	100
	VSS1 A2	99.2	100	100
	VSS2 A1	98.1	99.4	99.6
	VSS2 A2	99.9	100	100
	MBSM	100	100	100
DS7	VSS1 A1	95.7	99.9	100
	VSS1 A2	99.3	99.9	100
	VSS2 A1	99.9	100	100
	VSS2 A2	96.2	98.2	99.9
	MBSM	99.9	99.9	100

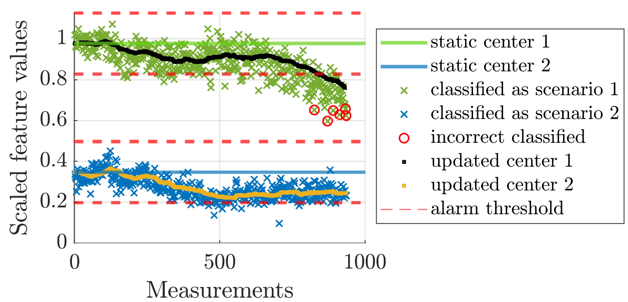


Figure 7: Classification of VSS2 A2 vibration measurements from dataset DS1 using static vs. adaptive centers. Updated centers allow a better accuracy over time and can track changes. An alarm is triggered once one of the thresholds is exceeded.

5 CONCLUSION AND FUTURE WORK

In this paper, we present an approach that allows accurate monitoring of different processes at medium-voltage switchgear units, which in turn enables a distributed and more fine-grained analysis of our electrical grid. The suitability of MEMS-based acoustic and vibration sensors is evaluated and best practices for the installation are given. The proposed system can thereby be used as an additional module for non-invasive, cost-effective switchgear supervision in a modular secondary substation monitoring system as described in [13]. Furthermore, an integration of the microphone in a central node addressing further use cases such as ambient noise monitoring for intrusion detection is conceivable. Additionally, a configuration for online classification based on on-site ranked feature selection is evaluated. This approach eliminates the need for time-consuming application-specific offline training. We show that, with this approach, switchgear actuations (that are automatically detected via a threshold) can be classified reliably for different scenarios. Furthermore, the selected features can be used to detect trends in the data for switchgear aging. An update of the cluster centers and a majority vote further improve the classification quality by 6.8 % on average in accuracy. Further investigations include the evaluation of using only one sensor system for monitoring a complete switchgear unit by extending the proposed approach to multi-class classification and evaluating trade-offs of our approach compared to offline methods e.g. in terms of computational power.

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