10133 Session 2022
A3 - TRANSMISSION & DISTRIBUTION EQUIPMENT
Preferential Subject PS3

Application of Machine Learning and Anomaly Detection for On-line Defect Identification in Wall Bushings in HVDC Systems

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SUMMARY

Statistical data on defects and failures specific to HVDC wall bushings are not easily found in literature, the bushing failure statistics on power transformers give us a glimpse of the high criticality of these devices: according to the statistics presented by Cigre in Technical Brochure 642 [1], on the reliability of transformers, bushings are the third most common cause of power transformer failures, being responsible for approximately 14% of them. When the reference becomes power transformers 500 ≤ kV <700, bushings are in the first place and represent approximately 30% of this total. To make the situation even more serious, failures caused by bushings are classified as "Major Failures", as they require, at least, the replacement of the bushings. Furthermore, approximately 50% of bushing failures cause an explosion or fire, originating human, financial, and structural damage.

In this way, it is increasingly necessary to develop new techniques and tools to assist asset management maintenance teams in online identifying defects in HVDC wall bushings that are still in an incipient stage, enabling these teams to better support their decision making to meet the utility's organizational objectives more efficiently.

In this context, this work presents a new approach to the application of unsupervised machine learning and anomaly detection to HVDC wall bushings. The methodology developed was applied to real operating data gathered from 600 kV and 300 kV HVDC wall bushings in the converter substation Ibiúna of Eletrobras Furnas, part of the first large HVDC system in Brazil.

The results obtained show that anomaly detection techniques are promising for this application, allowing the detection of unseen defect types not only in bushings but also in the HVDC system, overcoming the problem of lack of data.

This report presents the main results of the Research & Development (R&D) project PD-00394-1708/2017, proposed and financed by Furnas Centrais Elétricas and regulated by the ANEEL Program "Research and Technological Development for the Electric Sector."

KEYWORDS

Bushings, Transformers, Machine Learning, Fault Detection

1. INTRODUCTION

With the need to transmit large blocks of electrical energy over increasingly long distances, HVDC transmission has reached a high degree of importance, not only in the technical aspect, but mainly from an economic and strategic point of view. Thus, it is essential to guarantee the reliability of the high voltage equipment used. In this context, the wall bushings stand out as they are used as electrical interfaces between the interior of the valve rooms, where the power electronics are housed, and the external environment where the substation is located, usually outdoors.

Although statistical data on defects and failures specific to these types of HVDC wall bushing are not easily found in literature, the bushing failure statistics on power transformers give us a glimpse of the high criticality of these devices: according to the statistics presented by Cigre in Technical Brochure 642 [1], on the reliability of transformers, bushings are the third most common cause of power transformer failures, being responsible for approximately 14% of them. When the reference becomes power transformers 500 ≤ kV <700, bushings are in the first place and represent approximately 30% of this total. To make the situation even more serious, failures caused by bushings are classified as "Major Failures", as they require, at least, the replacement of the bushings. Furthermore, approximately 50% of bushing failures cause an explosion or fire, originating human, financial, and structural damage.

In this sense, it is increasingly necessary to develop new techniques and tools to assist asset management maintenance teams in online identifying defects in HVDC wall bushings that are still in an incipient stage, enabling these teams to better support their decision making to meet the utility's organizational objectives more efficiently.

Among these new technologies, the application of Machine Learning techniques, such as anomaly detection, stands out. Anomaly Detection, or Outlier Detection, is the identification of anomalous data points that differ significantly from most of the data in the set [2]. Usually, the cause of these events in the data is connected to some kind of variation in the standard process analyzed, such as a structural defect or equipment malfunction. The detection of these anomalies in the data set is a powerful tool from the point of view of machine diagnostics, since it makes it possible to identify failures that have never been seen before.

In this context, this work presents a new approach to the application of unsupervised machine learning and anomaly detection to HVDC wall bushings. The methodology developed was applied to real operating data gathered from 600 kV and 300 kV HVDC wall bushings in the converter substation Ibiúna of Eletrobras Furnas, part of the first large HVDC system in Brazil. These bushings are at least 30 years old. Data were collected on both AC and DC sides, totaling 9 bushings (3 of the DC side and 6 of AC side).

The results obtained show that anomaly detection techniques are promising for this application, allowing the detection of unseen defect types not only in bushings but also in the HVDC system, overcoming the problem of lack of data.

This report presents the main results of the Research & Development (R&D) project PD-00394-1708/2017, entitled "Monitoração On-line de Buchas de Parede de Alta Tensão em Corrente Contínua (HVDC)", proposed and financed by Furnas Centrais Elétricas and regulated by the ANEEL Program "Research and Technological Development for the Electric Sector."

2. LITERATURE REVIEW

2.1 CONDENSER BUSHING MODELING

The body of a condenser bushing is made up of several cylindrical insulating layers around a central conductor, interspersed with cylindrical conductive layers whose function is to uniformize the electric field as much as possible, as shown in Figure 1. The outermost conductive layer is connected to the bushing flange, and this in turn to ground potential. The intermediate conductive layers, on the other hand, remain insulated, with floating potential, except for one of the most external ones, which is grounded through a removable connection near the base of the bushing, called voltage tap or test tap [3].

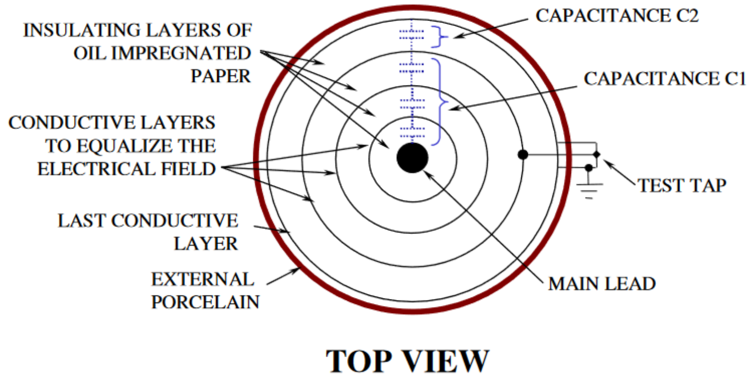

Figure 1 - Constructive Form of a Condenser Bushing [3].

As shown in Figure 1, the bushing body acts electrically like several capacitors connected in series, forming a capacitive voltage divider. This constitution causes the difference in the total potential of the main conductor in relation to the ground to be divided among the different capacitors.

When phase-to-ground voltage is applied to the bushing, a current, called leakage current, flows through its insulation, mainly due to its capacitance, and to a much lesser extent due to its dielectric losses (expressed by the dissipation factor or tangent delta) [3]. Figure 2 illustrates this situation.

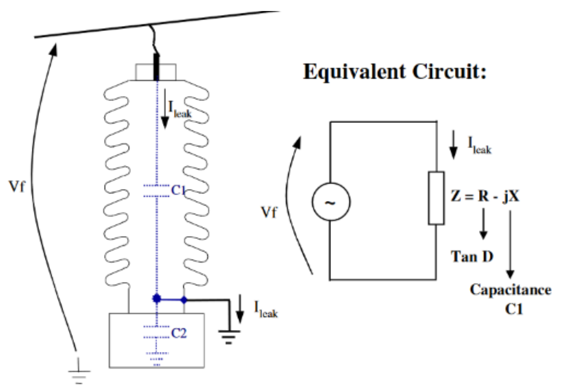

Figure 2 - Equivalent circuit of an energized condenser bushing [4].

In Figure 2, the electrical equivalent obtained with the construction shown in Figure 1 can be seen, with the bushing energized. This is the electrical equivalent "series" model. A "parallel" electrical model could also be applied, with the same results. With the adopted model, there is the following resulting leakage current:

$$I_{leak} = \frac{V_f}{Z} = \frac{V_f}{R - jX} \qquad (1)$$

Where "R" represents the resistive component of the insulation impedance, which generates the resistive part of the leakage current, associated with dielectric losses, and "X" represents the reactive component due to the insulation capacitance.

2.2 ONLINE BUSHING MONITORING

One of the first methods used for online monitoring of condenser bushings was the evaluation of variations in capacitance and tangent delta. These dielectric parameters are calculated from the bushing leakage current vectors, since there is often no real-time measurement of the voltage vectors in the bus, thus preventing the calculation of the power factor using the traditional formula.

The dielectric parameters of bushings are temperature dependent. In this way, their value must be corrected by it. There are no simple formulas for this correction, and although it is possible to use curves provided by some standards, in IEEE C57.12.90-2006 [5] it is stated that “experience has shown that the variation of the power factor with temperature is substantial and erratic so that there is no single correction curve that applies to all cases”.

Another method of bushing monitoring widely used in the industry is partial discharge monitoring. The measurement and location of partial discharge (PD) phenomena has been of interest since at least the early 1940s. The apparatus and techniques used in the early days of PD investigations were so basic that many things went unrecorded, even though they are known in the industry. For example, portable radios with extendable antennas have been used as “electronic sniffers” to provide raw location of externally generated PDs or corona discharges [4].

In [6], the author describes a new method of online bushing monitoring where he presents the development of an online monitoring system with high sampling rate and vertical resolution capable of detecting PD activities in power transformers from the capacitive coupling in test taps of high voltage (HV) condenser bushings. Taking measurements from the tap terminal has the main benefit of detecting the occurrence of PDs not only in the bushing insulation, but also in the insulation of the windings due to the capacitive and inductive coupling of the intrinsic elements of a transformer. However, online monitoring techniques for partial discharges in bushings are still in their incipient state, with most tests being simulated or carried out in laboratory conditions.

2.3 HVDC Wall Bushing Monitoring

Online monitoring of capacitance and tangent delta of AC bushings has achieved good results in its application in power transformers and reactors. However, its direct application in condenser bushings of converter transformers in HVDC systems, using the same hardware and software resources, is not possible, given the presence of harmonic components resulting from the conversion of direct current to alternating current in bushings of this equipment.

The AC/DC conversion process is, inevitably, accompanied by the effects of harmonic generation, being the odd-order harmonics generated on the AC side and the even-order harmonics being generated on the DC side.

This fact makes it impossible to directly apply the monitoring system in HVDC bushings with the same software and hardware resources used in AC bushing monitoring, described in item 2.2.

Faced with these complications, Treetech Sistemas Digitais conducted a field experiment with online monitoring of HVDC bushings of converter transformers at the Ibiúna substation. This experience is described in reference [7].

In the experience, changes were made in the data acquisition software and in the firmware of the BM Bushing Monitor system, but it was found that special alterations were also needed in the equipment's hardware to allow them to correctly read the leakage current and calculate capacitance and tangent delta. Such changes allowed the monitoring system to correctly acquire and interpret the signal (leakage current) coming from the bushing tap.

Two interface modules and five measurement modules were used to monitor the transformers of converter 4, at SE Ibiúna. These modules were installed in the individual panel of a transformer. The data acquired by the measurement modules were sent to a server, where the monitoring software was installed, through Wi-Fi wireless communication.

This pilot application reported in the article [7] was the only experience of applying online monitoring systems in HVDC bushings found. This reinforces the need for the development of an Online Monitoring System for High Voltage Direct Current (HVDC) Wall Bushings.

3. DETECTION OF ANOMALIES WITH AUTOENCODERS

Autoencoders are neural networks trained in order to copy their input to their output [8]. This interest may seem a bit strange, but in practice the goal is to learn representations (encodings) of the data, which can be used for dimensionality reduction or even file compression. Along with the reduction side, a reconstruction side is trained, where the autoencoder tries to generate from the reduced encoding a representation as close as possible to its original input.

The simplest architecture of an autoencoder is a feedforward neural network, such as a Multilayer Perceptron (MLP), with at least 3 layers and with the first and last layer having the same number of neurons. Figure 3 presents a basic autoencoder architecture.

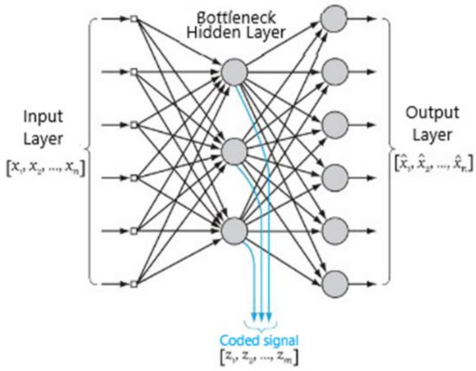

Figure 3 - Autoencoder example. Adapted from Siqueira (2019) [9].

For the detection of anomalies, the autoencoder is used with the function of generalizing the sensor readings to a lower dimension, which captures the correlations and interactions between the many variables or between different instants of time of the same variable.

Network training is done using data that represent the normal state of the equipment, making the network capable of reconstructing this behavior. The main idea is that as the monitored equipment degrades and the values measured by the sensors reflect this degradation, the network will start to show an increase in the reconstruction error of the input variables. By analyzing the probability distribution of the reconstruction error in the training set, it is possible to establish a threshold to identify whether a dataset is normal or anomalous.

4. CASE STUDY

This work presents a case study of the detection of defects in HVDC wall bushings using Anomaly Detection techniques. The developed methodology was applied to real operational data collected from 600 kV and 300 kV HVDC wall bushings at Eletrobras Furnas' Ibiúna converter substation, part of the first large HVDC system in Brazil. These bushings are at least 30 years old. Data were collected on both AC and DC sides, totaling 9 bushings (3 on DC side and 6 on AC side) and 1 resistive power divider (RPD). For the study, bushings in the DC and AC sides were evaluated separately.

Data sampling was performed between February 24, 2021 and March 3, 2021, with a rate of 20kHz. In addition, the sampling was carried out in periods of 100ms and with an interval of one minute between each sampling.

In Figure 4, the amplitudes of the 12th harmonics along the samples for the assets on the DC side are presented. In it, it is possible to see the high correlation existing between the bushings and the RPD.

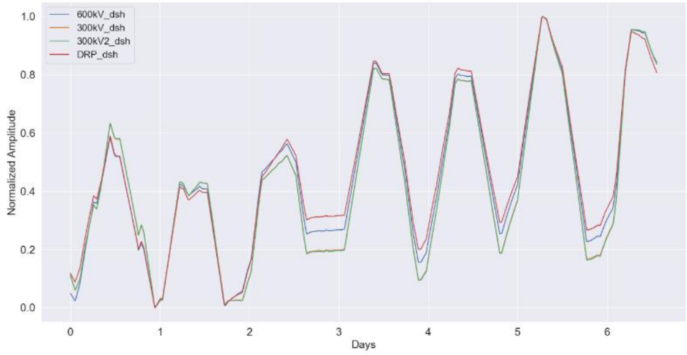

Figure 4 - Amplitude of the 12th Harmonics.

Table I shows the correlation values for these data.

Table I - Correlation of 12th Harmonics

	Bushing 600kV	Bushing 300kV	Bushing 300kV2	RPD
Bushing 600kV	1.000000	0.995981	0.995614	0.997585
Bushing 300kV	0.995981	1.000000	0.999991	0.998377
Bushing 300kV2	0.995614	0.999991	1.000000	0.998248
RPD	0.997585	0.998377	0.998248	1.000000

Similarly, in Figure 5, the amplitudes of the 3rd harmonics along the samples for the AC side bushings are presented. It is also possible to see the high correlation between the output bushings of the converter. Table II shows the voltage correlation values at the test terminal of these bushings.

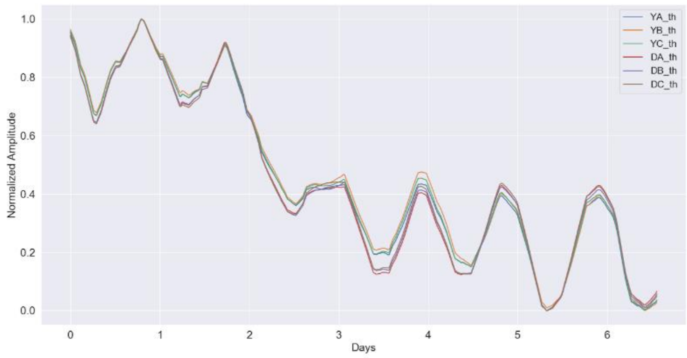

Figure 5 - Amplitudes of the 3rd Harmonics.

Table II - Correlation of the 3rd Harmonics at the Test Terminal

	YA_th	YB_th	YC_th	DA_th	DB_th	DC_th
YA_th	1.000000	0.999372	0.999833	0.995026	0.996557	0.995540
YB_th	0.999372	1.000000	0.999606	0.992562	0.994758	0.993918
YC_th	0.999833	0.999606	1.000000	0.995104	0.996736	0.996027
DA_th	0.995026	0.992562	0.995104	1.000000	0.999715	0.999565
DB_th	0.996557	0.994758	0.996736	0.999715	1.000000	0.999792
DC_th	0.995540	0.993918	0.996027	0.999565	0.999792	1.000000

4.1 EXTRACTION AND NORMALIZATION

For the input of the models, an extraction of features was performed by applying a sliding window over the signal. Due to expert knowledge, it was considered interesting to extract the characteristics below:

- Sum of values;
- Mean;
- Standard deviation;
- Median;
- Maximum Value;
- Minimum Value.

In addition, data normalization was applied to prevent attributes with higher values from impacting the model error more and being privileged during training.

4.2 TRAINING AND TESTING

4.2.1 DC SIDE

The training and testing sets were evenly split among the available data. The model was initially trained and tested on the data without any changes. The result obtained is shown in Figure 6.

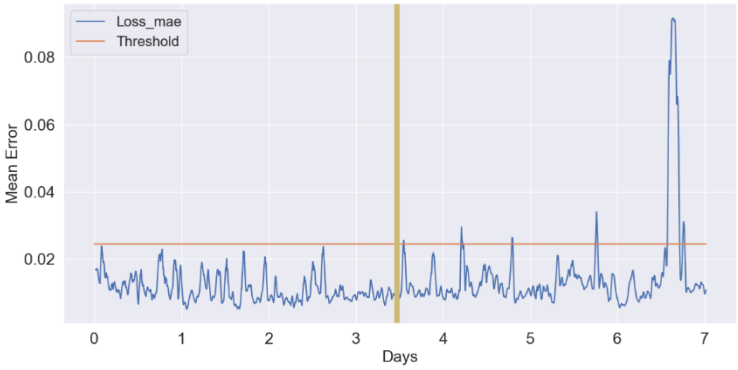

Figure 6 - Model Result for the DC Side.

As it is possible to notice, the model presented some cases of false positive alarms with very small occurrences, being the biggest one on the sixth day, lasting less than 3 hours. The probable cause of this alarm is the low amount of data used in the model training, that is, the model was not presented during the training for all the converter operation modes.

To validate the model's efficiency in detecting defects, an increase in the 600 kV bushing voltage was simulated for the test data. The increase was given by Equation 2.

$$voltage[x] = voltage[x] * (1 + 0.000007 * x + np.\sin\left(\frac{x}{10000}\right) * 0.02) \qquad (2)$$

where x is the sample number in the test set. Thus, for the last sample of the test set, the voltage increase was approximately 21.28% of the original value.

The model result for this scenario is shown in Figure 7.

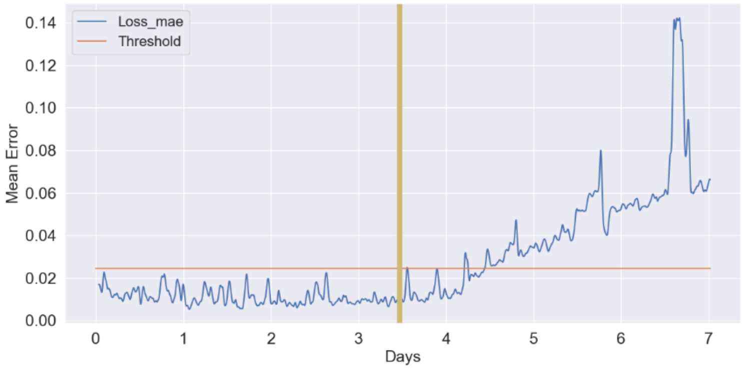

Figure 7 - Model Result for a simulated error in the 600kV Bushing.

For this simulation, the model showed a persistent anomaly for most of the test set. The increase in voltage at the initial moment of detection of the persistent anomaly was approximately 7.3%.

4.2.2 AC SIDE

As for the DC Side, the training and testing sets were evenly split among the available data. The model was initially trained and tested on the data without any changes. The result obtained is shown in Figure 8.

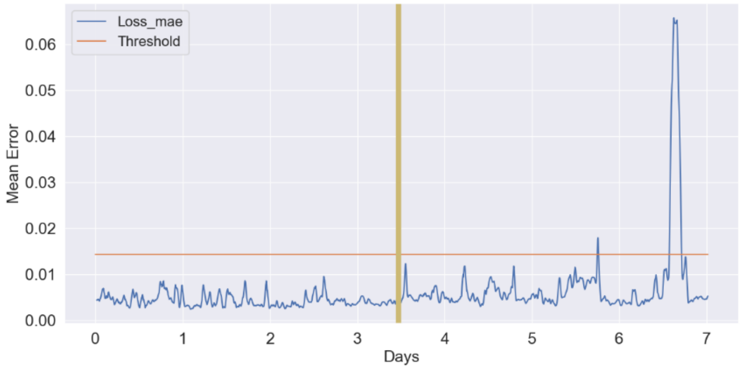

Figure 8 - Model Result for AC Side.

The model also presented some cases of false positive alarms with very small occurrence, the largest of which on the sixth day, lasting less than 3 hours, probably caused by the same factor as on the DC side.

To validate the model's efficiency in detecting defects, an increase in the voltage value of the star-connected B bushing test data was simulated. The simulated defect was the same as the 600kV bushing. The model result for this scenario is shown in Figure 9.

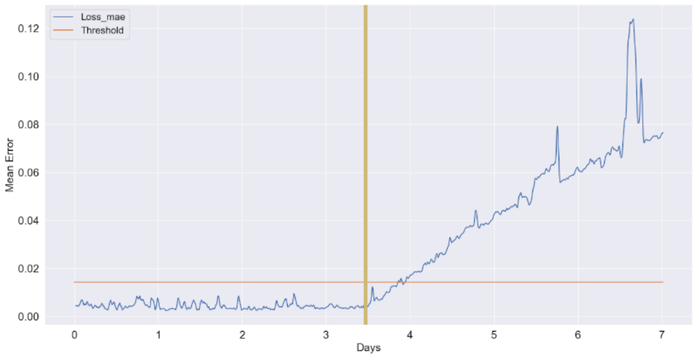

Figure 9 - Model Result for a simulated error in the star-connected B bushing.

For this simulation, the model was able to detect the defect at a very early stage. The increase in voltage at the initial moment of detection of the persistent anomaly was approximately 3.9 %.

5. CONCLUSION

Bushings are among the most important components in an HVDC as they provide the safe passage of an energized conductor through a grounded wall. However, they are among the main causes of failures in transformers, indicating that their condition must be monitored. Furthermore, failures generated by bushings are often catastrophic. Nevertheless, there are few data on bushing failures so that it is possible to establish a direct relationship between measurements and defects accurately and with few false positives.

Thus, an anomaly detection model based on autoencoders for HVDC bushings was developed. This model was based on capturing pattern changes in the variables measured in these components, such as the voltage on the capacitive tap. To avoid false positives, this model has the ability to learn from the data from bushings in good condition and then identify possible deviations from this state.

To prove the model's effectiveness, a simulated defect based on expert knowledge was inserted into an actual measurement taken in fieldwork. The algorithm was able to identify the defect right from the start, proving useful for the purpose of detecting anomalies in bushings. Furthermore, even considering a low amount of training data, the model only indicated false positives in the existence of changes in the operation mode of the converters. However, these false positives were not persistent, facilitating their mitigation in future versions of the algorithm.

The studies presented in this work proved the feasibility of applying anomaly detection techniques through autoencoder-type deep neural networks to identify possible defects in HVDC bushings.

The next steps in this development will be the field application of the algorithm to evaluate its performance in continuous use for real applications.

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