A Predictive Maintenance Approach for Complex Equipment Based on Petri Net Failure Mechanism Propagation Model

Olivier Blancke
Institut de recherche d'Hydro-Québec

Normand Amyot
Hydro-Québec

Dragan Komljenovic
Hydro-Québec

Antoine Tahan
École de Technologie Supérieure

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Olivier Blancke[1], Amélie Combette[2], Normand Amyot[3], Dragan Komljenovic[3], Mélanie Lévesque[3], Claude Hudon[3], Antoine Tahan[1] and Noureddine Zerhouni[2]

[1] *École de technologie supérieure (ETS), Montréal, Québec, QC H3C 1K3, Canada*
olivier.blancke.1@ens.etsmtl.ca; antoine.tahan@etsmtl.ca

[2]*FEMTO-ST Institute, AS2M Department, University of Franche-Comté/CNRS/ENSMM/UTBM, Besançon, 25000, France*
amelie.combette@ens2m.fr; noureddine.zerhouni@ens2m.fr

[3]*Institut de recherche d'Hydro-Québec (IREQ), Varennes, Québec, J3X 1S1, Canada*
komljenovic.dragan@ireq.ca; amyot.normand@ireq.ca; hudon.claude@ireq.ca; levesque.melanie@ireq.ca

ABSTRACT

The aim of this paper is to propose a comprehensive approach for predictive maintenance of complex equipment. The approach relies on a physics of failure model based on expert knowledge. The model can be represented as a multi-state Petri Net where different failure mechanisms have been discretized using physical degradation states. Each state can be detected by a unique combination of symptoms that can be measured from diagnostic tools. Based on actual existing diagnostic information, a diagnostic algorithm enables the identification of active failure mechanisms and estimates their progression in the Petri Net. Specific maintenance actions and their potential effect on the system can be associated with targeted states. Thereafter, a prognostic algorithm using a coloured Petri Net propagation method spreads active failure mechanisms though their related remaining states towards the targeted states. This allows specific maintenance actions to be proposed in a timeframe and thus enables predictive maintenance. Case study is presented for a real hydro generator. Finally, model limits are discussed and potential areas of further research are identified.

1. INTRODUCTION

Predictive maintenance is a discipline that allows the planning of maintenance actions based on prognostic models. From an organization's perspective, it is an integral part of the asset management process defined as *a set of coordinated activities of an organization to realize the value of assets* (ISO, 2014). Unlike preventive maintenance or reliability-based maintenance approaches, predictive maintenance approaches take into account the dynamic and individual aspect of each asset's data. Prognostic models allows predicting the occurrence of equipment failure modes taking into account their condition, operation and environment loads and their related uncertainties (Goebel et al., 2017, Atamuradov et al., 2017). The predicted information is updated as new asset health information becomes available. Maintenance actions are then proposed in advance to avoid the predicted failure modes. In order to ensure strategic planning within the fleet, different aspects also need to be taken into account to optimize maintenance planning such as equipment's criticality, operational resource constraints, organizational objectives to name a few (IAM, 2015).

For the last decade, the development of prognostic models has been intensive research topic from both an academic and an operational point of view. In the literature, the vast majority of prognostics research to date have been focused on the prediction of *remaining useful life* (RUL) of individual components (Atamuradov et al., 2017, Chiachío et al., 2017). Moreover, much of this research focuses on the propagation of a single mechanism leading to a single failure mode.

However, industrial complex equipment can have concurrent multi-failure modes and multi-failure mechanisms leading to them involving various components and sub-components (Blancke et al., 2015, Atamuradov et al., 2017). The propagation of failure mechanisms may also involve several components and various diagnostic tools can be used to detect and track them at different system scales. Once predetermined degradation thresholds are reached, specific maintenance actions should be taken to avoid a system failure. Depending on the types of active failure mechanisms and their progression, maintenance actions may not have the same effect to stop or slow down their propagation towards their related failure modes. It is therefore important to understand how the mechanisms have and will propagate when we want to apply specific maintenance tasks to extend the remaining useful life of complex equipment.

This paper will focus on how to suggest specific maintenance tasks based on prognostic models. The optimization of these tasks among the fleet will not be considered here. Thus, the aim of this paper is to propose a comprehensive approach for predictive maintenance of complex equipment. The approach relies on a Physics of Failure (PoF) model based on expert knowledge and is dynamic since it also uses diagnostic data. The main contributions of this paper are: (1) to propose a system-level prognostic model that enables to predict intermediate states of degradation; (2) to integrate expert knowledge and diagnostic data into a dynamic model; (3) to suggest specific maintenance tasks and to predict when they can be actionable depending on detected active failure mechanisms.

The reminder of the paper is organized as follows. Section 2 proposes a brief overview of prognostic models in the context of predictive maintenance. The proposed prognosis model identified as a failure mechanisms propagation model is presented in section 3 and its application to predictive maintenance is explained in section 4. Then, a case study is presented for a real hydrogenerator in section 5. Finally, model limits are discussed and potential areas of further research are identified in the last sections.

2. PROGNOSTIC MODELS IN THE CONTEXT OF PREDICTIVE MAINTENANCE: AN OVERVIEW OF THE LITERATURE

Several classifications of prognostic approaches are proposed in the literature. In this paper, we suggest using the classification proposed by Elattar et al. (Elattar et al., 2016). Prognostics approaches can be classified into four types:

- reliability based approach;
- physics-based approach;
- data-driven approach;
- hybrid approach;

As explained in the introduction, knowledge about the physics of degradation is needed to identify specific maintenance tasks which may have a positive effect on the system. That's why this work will focus on the physics-based approach.

2.1. Physics of Failure (PoF) Prognostic Models

Physics-based approaches focus on equipment degradation process. They aim to model the propagation of equipment failure mechanisms by taking into account knowledge of physics of degradation and feedback from domain experts (Gu and Pecht, 2008, Kulkarni et al., 2013). In such approach, diagnostic data are often used to update initial conditions and to fine tune model parameters (Javed et al., 2017, Corbetta et al., 2014, Chiachío et al., 2015). One of the main advantages of the PoF approach is that it is applicable even if the data is scarce, taking advantage of the knowledge gained. A generic methodology has been proposed by Gu and Petch (Gu and Pecht, 2008) for PoF prognostic models. Figure 1 present an adapted illustration of the methodology proposed by Gu and Petch (Gu and Pecht, 2008).

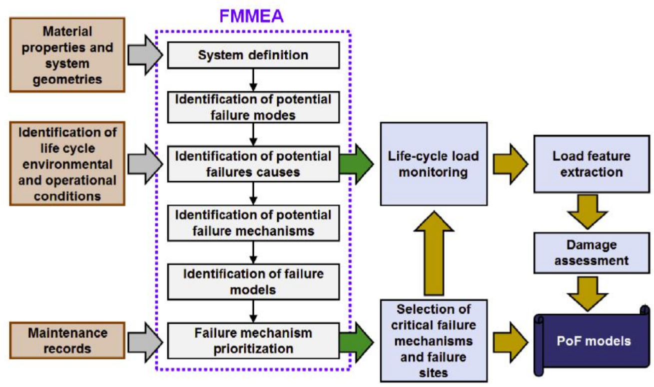

Figure 1. PoF-based PHM methodology (Kwon et al., 2016)

The methodology is based on the identification of failure modes as in the case of the FMEA but it also identifies the failure mechanisms that can lead to them. Once identified, prognostic models can be applied on critical failure mechanisms. As mentioned previously, complex equipment may have different failure modes and many failure mechanisms. Different diagnostic tools can then be used to detect their state of evolution. For this purpose, Amyot et al (Amyot et al., 2014) proposed an extension of the FMMEA by discretizing the mechanisms using physical state of degradation. Each state can be detected by a unique combination of symptoms that can be obtained with diagnostic tools. The proposed model consists of a causal graph where the nodes are physical states and the edges represent all the identified failure mechanisms. Failure mechanisms propagate from a root cause to their related failure mode through a physical state succession as shown in Figure 2. A methodology has been proposed to discretize failure mechanisms (Blancke et al., 2015). As a physical state can be present in different failure mechanisms, the causal graph enable failure mechanism to share physical states. Thus, Amyot et al.(Amyot et al., 2014) have introduced an algorithm to detect active failure mechanisms based on combination of active and inactive physical states. These algorithms will be detailed in this paper and integrated into the proposed prognostic model.

The dynamic causal graph model proposed by Amyot et al. (Amyot et al., 2014) enables to aggregate various diagnostic data from different diagnostic tools at a system level. In order to make it evolve towards a predictive maintenance, it is necessary to introduce the temporal aspect of causalities.

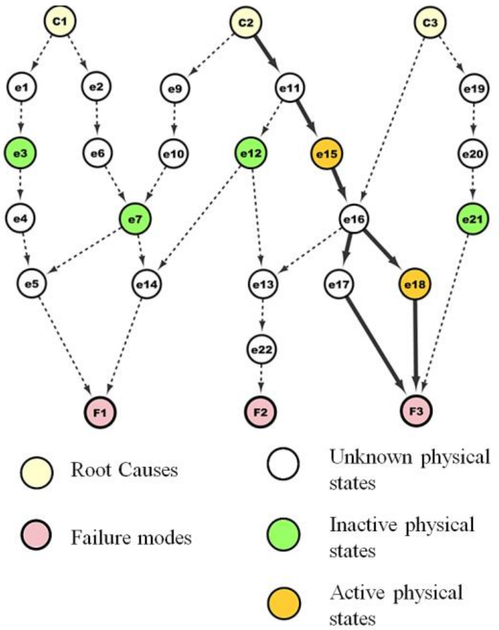

Figure 2. Causal graph model illustrating identified failure mechanisms

Chemweno et al. (Chemweno et al., 2018) have proposed a review of dependability modelling approaches in the context of risk assessment. Based on this review, two main approaches seem to be applicable to causal graphs in a stochastic propagation process: Dynamic Bayesian Networks and Stochastic Petri Net (PN). In this paper, the formalism of Stochastic Petri Nets (SPN) has been chosen mainly because of the variety of extensions that it contains.

2.2. Existing Petri-Net in Prognostic and Predictive Maintenance Model

Petri Nets have been initially introduced by Carl Adam Petri in 1966 (Petri, 1966). PNs are bipartite direct graphs mainly used to model multi-state dynamic systems in various disciplines. Graphs of a PN consist of two types of nodes, *transitions* and *places* linked by *arcs* or *edges*. A *place* can be used to specify the current state of a system and are visited by *tokens* that propagate from *place* to *place* as defined by the PN. Transitions enable to represent the dynamic behavior of the system. They comprise time transitions from one *place* to another (Chiachío et al., 2017). For further information, several references present the formalism of PN (Peterson, 1981, Murata, 1989, Chiachío et al., 2017).

In the literature, different works have used PN in the context of predictive maintenance (Chiachío et al., 2017, Zhouhang et al., 2014, Ammour et al., 2016). Zhouhang et al. (Zhouhang et al., 2014) have proposed an application of PN to model the reliability and maintenance analysis of multi-state multi-unit systems. The approach takes into account 3 degradation states: healthy, degraded and failed. The PN model enables to simulate transition between those states in different components. A fault tree model enables to assemble the different degraded or failed components into the system behavior. It also takes into account maintenance operator availability and the maintenance process. In this work, the model does not suggest specific maintenance but focus more on the operational aspects on predictive maintenance.

Ammour et al. (Ammour et al., 2016) have proposed a fault prognosis approach of stochastic discrete event systems. The PN is used to model the system and its sensors. Measurement has been attached to some places of the PN and an incremental approach enables to identify sets of consistent trajectories based on historical measurement data. Then based on those time-measurement trajectories, the PN model estimates the current state of the system and the occurrence probability of future states. In this approach, historical data have been chosen to identify failure mechanism trajectories. This enables the on-line application. However, domains experts experience feedback has not been taken into account. The approach ends on fault prognosis and does not identified specific maintenance.

Finally, Chiachío et al. (Chiachío et al., 2017) have proposed a mathematical framework for modelling prognostic at a system level based on Plausible Petri Net (PPN) formalism. The model integrates maintenance actions, various prognostic information from different components, expert knowledge and resource availability. To do so, two interacting sub-net form are introduced: *symbolic sub-net* (integer moving unit) and *numerical sub-net* (states of information). The model predicts the End Of Life (EOL) of different components by taking into account the overall process. In this approach, the model relies on expert knowledge and diagnostic data. Maintenance tasks can be suggested and component failure can be predicted. However, the approach cannot identify physical failure mechanisms that lead to the predicted failure of components.

From the literature to date, it seems that no predictive maintenance approach using PN have been proposed so far to enable the prediction of specific maintenance actions according to the active failure mechanisms that have been detected in an equipment failure mechanism propagation model.

The model presented in this paper is based on previous approach proposed by Amyot et al. (Amyot et al., 2014) based on Failure Mechanisms and Symptom Analysis (FMSA). Research work is currently underway on the development of the failure mechanisms propagation model to predict failure modes of complex equipment. Thus, this part aims to present only the main principles of the failure mechanisms propagation.

In this paper, the predictive maintenance approach aims at predicting the occurrence of some specific targeted physical degradation states where some specific maintenance actions can be implemented and will start to have an effect on the system. To do so this section presents the failure mechanism propagation model that predicts targeted degradation states. Then, the Section 4 will present how to apply predictive maintenance based on the propagation of these mechanisms.

2.3. Model Assumptions:

Before applying the formalism of PNs to the causal graphs introduced by Amyot et al. (Amyot et al., 2014), the propagation model assumptions were identified by an expert group based on their experience. No mathematical constraint was initially imposed. The proposed assumptions are defined for all types of complex equipment that have competing failure mechanisms leading to one or more failure modes. They are applied as stated for each prediction date chosen to update the model results. Assumptions have been split in categories presented below.

- Assumptions of degradation states:

Physical states are considered as discrete events constituting failure mechanisms. They are detected by a unique combination of symptoms acquired from diagnostic tools. When not detected, they are considered as unknown. When they become detectable by appropriate diagnostic tools, they can be active or inactive.

- Assumptions on causal graph:

The causal graph identifies all possible failure mechanisms that could occur within the system. A failure mechanism is considered as a possible path identified by experts and is a single sequence of physical states starting from a root cause and leading to a failure mode. If none of its physical states can be detected, the failure mechanism is defined as unknown (none of the diagnostic tools could detect the relevant symptoms identifying any physical states). If at least one of its physical states can be detected, the failure mechanism is identified as active or inactive depending on the relative symptoms threshold to meet.

- Assumptions on failure mechanism propagation:

Even if failure mechanisms are interrelated by propagating through some common degradation state, their propagation is considered independent. Thus, failure mechanisms are non-mutually exclusive (they can evolve in parallel to reach their corresponding failure modes) and they are independent (their progression is considered as uninfluenced by other mechanisms). In addition, failure mechanism propagation is considered as a stochastic process with memory. Thus transition times from one physical state to the other within a failure mechanism have a probability distribution that may be influenced by the failure mechanism history.

The state of a failure mechanism at a specific prediction date is considered as its last active state within the sequence of physical states.

For this paper, the influence of duty cycle, environment and regular maintenance actions has not been taken into account.

- Assumptions on targeted state occurrence:

Failure mechanisms are considered in competition. The first failure mechanism to reach a targeted state defines its occurrence probability (pessimistic assumption).

- Assumptions on predictive maintenance:

Maintenance is considered to have a positive effect on the system once a specific degradation threshold is reached.

Based on those assumptions, the causal graph introduced by Amyot et al. (Amyot et al., 2014) could be considered as a PN where physical states are *places* identified by health data and *transitions* are the different stochastic transition times. A colored PN can be considered as a generic representation for the fleet. This type of PN makes it possible to represent all possible failure mechanisms in a graph.

In the proposed approach, all visual representation of PN will not represent transition nodes as rectangles as defined in PN formalism. This will enable to simplify the graph.

2.4. Diagnostic Algorithm

2.4.1. Fault Detection: Active Physical States Detection Algorithms

The fault detection consists in detecting active or inactive physical states. For each physical state a detection algorithm has been defined by experts using ruled based combination of symptoms. Result is binary: A physical state can be detected as inactive or active. If the physical state is detected as active, an activation interval is estimated based on the inspection interval that can detect the state. Figure 3 presents the physical state detection algorithm. For each prediction date required the detection algorithm is performed.

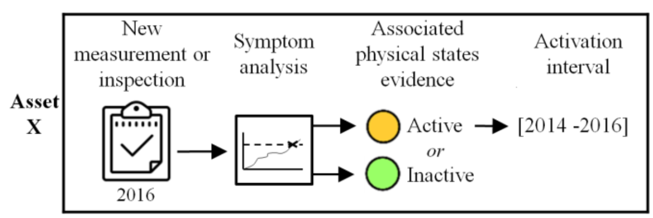

Figure 3. Physical states detection algorithms based on symptom analysis

2.4.2. State Estimation: Active Failure Mechanism Detection Algorithm

Following the fault detection, the state estimation consists of estimating the actual state of the system for a specific prediction date. In our case, the state estimation consists of detecting active failure mechanisms based on detected active and inactive physical states and then estimate their propagation through the PN.

The failure mechanism detection algorithm analyzes each failure mechanism physical state sequences. If at least one physical state is active, the failure mechanism is detected as active. However, in order to eliminate incoherent failure mechanisms, if inactive physical states are located before some active physical states in the sequences, the whole failure mechanism is detected as inactive. Figure 4 illustrates the failure mechanism process for an asset on two different prediction dates.

The state estimation relies on the assumption that the last active state of active failure mechanisms defines his state.

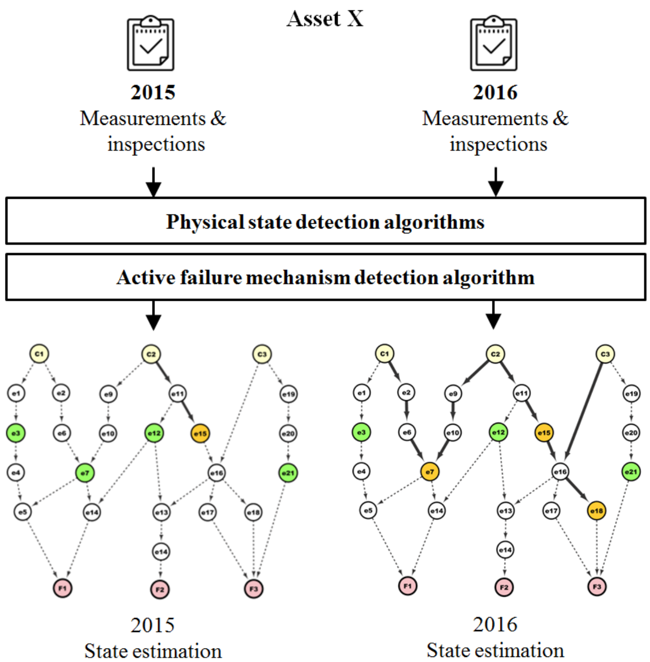

Figure 4. Asset-specific state estimation process based on active failure mechanism detection algorithm

In figure 4, the physical state and failure mechanism detection algorithms have been performed for the prediction dates 2015 and 2016. In 2015, based on available symptoms of asset X, one (1) physical state has been detected as active (orange node) and four (4) as inactive (green nodes). Thus, three failure mechanisms have been detected has active. In 2016, three (3) physical states have been detected has active and four as inactive. Thus, nine (9) failure mechanisms have been detected has active. The state estimation can be visualized in figure 4. The path of the active failure mechanisms is represented in bold. From a visual point of view, this enables to see how far failure mechanisms have progressed for each prediction date.

2.5. Failure Mechanism Propagation Algorithm

In order to propagate active failure mechanisms, the formalism of PNs has been chosen. However, from the basic PN model including homogenous Markovian process to the customized model that fit with all experts assumption, different extensions and rules have been defined in the algorithm. Figure 5 illustrates the algorithm evolution.

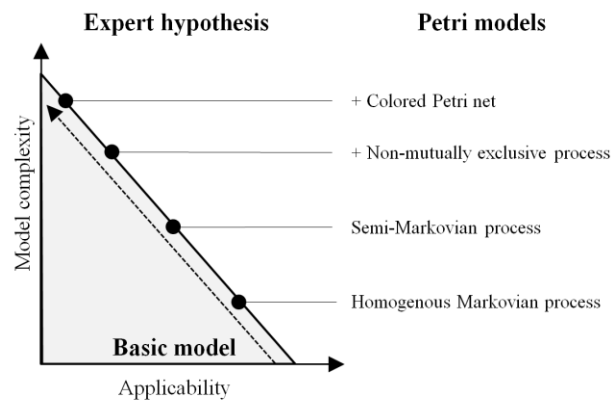

Figure 5. From basic Petri Net model to complex PN model satisfying expert assumption

Transition times has been defined as Weibull distributions by experts. Thus the model has to move to semi-Markovian process. Then, as failure mechanisms are non-mutually exclusive, each failure mechanism has been propagated independently. Finally, as the propagation is a memory process, the extension of coloured PN has been implemented. As not every path from a root cause towards a failure mode constitutes a failure mechanism as defined by the experts, the coloured PN makes it possible to take into account only those paths that are real failure mechanisms in the graph representation.

The resulting algorithm propagates any active failure mechanism independently. The initial state or the mechanism defined by the last active physical state in the sequence considers its activation interval as the starting date of the propagation. Then, the stochastic PN propagates through the remaining states of the failure mechanism to the targeted state. Some illustrated results are presented in figure 6 below.

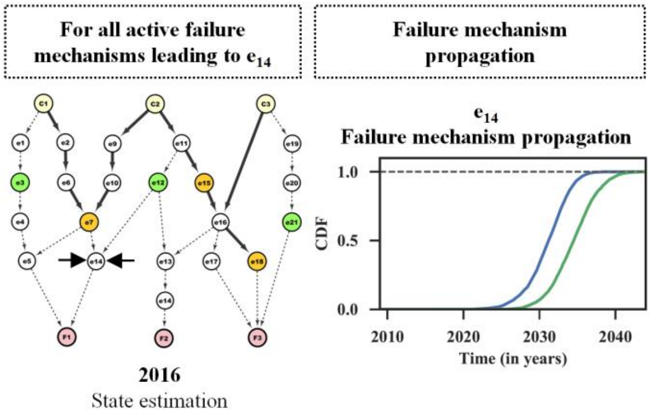

Figure 6. Illustration of the failure mechanism propagation algorithm

Figure 6 shows the propagation of each active failure mechanism to the targeted state e14. In 2016, even though nine (9) failure mechanisms were detected active, only two (2) of them lead to the e14 state. So only two failure mechanisms have been propagated. The Cumulative Density Function (CDF) of the two failure mechanisms propagated to state e14 is shown in figure 6. Those CDFs represent the probability predicted in 2016 that each failure mechanism reached the state e14.

2.6. Targeted States Occurrence Prediction:

Then the last step consists of aggregating failure mechanisms propagation in order to estimate the occurrence of targeted physical states. Based on the assumption that failure mechanisms are in competitions, the occurrence of the targeted states has been defined has the upper envelope of all CDF functions. The equation 1 presents the aggregated function.

$$Pr\left(e_{targeted}\right) = Max\left(CDF_{active\ failure\ mechanisms}\right) \qquad (1)$$

3. FROM FAILURE MECHANISM PROPAGATION TO PREDICTIVE MAINTENANCE

The algorithm allows us to estimate the state of our system for different prediction date and to propagate detected active failure mechanisms until targeted physical states. Predictive maintenance aims at predicting and suggesting maintenance actions based on prognosis algorithms. On the assumptions of experts, a maintenance action is considered to have a positive effect on the system once a specific degradation state is reached. From a PN point of view, it can be considered that once targeted physical states are reached, specific maintenance actions which can be related to their physical degradation will have a positive effect on the system. Thus maintenance actions can be attached to specific states of the PN. Moreover, for each proposed maintenance actions, experts may have knowledge of the impact of maintenance and may suggest a possible effect expected. As examples, those effects could be:

- Inhibit associated failure mechanisms propagation
- Reset associated failure mechanisms propagation
- Slow down associated failure mechanism propagation

Figure 7 illustrates an example of predictive maintenance that has been attached to a state. The predicted confidence interval of these states is between 2018 and 2022. Thus the lubrication of the shaft bearing task may be applicable until 2022 if we want the action to have the expected impact on the equipment.

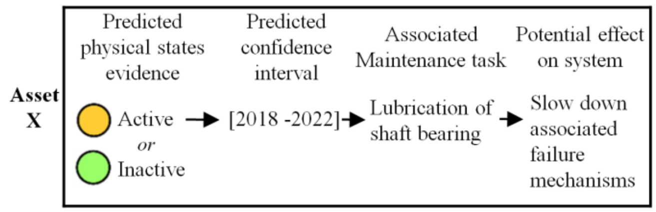

Figure 7. Illustration of the failure mechanism propagation algorithm

4. CASE STUDY: HYDRO-GENERATORS

4.1. Industrial Context

The proposed case study is based on real historical data of a hydrogenerator from Hydro-Quebec's generating fleet. Hydrogenerators are heavy electro-mechanical machines. Figure 8 present a picture of a hydro generator.

Figure 8. Hydro-Québec generating unit photography.

A group of experts have been involved to identify possible failure mechanisms for the stator of hydrogenerators based on a literature review and their own experience. Three failure modes have been identified for the stator, as presented in Figure 9, and over than one hundred failure mechanisms have been identified as possibly occurring in the stator of hydrogenerators. Over seventy different physical states have been defined. The causal graph representing all failure mechanisms of the stator is presented in the figure 9 bellows.

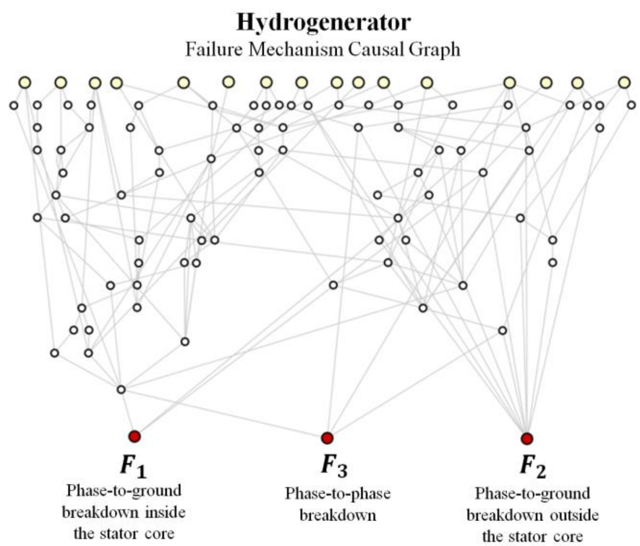

Figure 9. Hydro generator stator causal graph representing identified failure mechanisms leading to three failure modes

At Hydro-Québec, a web-based application has been implemented since 2008. It gathers symptoms from diagnostic tools. Thus, some historical data are available. The case study is proposed based on those historical data.

4.2. Associated Maintenance Task

For the case study of this paper, a brief analysis of available data has been carried out to identify targeted physical states that may have some validation data available. Moreover targeted physical states may have possible maintenance actions associated to them. Thus, four physical states have been targeted and are presented in table 1.

Table 1. Targeted physical states

ID	Physical states
t6	Thermal aging of ground wall insulation
m31	Stator lamination insulation wear
m21	Mechanical erosion of ground wall insulation inside the stator core
e12	Erosion of the semiconducting coating

Based on expert experience feedback, maintenance tasks have been associated to them and their potential effects on the system have been estimated. Results are presented in the table 2.

Table 2. Associated maintenance tasks and their potential effect on the system.

ID	Associated Maintenance Task	Potential effect on system
t6	Stator re-winding (replacement)	Reset stator winding failure mechanisms
m31	Stator lamination epoxy injection	Slow down associated failure mechanisms
m21	Replacement of few stator bars	Reset local failure mechanisms (extend the average useful life of the entire winding)
	Stator re-winding (replacement)	Reset stator winding failure mechanisms
e12	Stator semiconducting insulation painting	Inhibit failure mechanisms associated for a period of time

4.3. Hydro generator Case Study

4.3.1. Application of Prognostic Model

In order to illustrate the methodology, this case study is proposed on a hydro generator where several measurements and inspection data are available. In this paper, the selected hydro generator will be called a. Table 3 presents the list of historical measurement, inspections and maintenance actions that have been carried out on hydro generator a.

Table 3. Historical measurements, inspections and maintenance actions on hydro generator a

Hydro generator a	
Date	Diagnostic tools/Intervention
1932-09	COMMISSIONING
1989-01	Rewinding_without_uprate_and_core_replacement
1992-01	Partial Discharge Analysis (PDA)
2008-01	DC Ramp test (DCRT)
2009-06	Partial Discharge Analysis (PDA)
2010-05	Polarization/Depolarization Current test (PDC)
2010-05	DC Ramp test (DCRT)
2010-05	Semiconductor assessment
2010-05	Visual Inspection
2011-04	Phase Resolved Partial Discharge (PRPD)
…	**…**
2014-02	Phase Resolved Partial Discharge (PRPD)
2014-04	Ozone detection test
2015-10	Partial Discharge Analysis (PDA)
2016-03	Polarization/Depolarization Current test (PDC)
2016-06	Semiconductor assessment
2016-07	DC Ramp test

To apply the model, the different assumptions and resulting algorithms described in the methodology are applied for each date of prediction. Five dates of prediction have been chosen: one for each year between 2010 and 2015. As an example, the year of prediction 2012 is described in detail in this case study. The model aims at predicting the occurrence of targeted states and then predicts the date when their associated maintenance tasks will be applicable.

- **<u>State estimation in 2012:</u>**

Based on existing diagnostic data in 2012, the detected active physical states and their activation intervals are shown in table 4 below.

Table 4. Active physical state in 2012 on the hydro generator and their activation intervals

Hydro generator a in 2012		
ID	Active state appellation	Activation interval
a1	Conductive contamination on coil ends or end-winding	[1996 ; 2010]
a3	Presence of dust	[2002 ; 2010]
e21	Iron core hotspot due to Eddy currents	[2002 ; 2010]
t2	Thermal shield	[2006 ; 2010]
m34	Buckling of stator iron core	[2009 ; 2010]

For the activation intervals, the upper limit corresponds to the detection date and the lower limit to the last date on which the state was detected inactive. Based on those results the failure mechanisms detection algorithm has been performed and the result can be visualized using graph visualization of the PN in figure 10.

In 2012, five (5) physical states have been detected as active and twenty eight (28) as inactive on hydro generator a. Based on this, a total of thirty (30) failure mechanisms have been detected as active. In the figure 10, targeted physical states have been identified with a cross in the middle of their nodes. As an example, fourteen (10) of the active failure mechanisms lead to the targeted state t6, six (6) to targeted state m31 and only three (3) to the targeted state e12 in 2012.

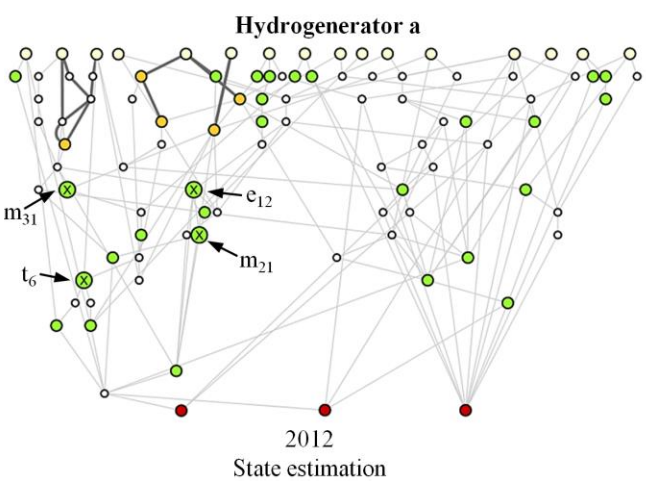

Figure 10. State estimation in 2012 of hydrogenerator a

- **Failure mechanism propagation in 2012:**

All active failure mechanisms leading to the targeted physical states have been propagated using the PN algorithm. Transition times have been estimated based on rigorous elicitation process. Aggregation of different expert estimation has been performed for this purpose. Their level of confidence has been taken into account in the aggregation process. Results of the failure mechanisms propagation and the resulted occurrence probabilities of the targeted states are presented in figure 11.

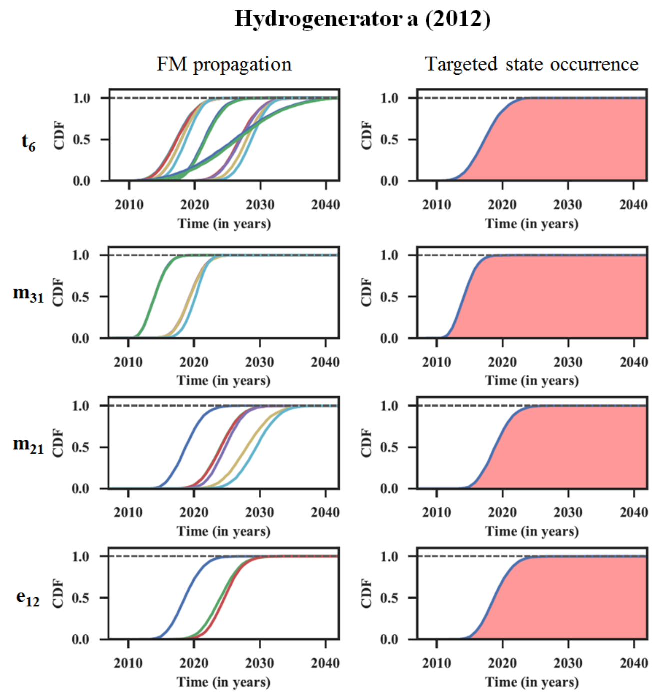

Figure 11. Failure mechanism propagation of hydro generator a in 2012 until targeted states

The prediction for a confidence interval of 50% for each targeted physical states are presented in table 5.

Table 5. Prediction confidence intervals for each targeted physical states in 2012.

Hydro generator a		
ID	State appellation	Predicted confidence interval
t6	Thermal aging of ground wall insulation	[2015 ; 2019]
m31	Stator lamination insulation wear	[2012 ; 2015]
m21	Mechanical erosion of ground wall insulation inside the stator core	[2017 ; 2020]
e12	Erosion of the semiconducting coating	[2017 ; 2020]

- **Predictive maintenance suggested in 2012:**

Then based on the predicted occurrence of the targeted states, some predicted maintenance tasks and their predicted dates of application have been proposed in 2012 and are presented in table 6.

Table 6. Predicted suggested maintenance actions and related dates of application

Predicted date for maintenance applicability	Suggested Maintenance Task	Potential effect on system
2015	Stator lamination epoxy injection	Slow down associated failure mechanisms
2019	Stator re-winding (replacement)	Reset stator winding failure mechanisms
2020	Replacement of few stator bars	Reset local failure mechanisms (extend the average useful life of the entire winding)
	Stator re-winding (replacement)	Reset stator winding failure mechanisms
2020	Stator semiconducting insulation painting	Inhibit failure mechanisms associated for a period of time

Those steps are performed for each chosen date of prediction.

4.3.2. Validation of prognostic algorithm

In order to validate the prognostic algorithm predictions, the activation date of the targeted physical states have been identified from historical diagnostic data. The historical detection state of the targeted physical state resulting from the symptom analysis for each measurement dates are presented in table 7.

Table 7. Historical detection state of targeted physical states on hydro generators a

Hydrogenerator a				
Symptom analysis date	t6	m31	e12	m21
2010-05	0	x	x	x
2010-05	x	0	0	0
2010-05	x	0	0	0
2011-04	x	x	x	x
…	…	…	…	…
2014-02	x	x	x	x
2014-02	x	x	x	x
2014-04	x	x	x	x
2015-10	x	x	x	x
2016-03	x	x	x	x
2016-03	x	1	x	x
2016-06	x	x	1	1
2016-07	1	x	x	x

In table 7, the symbol 0 means that the targeted states were detected as inactive at this date. The symbol 1 means that it has been detected active and x means that the measurement or inspection at this date does not allow to detect the state. It can be considered as unknown. As an example, in 2016-03, the Polarization/Depolarization Current test (PDC) has detected m31 active but was unable to detect t6, e12 and m21.

Then based on those results we can deduce the observed activation interval of the different targeted states. Results are presented in the table 8.

Table 8. Observed detection dates of targeted states from historical data

Hydro generator a		
ID	State appellation	Historical activation interval
t6	Thermal aging of ground wall insulation	[2010 ; 2016]
m31	Stator lamination insulation wear	[2010 ; 2016]
m21	Mechanical erosion of ground wall insulation inside the stator core	[2010 ; 2016]
e12	Erosion of the semiconducting coating	[2010 ; 2016]

In this case study, all targeted physical states have been detected as active in 2016. The last date when they have been detected as inactive was 2010 for all of them.

The validation of the prognostic algorithm for the date of prediction from 2010 to 2015 is presented in figure 12. Results show the evolution of the prediction for each time prediction (boxplot). As new diagnostic data becomes available, the algorithm updates predictions by computing again the diagnostic and prognostic algorithms. The dotted lines illustrate the observed detection date and the grey area the observed interval of possible activation.

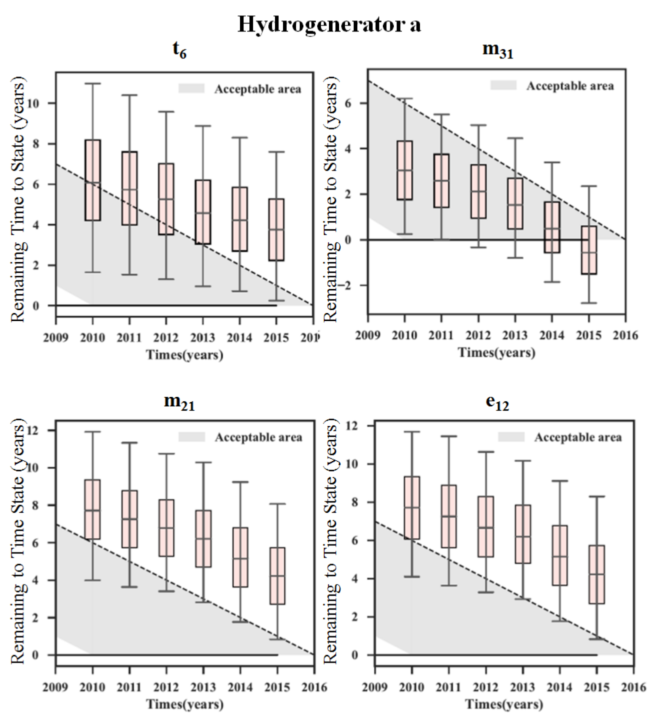

Figure 12. Observed activation intervals VS predicted activation intervals for targeted states

Results show that all predictions stay within the observed activation intervals for a confidence interval higher than 80% (boxplot lines). The prediction with a confidence interval of 50% stay in the acceptable zone for the date of prediction from 2010 to 2015 for physical state m31 and until 2013 for physical state t6. From a general perspective, the prediction has been closer to the detection date from 2010 to 2012. The uncertainty range of predictions goes approximately from 9 years to 6 years for a confidence interval of 80% and from 2 years to 4 years for a confidence interval of 50%.

As this study is conducted in 2018, the hydro generator is still under operation and no failure mode has been reached so far. In addition, no maintenance actions have been carried out on the hydro generator so far from 2010.

5. DISCUSSION

From the point of view of the predicted maintenance, the results seem consistent with observed behavior of the hydro generator a from 2017 to 2018. Indeed, in 2012, the model has suggested the realization of a minor maintenance action from 2015 and major maintenance actions starting from 2019. The generator has not experienced a failure to date in 2018. In addition, according to records of interventions, no major maintenance has been carried out since 2010. Thanks to the proposed model, decision makers can move from a wide range of possible maintenance actions to a selection of specific maintenance actions that can have a positive effect on the system. As an example, the model could have extended the life of the equipment by suggesting an epoxy injection into the stator laminations from 2015. In cases where a suggested maintenance action is performed, the state of the system will be impacted. Thus, other suggested maintenance actions that follow may not be more relevant. Future work can be considered to estimate more accurately the effect of maintenance actions on the system in order to suggest successive scenarios of maintenance actions. Moreover, in this paper, the model enables to predict a minimum applicability date of a specific maintenance action. Some further work could be conducted to predict a maximum date when the maintenance action must have been performed to avoid failure or to mitigate a high risk of failure.

In terms of the results of the prognostic algorithm, the width of uncertainty ranges comes from two factors: the estimation of the state of the system (state activation intervals) and the propagation of the failure mechanisms (range of uncertainties of transition times). Firstly, in this study case, the intervals of inspections of the different diagnostic tools are significant and are carried out at the scale of one year or several years. Thus, the potential activation intervals of physical states are important. This induces large uncertainties in the state estimation of the system. For example, in table 4, based on 2012 data, state e21 has a potential activation interval of 8 years.

Then, from the point of transition times, because they were estimated based on an elicitation process, it is possible that the lack of knowledge of the experts and various biases such as overconfidence may have induced transition times not completely representing the reality of the generation fleet.

CONCLUSION

In conclusion, a predictive maintenance approach for complex equipment has been proposed in this paper. The model is based on a causal graph that identifies and discretizes all possible failure mechanisms that can occur on the equipment. As diagnostic data are associated with the discretized degradation states, the graph is dynamic on data. In order to develop the prognostic model, assumptions have been firstly defined based on expert knowledge. Thus, a customized PN model has been defined to propagate active failure mechanisms from their initial states to some targeted degradation states where maintenance tasks are associated. Once targeted states are predicted to be reached the application date of their maintenance tasks can thus be predicted. Results showed that the model makes it possible to predict specific maintenance actions according to failure mechanisms detected as active by the diagnostic tools. In addition, the model predicts a date when maintenance actions may be applicable in the sense that they will begin to have an effect on the system. The validation results presented in Figure 12 show that the prognostic model is dynamic on the diagnostic data. Moreover, it accounts for both the uncertainties contained in the state estimation and in the propagation of the mechanisms.

ACKNOWLEDGEMENT

This work described in this paper was fully supported by the “Pronostic des équipements majeurs” project at IREQ, the Hydro-Québec research institute in Varennes, Québec, and by MITACS scholarship program.

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BIOGRAPHIES

Olivier Blancke received the M Eeng. degree in mechanical engineering from the École de Technologie Supérieure de Montréal in 2015. His M. Eng 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.

Amélie Combette received her engineering degree in mechanical engineering from the National institute in mechanics and micro-technologies, Besancon in 2017. Her final study project's was done in collaboration with the Research Institute of Hydro-Québec (IREQ) on the development prognostic algorithm based on Petri nets. She is currently working in ALTEN S.O. as an application engineer.

Normand Amyot received the B.Eng and M.A.Sc degrees in Physics Engineering from École Polytechnique de Montréal respectively in 1987 and 1990. He taught Physics one year at the Université des Sciences et Techniques (USTM) de Masuku in Gabon, after which he joined, in 1991 the Research Institute of Hydro-Québec (IREQ), where he is now employed as a research scientist. His fields of expertise include electrical insulation aging and characterization, diagnostic techniques, condition based maintenance and prognostics. He is currently leader of the Hydrogenerator Prognostics Project at IREQ. He is an active member of CIGRÉ working groups and Senior Member of IEEE. He is also active in SCC, ISO and member of the PHM Society. He is the author or co-author of more than 50 scientific papers.

Dragan Komljenovic received his BSc at the University of Tuzla, MSc at the University of Belgrade, and PhD at Laval University, Canada. Dragan works as a researcher at the Hydro-Quebec's Research Institute (IREQ) in the field of reliability, asset management, risk analysis, and maintenance optimization. Prior to joining IREQ, he worked as a Reliability and Nuclear Safety Engineer at the Nuclear Generating Station Gentilly-2, Hydro-Quebec. He is also appointed as Adjunct Professor at the University of Waterloo, Canada (Industrial Research Chair "Risk-Based Life Cycle Management of Engineering Systems") and Laval University in Quebec-City (mining engineering). He has published more than 70 refereed journal and conference papers. He also worked in the mining industry as well as a researcher and lecturer at the University of Tuzla and Laval University**.**

Mélanie Lévesque 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.

Claude Hudon received the PhD 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.

Noureddine Zerhouni received the Engineering degree from the National Engineers and Technicians Institute of Algiers, Algiers, Algeria, in 1985, and the PhD degree in automatic control from the Grenoble National Polytechnic Institute, Grenoble, France, in 1991. He joined the National Engineering Institute of Belfort, Belfort, France, as an Associate Professor in 1991. Since 1999, he has been a Full Professor with the National Institute in Mechanics and Microtechnologies, Besançon, France. He is a member of the Department of Automatic Control and MicroMechatronic Systems at the FEMTO-ST Institute, Besançon. He has been involved in various European and national projects on intelligent maintenance systems. His current research interests include intelligent maintenance, and prognostics and health management.

Antoine Tahan received his PhD in Electrical Engineering from Laval University (Québec), and his Master's Degree in Mechanical Engineering from the same university. He worked for ten years as consulting engineer for the aerospace industry, after which he joined in 1994 the École de technologie supérieure (ÉTS) in Montreal (Quebec, Canada) as professor in the Department of Mechanical Engineering. His research interests are in the area of industrial statistics, and include productivity improvement, quality control, metrology and probabilistic approach.