Improvement of a Hydrogenerator Prognostic Model by using Partial Discharge Measurement Analysis

Mélanie Lévesque[1], Normand Amyot[1], Claude Hudon[1], Mario Bélec[1], and Olivier Blancke[2]

[1] *Institut de recherche d'Hydro-Québec (IREQ), Varennes, Québec, J3X 1S1, Canada*

levesque.melanie@ireq.ca
amyot.normand@ireq.ca
hudon.claude@ireq.ca
belec.mario@ireq.ca

[2] *École de technologie supérieure (ETS), Montréal, Québec, QC H3C 1K3, Canada*

olivier.blancke.1@ens.etsmtl.ca

ABSTRACT

Availability and performance of hydrogenerators are key features that have driven electrical utilities to implement monitoring and diagnostic methods in order to evolve to condition based maintenance (CBM). Ten years ago, Hydro-Quebec has implemented a home-built web-based application, called MIDA, to cover most of its power plants. MIDA centralizes diagnostic data from several tools, aggregates all diagnostic results and calculates a health index for each hydrogenerators. Data from MIDA used in conjunction with PHM techniques can feed a prognostic model that will provide useful equipment information and lead to the implementation of predictive maintenance. The prognostic framework used for hydrogenerators is based on a failure mechanism and symptom analysis (FMSA) approach. For the stator, a major component of hydrogenerators, more than 100 failure mechanisms have been consigned in the form of causal trees or graphs. A large number of these failure mechanisms involve the presence of partial discharges (PD) before failure occurs. At Hydro-Quebec, PD measurements on hydrogenerators have been carried out over the past 30 years and a significant PD database is integrated in MIDA. The analysis of this huge amount of data is of paramount importance to understand the behavior and evolution of the discharge activity in order to build a robust prognostic approach using physics based as well as data driven models. To that end, this paper presents case studies that shed some light on key features related to the evolution of PD activity in hydrogenerators. The paper discusses how to use this data in the prognostic model to assess warning signs before failure occurs.

1. INTRODUCTION

Hydro-Quebec has an electric generating capacity of 36 GW from its 62 hydroelectric power plants. Its generating fleet comprises more than 350 hydrogenerators. These important assets are worth several million to tens of millions of dollars each and are subject to preventive maintenance comprising both systematic and conditional maintenance. An integrated diagnostic system (MIDA) for hydrogenerators was implemented in 2008 based on the aggregation of individual health indices of seven diagnostic tools (Hudon, Bélec, Nguyen, 2009). As of 2017, more than 320 hydrogenerators have their condition assessed with a health index ranging from 1 (excellent condition) to 5 (very bad condition). MIDA gives a ranking of all generators and thus helps the power plant management prioritize the generators for maintenance. The MIDA centralized database contains all diagnostic measurements performed on each generator.

The diagnostic data from MIDA can then be used to identify symptoms of physical degradation states in a failure mechanism and symptom analysis (FMSA) approach applied to hydrogenerator prognostics (Amyot, Hudon, Lévesque et al., 2014). In this approach, we use the symptoms provided by measurements performed on hydrogenerators to activate physical degradation states within failure mechanisms. Active failure mechanisms are those containing active physical states. A failure mechanism is defined as a single existing path from root cause to a failure mode with a unique sequence of physical states. Physical states are defined by a unique set of symptoms and associated thresholds. Different failure mechanism can lead to the same failure mode and a physical state can be present in different failure mechanisms. Figure 1 shows a single failure mechanism initiated by a root cause (C_1), containing a sequence of three physical states (e_1...e_3) and ending with a failure mode (F_1). On the right hand side, sets of symptoms and thresholds in rectangular boxes, identify each physical state. When these symptoms are measured or observed and their severities exceed the associated threshold, the related physical state becomes active.

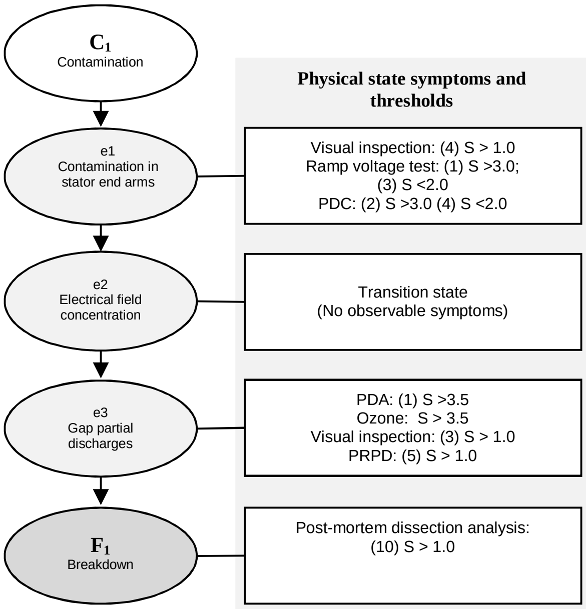

Figure 1. Failure mechanism with symptoms and thresholds defining physical states (**e_n**). Between parenthesis are symptoms specific to each diagnostic tool. **S** is the severity ranging from 1 to 5. (Amyot et al. 2013)

For complex equipment such as generators, failure mechanisms can be best represented as causal trees or graphs. In causal trees, physical states are duplicated as many times as they appear, which offers an easy way to visualize each individual failure mechanism from its root cause to its failure mode through a set of physical states. The advantage of the causal graph is to show each physical state as a node which may have several inputs and outputs. It is thus a more compact representation and it allows the use of graph metrics (Blancke, Tahan, Komljenovic et al., 2016).

It should be noted that the failure mechanisms were generated by a panel of experts comprising field experienced maintenance personnel as well as scientists providing the knowledge of the materials degradation processes involved in each component of the stator under operational stresses (thermal, electrical, mechanical and environmental). About two hundred failure mechanisms were identified as likely to occur in the stator.

The causal graph of the hydrogenerator stator is schematized in Figure 2 (a). Failure mechanisms are paths taking their origin in root causes (yellow dots) through physical degradation states (white dots) towards failure modes (red dots). The last physical states before failure modes occur are aligned on the same level just above the level of failure modes. Amongst them, the grey dots represent physical states that are related to PD activity, one of the symptoms from diagnostic measurements in MIDA. These last physical states involving PD are present in 85% of all stator failure mechanisms. In hydrogenerators, PD comes from different types of sources in the stator insulation system. Each type of PD source has its own percentage of presence as last physical state in the graph. For example, as it can be seen in Figure 2 (b), slot PD activity which is recognized as being harmful to the stator groundwall insulation, are present in a large part of these mechanisms.

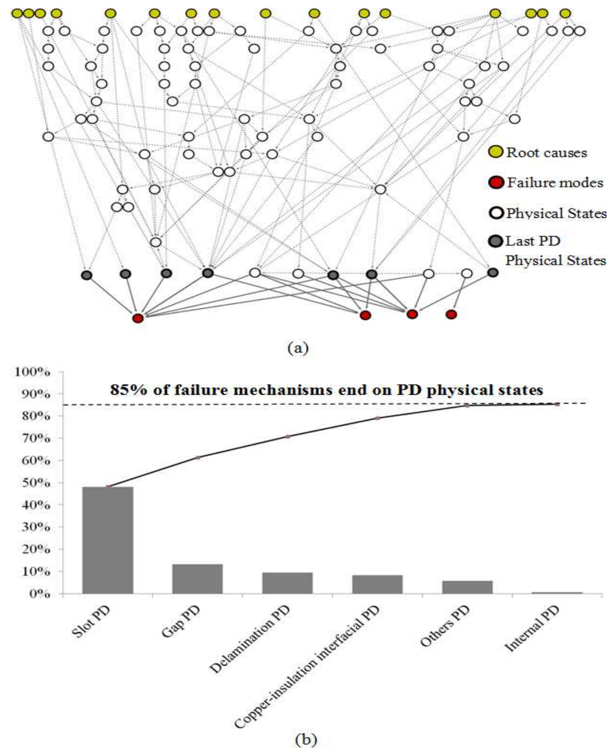

Figure 2. (a) Schematic view of the stator failure mechanisms graph. (b) Percentage of last physical states for each type of PD.

To carry out a prognostic, it is necessary to determine the transition times between each pair of physical states (nodes) pertaining to a failure mechanism in the graph. This can be achieved by using expert elicitation and/or by using data from our physical state activity database. This database contains dates at which measurements were made and physical states were found active.

In the context of preventing a failure, the transition time between the last detectable physical state and the failure becomes of utmost importance. It should be pointed out that hydrogenerator failure rate is in the range of 1.5%, but when it occurs it can be excessively costly or even lead to premature replacement of the asset. This motivates the detailed analysis of diagnostic data, specifically related to PD behavior through time, in order to improve the prognostic model for hydrogenerators.

2. PARTIAL DISCHARGE ANALYSIS

PD activity occurs within voids in insulation and around insulating system exposed to high voltage. This phenomenon is the result of local concentrations of electrical stress. It is always present in the stator insulation of air-cooled hydrogenerators due to the design and manufacturing process. Each PD event is a minute local electrical discharge that will slowly erode the stator insulation system and will lead to breakdown in years to decades. The PD impulses can be detected on-line from sensors connected to the generators. During normal operation, it is therefore possible to detect different sources of PD which present different risks of premature failure. Identification of the source of PD activity is thus essential for improving the diagnosis of high voltage hydrogenerators. An analogy would be the diagnosis of the heart using an electrocardiogram where different characteristic signatures can be recognized and associated with health issues. As for the medical specialist, identification of PD sources requires a good knowledge of the system to diagnose. Understanding of PD phenomena has progressed considerably in recent years, suggesting that PD measurements could now be used to improve prognostic models for hydrogenerators.

Over the past 30 years, Hydro-Quebec has built an extensive Partial Discharge (PD) database including two types of measurement instruments. One of the instruments used is the Partial Discharge Analyzer (PDA) which gives a simple 2D representation of the PD activity as illustrated in Figure 3 and is measured yearly by plant personnel. Here the graph shows the discharge rate (PD/s) as a function of the amplitude in mV of positive discharges (in red) and of negative discharges (in yellow). Up to now, over 20 000 measurement files have been recorded using the PDA technique on about 170 hydrogenerators.

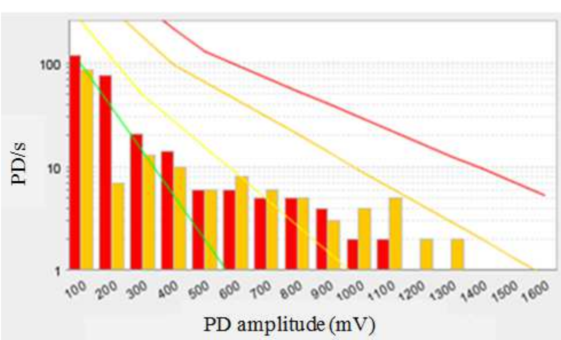

Figure 3. Example of a PDA measurement result.

The second instrument uses the Phase Resolved Partial Discharge (PRPD) technique, which gives a three dimensional (3D) representation of the PD activity. A typical PRPD result is shown in Figure 4. In this pattern, the PD amplitude is plotted against the position with respect to voltage phase angle and a color code is used to show the pulse count. PRPD measurements are carried out as needed to improve the recognition of the active PD sources previously detected with the PDA. More than 5000 measurement files have been recorded using the PRPD instrument on about 100 hydrogenerators.

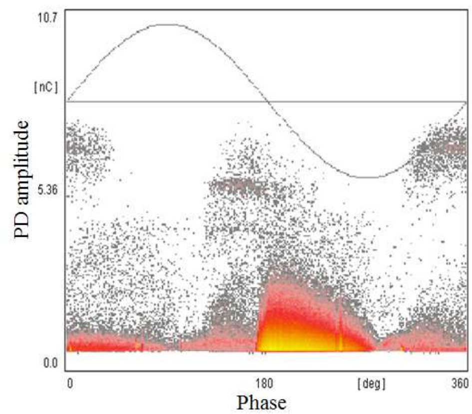

Figure 4. Example of a PRPD measurement result.

The goal of this paper is not to elaborate on the knowledge of PD, but for readers who would want to learn more on PD detection and signal interpretation for generators, they can read the technical specification (IEC, 2012), the standard (IEEE, 2000) and the technical paper (Hudon & Bélec, 2005). Differences between recognizable PD sources are listed in Table 1. Each PD source has its own set of characteristics based on the pulse amplitude (Q), discharge rate (PD/s), overall PD intensity (NQN : Normalized Quantity Number), ratio of positive to negative pulses (NQN+/NQN-) and typical shape of the 3D PRPD patterns. Although PRPD facilitates source recognition especially when several sources are superimposed, its greatest value over the PDA is to be able to discriminate between corona PD activity and slot PD. This is highly relevant, because, as shown in Figure 2 (b), the presence of slot PD activity will activate close to 50% of PD related failure mechanisms in the prognostic approach.

The maximum pulse amplitude (Q_{max}) and the PD intensity (NQN) are most of the time, the main criteria used in the industry to quantify PD (Stone & Warren, 2006). However, analysis of our database shows that these criteria alone are too coarse to feed our prognostic approach. As we will show with the next case studies, sometimes even a switch in discharge behavior should be used as trigger to indicate warning signs of imminent failure.

Table 1: Recognizable PD sources with the two types of instrument used at Hydro-Quebec.

PD Sources	Characteristics	PRPD	PDA
Internal	PD+ = PD-	✓	✓
Delamination	PD+ = PD-	✓	
Copper-insulation interfacial PD	PD+ < PD-	✓	✓
Gap	PD increase at high amplitude	✓	✓
Corona	PD+ > PD-	✓	✓
Slot	PD+ > PD-	✓	

It is important to understand such characteristic warning signs precursor to failure, but one of the challenges is that breakdowns are not that frequent. When failures occur they can be catastrophic, so preventive maintenance has been used in the past with success, but at a great cost. Predictive maintenance is a much more efficient and less expensive means of keeping failure risk low. However, it requires a detailed knowledge of failure mechanisms and a reliable prognostic model that uses diagnostic data.

3. CASE STUDIES

3.1. Case study 1

The first case study was made on unit 2 from a power plant of six 13.8 kV / 56 MVA hydrogenerators commissioned between 1950 and 1955. The stator's insulation of these six units was made of asphaltic resin mixed with mica flakes, a main stream technology in the fifties. All units from this power plant have been a major cause of concern due to the detection of high ozone concentrations in ambient air near the units generated by intense PD activity. Some areas even exceeded the safety limit of 100 ppb for personnel working in their vicinity. In order to have few more years of operation before rewinding all of them, it was decided in 2007 to perform an inversion of the neutral and phase lead terminals of the stator on all units except on unit 1 (Millet, Nguyen et al., 2009). A phase-to-ground failure occurred on phase B of unit 2 in May 2016, 9 years after the overhaul. PD measurements were made on unit 2 using the PDA almost yearly since the overhaul in 2007 and PRPD measurements were also carried out to recognize which type of PD sources were active.

In December 2008, three types of PD sources were active in unit 2, gap PD, corona PD and delamination PD. During the following years, these three types of PD sources were most of the time superimposed in the PDA patterns and their relative individual contributions varied from one year to the next. The evolution of the PD intensity on Phase B represented by the NQN values between 2008 and the last PD measurement made in January 2016, is presented in Figure 5. This last measurement was made just before the failure in May 2016. Because several PD sources are simultaneously present, this case is the perfect example why PD intensity alone cannot be used as the only criteria to trend activity. As can be seen in Figure 5, the PD trend is completely different when the larger gap PD contribution is removed from the analysis. It should be pointed out that even at much higher magnitude, gap PD represent less risk than other types of PD.

Unfortunately, it is not possible to discriminate corona PD from delamination PD when using PDA results alone. Thus without other data than the amplitude and the rate of PD obtained from the PDA results, it is not possible to assess which failure mechanisms are truly active.

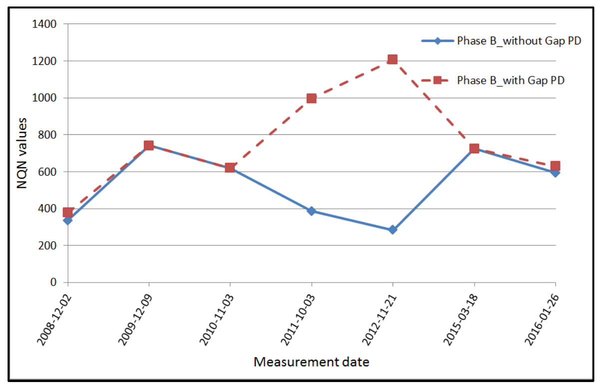

Figure 5. Evolution of PD intensity on phase B of unit 2 between December 2008 and January 2016.

At the last PD measurement made in January 2016 (in Figure 6 (right)) just prior to the failure, a new type of PD activity, showing signs of copper-insulation interfacial PD became active as suggested by the predominance of smaller negative PD pulses. Figure 6 (left) shows that this asymmetry was absent of the PDA results on phase B in March 2015. At that time, and for all previous measurements, delamination PD was the main cause of activity.

Instead of using the PD amplitude as criteria, the ratio of the NQN+ on the NQN- (NQN+/NQN-) was used to assess when the PD activity changed from one physical state to the next. The evolution of this ratio for phase B (after removing the gap PD contribution) is illustrated in Figure 7. From the PD database, we estimated that when the ratio is between 1 and 1.3, the main PD source is related to internal or delamination type, whereas above 1.3, it indicates the presence of corona PD or slot PD. Similarly, when the ratio goes below 0.90, the discharge process is mostly related to copper-insulation interfacial PD. We see that in some cases, the change in PD process is a better indicator of imminent failure than trending only overall PD intensity.

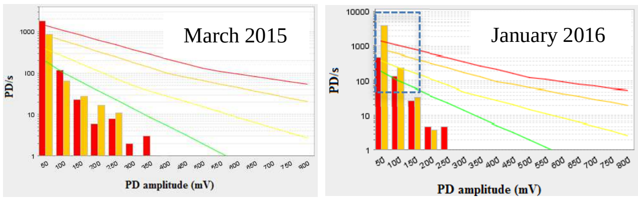

Figure 6. PDA results on phase B of unit 2 in March 2015 (left) and in January 2016 (right).

The transition from the internal delamination PD to the cooper-insulation interfacial PD was observed in January 2016, four months before the failure. However, this transition may have occurred at any time after the PD measurement in March 2015 when copper-insulation interfacial PD activity was still not active. This information (left-censored) is useful to help determining time to failure, but it must be analyzed with all other similar cases to give a transition time distribution that it is possible to implement in our prognostic model.

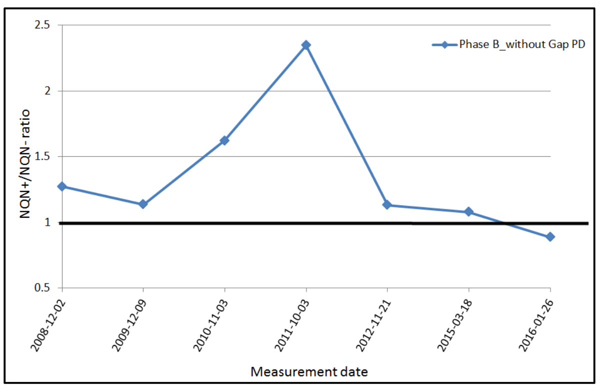

Figure 7. Evolution of NQN+/NQN- ratio on phase B of unit 2 between December 2008 and January 2016.

Our hypothesis is that in the case of unit 2, the failure mechanism is coming from a thermal root cause. This is not surprising because the neutral side of the hydrogenerator has never been exposed to electrical aging, but was exposed to the same thermal aging than the phase lead terminals. The same profile was also observed on phase A and C where no failure has yet happen 18 months after the same transition. In addition, unit 3 of this power plant also showed the same transition from delamination PD to copper-insulation interfacial PD on phase A and B, since March 2015. Such right-censored data is also useful in the determination of the distribution of transition time. Figure 8 shows the failure mechanism (right) from which delamination PD physical state was split in two states by adding the transition to copper-insulation interfacial PD.

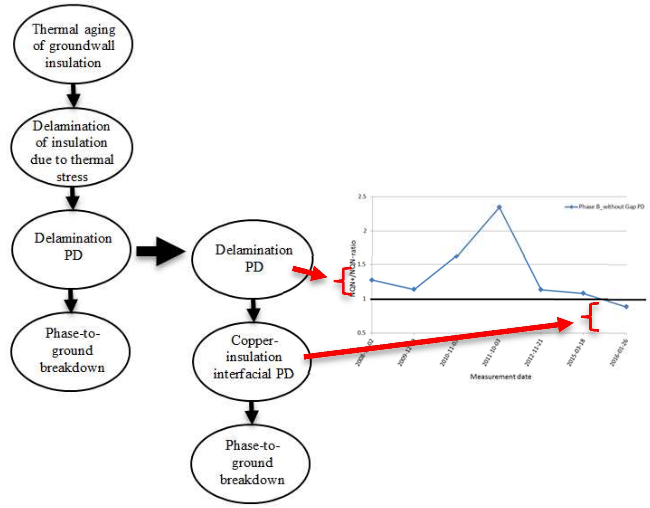

Figure 8. Failure mechanism involved in case study 1.

3.2. Case study 2

The second case study concerns unit 2 from a power plant of six 13.8 kV / 244 MVA hydrogenerators commissioned in 1975. The stator's insulation of these units is made of modern epoxy resin and mica paper. In comparison with the previous case study where the groundwall insulation was based on asphaltic resin, epoxy resin is harder and does not easily delaminate. A phase-to-ground failure occurred on phase A of unit 2 in October 2010 when slot PD activity was identified using PRPD measurements.

The first PDA measurement was made after 19 years in service, in March 1994. It showed the characteristic asymmetry typical of slot PD activity (see Table 1), but there is no way of knowing for how long this PD source had been active. The next PDA measurement was carried out in February 2002 when internal PD was dominant with slight gap PD. In the following years, internal PD stayed dominant in the PDA results. In October 2009, one year before failure occurred, there was a transition to copper-insulation interfacial PD. The evolution of the NQN+/NQN- ratio on one parallel circuit of phase A is illustrated in Figure 9. Again this data had to be cleaned from the high amplitude pulses coming from gap PD contribution. In this case, the NQN+/NQN- ratio indicates a transition from slot PD, active in March 1994, to internal PD, active for at least six years from February 2002 until March 2008. The last transition to copper-insulation interfacial PD activity became active in October 2009.

During the same period of time, the evolution of the global PD intensity showed a slightly decreasing trend as presented in Figure 10. Again, no clear indication of a possible failure can be assessed by only trending the PD intensity represented by the NQN values.

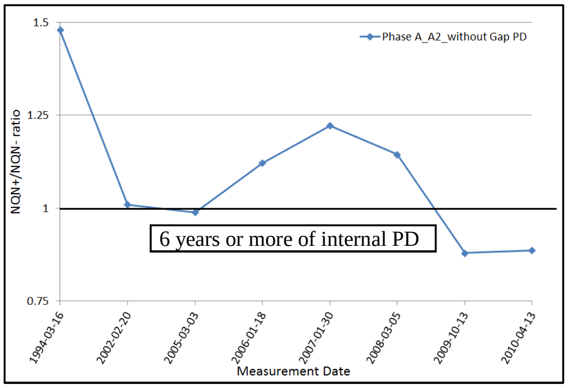

Figure 9. Evolution of NQN+/NQN- ratio on phase A parallel circuit A2 of unit 2 between March 1994 and April 2010.

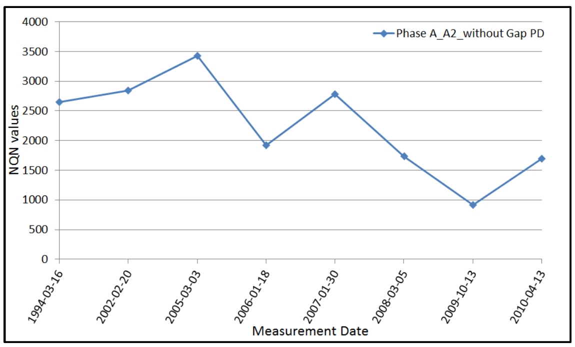

Figure 10. Evolution of PD intensity on phase A parallel circuit A2 of unit 2 between March 1994 and April 2010.

The transition time interval between internal PD and copper-insulation interfacial PD can be used as left-censored data in the prognostic model to determine time to failure. Indeed, even though this transition has been detected during the PD measurement made in October 2009, it may have occurred at any time after the previous PD measurement in March 2008.

Figure 11 shows the split of last physical state before breakdown into internal PD and copper-insulation PD. The different PD sources are related to the behavior of the NQN+/NQN- ratio.

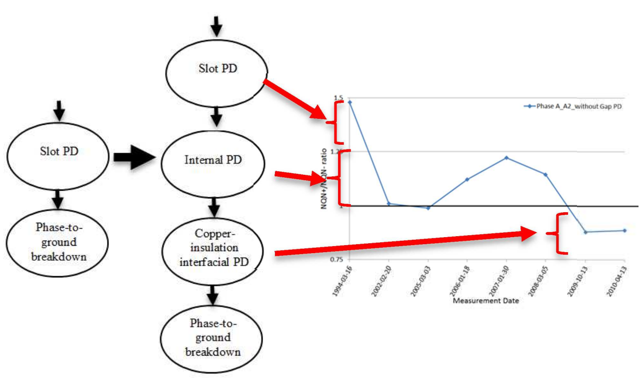

Figure 11. Failure mechanism involved in case study 2.

Other units in the fleet indicate the same pattern from slot PD into internal PD. For instance, Figure 12 illustrates an example from one parallel circuit of phase C of a 13.8 kV / 210 MVA hydrogenerator where a transition from slot PD activity into internal PD occurred. This unit must be carefully monitored in order to capture the activation of the last warning sign related to the transition from internal PD into copper-insulation interfacial PD.

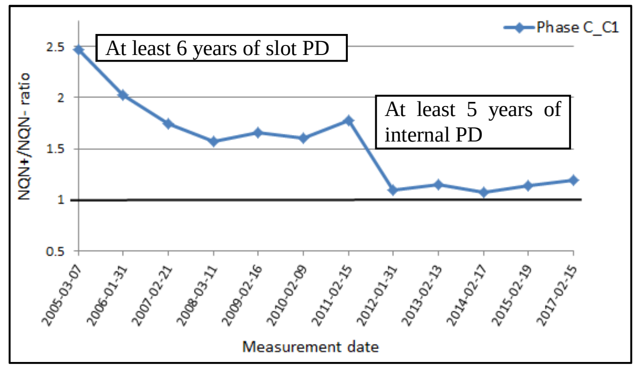

Figure 12. Evolution of NQN+/NQN- ratio on phase C parallel circuit C1 of a 13.8 kV/210 MVA hydrogenerators between March 2005 and February 2017.

4. DISCUSSION

The use of a prognostic model based on FMSA gives the possibility to pick active mechanisms out of the bulk of all possible failure mechanisms. In addition, within each active mechanism, the model allows to track the degradation process by using transition times between pairs of physical states before failure. Physical states close to the end of the failure mechanism are more critical than those close to the root cause, since they constitute the last warning signs before failure. In the proposed model built for hydrogenerators, the very last physical states before failure occurs are related to PD activity in 85% of all failure mechanisms. It is therefore on these physical states that considerable efforts are devoted.

Results presented in this paper indicate that it is essential to understand the fine details of each degradation process in order to properly correlate the PD diagnostic data to the physics of the degradation. In some cases, coarse data such as PD intensity, as often used in this industry, may be an acceptable indicator of incipient failures, but in both case studies presented in this paper, it is demonstrated that monitoring and trending of PD intensity is not an adequate criterion to assess the imminence of a failure. It is only by following the transition from one type of PD to another, using accurate features that it is possible to provide warning signs before failure. Regardless of the prognostic approach, it is always important to identify a set of relevant data before performing analysis of large data sets constituting the whole PD database. Once the determinant factors to track are identified, here specific transition of discharge mode, the next step is to perform a complete analysis of the PD database with the help of appropriate data driven methods. The use of these techniques should make it possible to determine the frequency of occurrence of specific transition between each PD process over the entire database. However, since failure rate of generator is low and measurement data is relatively scarce we have to deal with left as well as right censored data to evaluate all transition times in our proposed prognostic model for hydrogenerators.

5. CONCLUSION

In the hydrogenerator's prognostic model based on FMSA, the last physical state before failure is in most of the cases related to PD activity. Data analysis has shown that we must first understand the degradation process and look for patterns, and then use data driven methods to extract specific parameters. The two case studies presented in this paper pointed out the importance of understanding the physics of degradation in order to assess warning signs coming from PD measurements. Then, accurate features can be used as an input for data driven methods to explore the PD database and refine more accurately the prognostic model.

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BIOGRAPHIES

Mélanie Lévesque was born in Chicoutimi, Québec, Canada on 24 November 1980. She received the PhD degree in electrical engineering from the École de Technologie Supérieure (ÉTS) of Montréal in 2012. Her PhD's degree was done in collaboration with the Research Institute of Hydro-Québec (IREQ). She is currently working as a research scientist at IREQ on generator diagnostics and prognostics.

Normand Amyot was born in Sorengo Switzerland in 1964. He received the M.Sc.A. degree in physics engineering from École Polytechnique de Montréal in 1990. He has worked one year at the Université des Sciences et Techniques (USTM) de Masuku in Gabon, after which he joined the Research Institute of Hydro-Québec (IREQ), where he is now employed as a senior research scientist. His field of expertise includes electrical insulation aging and characterization, diagnostic techniques, condition based maintenance and more recently prognostics. He is an active member of CIGRÉ working groups and member of IEEE DEIS. He is the author or co-author of more than 40 scientific papers.

Claude Hudon was born in Montreal, Québec, Canada on 21 December 1963. He received the Ph.D. degree in engineering physics from École Polytechnique de Montréal in 1993. He worked for two years at the Corporate Research and Development center of General Electric, after which he joined Hydro-Québec's Research Institute, IREQ, where he is now employed as a senior researcher. His fields of interest are generator and motor diagnostics, the development of diagnostic tools and the measurement and analysis of partial discharges. He is the author of more than 45 scientific papers.

Mario Bélec was born in Ste-Anne-du-Lac, Québec, Canada on 20 March 1962. He has received the B.Ing.

degree in electrical engineering from École Polytechnique de Montréal in 1987. He joined the Research Institute of Hydro-Québec (IREQ) in 1987 as a researcher. As a generator diagnostic specialist, he has been involved in partial discharge recognition activity, and development of new diagnostic tools and correction methods for high voltage rotating machines. He is also working on a condition-based maintenance diagnostics methodology of generators. During the recent years, he is also working on development of partial discharge monitoring system for gas-insulated system (GIS). He is active member of IEC and CIGRE working groups. He is the author of more than 50 scientific papers.

Olivier Blancke was born in Oullins, France in 1991. He received the M.ing. degree in mechanical engineering from the École de Technologie Supérieure de Montréal in 2015. His M.ing project's degree was done in collaboration with the Research Institute of Hydro-Québec (IREQ) on failure mechanisms identification of hydroelectric rotors. He is currently doing a PhD degree on the development of a prognostic approach for complex equipment to support asset management.