

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

Olivier Blancke¹, Amélie Combette², Normand Amyot³, Dragan Komljenovic³, Mélanie Lévesque³,
Claude Hudon³, Antoine Tahan¹ and Noureddine Zerhouni²

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 the predictive maintenance of complex equipment. The approach relies on a physics of failure (PoF) model based on expert knowledge and data. The model can be represented as a multi-state Petri Net where different failure mechanisms have been discretized using physical degradation states. Each physical state can be detected by a unique combination of symptoms that are measurable using diagnostic tools. Based on actual diagnostic information, a diagnostic algorithm is used to identify active failure mechanisms and estimate their propagation using the Petri Net technique. Specific maintenance actions and their potential effects on the system can be associated with target states. A prognostic algorithm using a colored Petri Net propagates active failure mechanisms through the target physical states. A predictive maintenance approach is therefore proposed by allowing specific maintenance actions to be determined in a reasonable timeframe. A case study is presented for an actual hydro-generator. Finally, model limits are discussed and potential areas for 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 value from assets* (ISO, 2014). Unlike preventive maintenance or reliability-based maintenance approaches, predictive maintenance approaches take into account the dynamic and individual

aspects of each asset's data. Prognostic models predict the occurrence of equipment failure modes taking into account their condition, operation and environment loads and their related uncertainties (Atamuradov, Medjaher, Dersin, Lamoureux, & Zerhouni, 2017; Goebel et al., 2017). The predicted information is updated as new asset health information becomes available. Maintenance actions are then proposed in advance to avoid occurrence of the predicted failure modes. Different aspects also need to be taken into account to optimize maintenance planning so as to ensure strategic planning within the fleet. Those aspects include equipment criticality, operational resource constraints and organizational objectives, to name just a few (IAM, 2015).

For the last decade, the development of prognostic models has been an intensive research topic from both an academic and operational point of view. In the literature, the vast majority of prognostics research to date has been focused on the prediction of the *remaining useful life* (RUL) of individual components (Atamuradov et al., 2017; M. Chiachío, Chiachío, Sankararaman, Andrews, & Targett, 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 (Atamuradov et al., 2017; Blancke, Amyot, Hudon, Lévesque, & Tahan, 2015; Blancke, Tahan, et al., 2018). 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

Olivier Blancke et al. This is an open-access article distributed under the terms of the Creative Commons Attribution 3.0 United States License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

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 past and future mechanism propagation when we want to apply specific maintenance tasks to extend the RUL of complex equipment.

This paper focuses on how to suggest specific maintenance tasks based on prognostic models. The optimization of these tasks within the fleet will not be considered here. Thus, the aim of this paper is to propose a comprehensive approach for the 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 incoming diagnostic data. The main contributions of this paper are: (1) to propose a system-level prognostic model that is used 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 the time interval when they can be actionable depending on active failure mechanisms and their kinetics.

The paper is organized as follows. Section 2 proposes a brief overview of prognostic models in the context of predictive maintenance. The proposed prognostic model identified as a failure mechanism 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 hydro-generator in Section 5. Finally, model limits are discussed and potential areas for further research are identified in the last section.

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, Elminir, & Riad, 2016). Prognostics approaches can be classified into four types: (1) reliability-based approach, (2) physics-based approach, (3) data-driven approach and (4) hybrid approach.

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

2.1. Physics of Failure (PoF) Prognostic Models

Physics-based approaches focus on the equipment degradation process. They aim to model the propagation of equipment failure mechanisms by taking into account knowledge of the physics of degradation and feedback from domain experts (Gu & Pecht, 2008; Kulkarni, Biswas, Celaya, & Goebel, 2013). In such approaches, diagnostic data are often used to update initial conditions and to fine-tune model parameters (J. Chiachío, Chiachío, Sankararaman,

Saxena, & Goebel, 2015; Corbetta, Sbarufatti, Manes, & Giglio, 2014; Javed, Gouriveau, & Zerhouni, 2017). As one of its main advantages, the PoF approach is applicable even if data is scarce because it takes advantage of the knowledge gained. A generic methodology has been proposed by Gu and Pecht (Gu & Pecht, 2008) for PoF prognostic models (Figure 1 presents an adapted illustration of the proposed methodology).

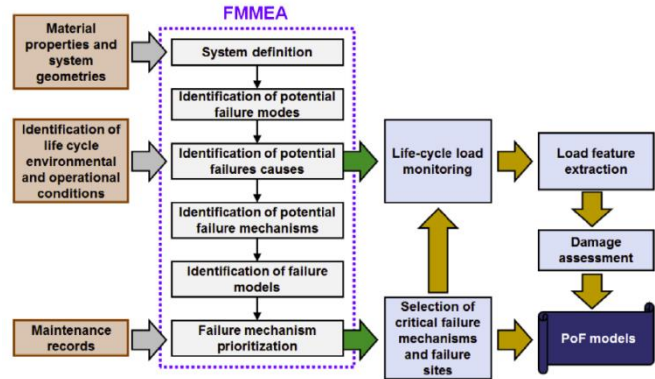


Figure 1. PoF-based PHM methodology (Kwon, Hodkiewicz, Fan, Shibutani, & Pecht, 2016)

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 to critical failure mechanisms. As mentioned previously, complex equipment may have various failure modes and many failure mechanisms. Various 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 states of degradation. Each physical state can be detected by a unique combination of symptoms obtainable with diagnostic tools. The proposed model has been developed through different publications (Amyot et al., 2014; Blancke et al., 2015; Blancke, Combette, et al., 2018; Blancke, Tahan, et al., 2018). It 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 succession of physical states 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 enables failure mechanisms to share physical states. Thus, Amyot et al. (Amyot et al., 2014) have introduced an algorithm to detect active failure mechanisms based on a 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) is used to aggregate various diagnostic

data from different diagnostic tools at a system level. In order to make it evolve towards predictive maintenance, the temporal aspects of causality must be introduced.

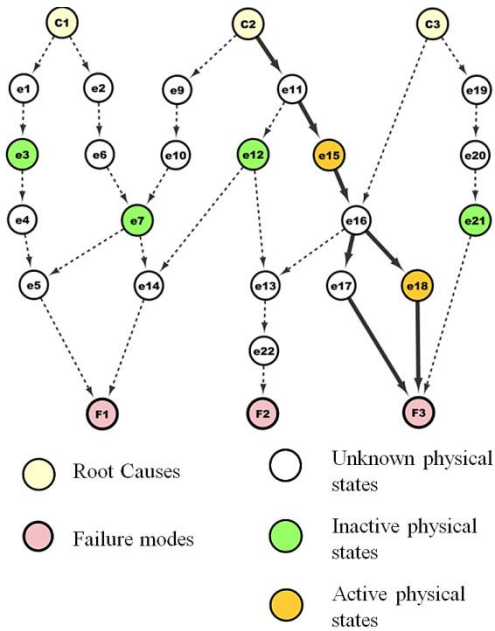


Figure 2. Causal graph model illustrating failure mechanisms

Chemweno et al. (Chemweno, Pintelon, Muchiri, & Van Horenbeek, 2018) have proposed a review of dependability modeling 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 Nets (SPN). In this paper, the formalism of SPN has been chosen mainly because of the variety of extensions that it contains.

2.2. Petri Nets in Prognostic and Predictive Maintenance Models

Petri Nets (PNs) were initially introduced by Carl Adam Petri in 1966 (Petri, 1966). PN are bipartite directed graphs used mainly 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 is visited by *tokens* that propagate from *place* to *place* as defined by the PN. *Transitions* represent the dynamic behavior of the system. They comprise time transitions from one *place* to another (M. Chiachío et al., 2017). For further information, several references present the formalism of PN (M. Chiachío et al., 2017; Murata, 1989; Peterson, 1981).

In the literature, various authors have used PN in the context of predictive maintenance. Zhouhang et al. (Zhouhang, Maen, & H., 2014) have proposed an application of PN to model the reliability and maintenance analysis of multi-state and multi-unit systems. The approach considers three

degradation states: healthy, degraded and failed. The PN model simulates the transition between those states in different components. A fault tree model allows different degraded or failed components to be integrated 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 tasks but focuses more on the operational aspects of predictive maintenance.

Ammour et al. (Ammour, Leclercq, Sanlaville, & Lefebvre, 2016) proposed a fault prognosis approach of stochastic discrete event systems. The PN is used to model the system and its sensors. Measurements have been attached to some places in the PN and an incremental approach identifies 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. However, feedback from domain experts has not been taken into account. The approach ends at fault prognosis and does not identify any specific maintenance action.

Finally, Chiachío et al. (M. Chiachío et al., 2017) have proposed a mathematical framework for prognostic modeling 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. Two interacting sub-net forms are introduced to do this: *symbolic sub-net* (integer moving units) 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.

A review of the literature to date seems to show that no predictive maintenance approach using PN has been proposed to predict specific maintenance actions based on the active failure mechanisms detected in equipment through a failure mechanism propagation model.

The model presented in this paper is based on the Failure Mechanisms and Symptom Analysis (FMSA) approach proposed by Amyot et al. (Amyot et al., 2014). Blancke et al. (Blancke, Tahan, et al., 2018) recently published papers on the development of the failure mechanism propagation model to predict failure modes of complex equipment. In another publication, Blancke et al. (Blancke, Combette, et al., 2018) proposed a failure mechanism propagation algorithm that can predict remaining physical states and an applicability timeframe for specific maintenance tasks. This paper is a journal extension of the previous conference paper (Blancke,

Combette, et al., 2018). It combines both predictions of remaining physical states and failure mode occurrence.

In this paper, the predictive maintenance approach aims to forecast the occurrence of some specific target physical degradation states where some maintenance actions can be implemented and will start to affect the system. Furthermore, the approach predicts the applicability time interval for maintenance tasks based on the predicted occurrence of resulting failure modes through the propagation of related failure mechanisms. In this section, we present the failure mechanism propagation model that predicts target degradation states and failure mode occurrence. Section 3 presents the model for moving from failure mechanism propagation to predictive maintenance. Section 4 describes 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), an expert group identified propagation model assumptions 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. For more details on the identification of these hypotheses, Blancke et al. (Blancke, Tahan, et al., 2018) presented the hypotheses governing the discretization and propagation of the failure mechanisms that compete in complex equipment. The hypotheses proposed above are based on this work. Assumptions have been classified into the categories presented below.

- Assumptions on degradation states

Physical states denoted v^{ei} , are considered as discrete events constituting failure mechanisms FM^j . They are detected by a unique combination of symptoms acquired from diagnostic tools. When not detected, their evidence ε at a discrete time of prediction k_p is considered as unknown ($v_\varepsilon^{ei}(k_p) = \emptyset$). When they become detectable by appropriate diagnostic tools, they can be active ($v_\varepsilon^{ei}(k_p) = 1$) or inactive ($v_\varepsilon^{ei}(k_p) = 0$).

- Assumptions on the causal graph

The causal graph G identifies all possible failure mechanisms FM^j 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 v^{ei} starting from a root cause v^{RCa} and leading to a failure mode v^{Fb} ($FM^j = \langle v^{RCa}, v^{e1}, \dots, v^{ei}, v^{Fb} \rangle$). If none of its physical states can be detected at a discrete time of prediction k_p , the failure mechanism activity is defined as unknown ($FM_\varepsilon^j(k_p) = \emptyset$). This means that 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 ($FM_\varepsilon^j(k_p) = 0$ or 1) depending on the relative symptom intensity 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 to be uninfluenced by other mechanisms). In addition, failure mechanism propagation is considered 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 discrete time of prediction is considered to be its last active state within the sequence of physical states denoted in $FM_{\varepsilon_x}^j(k_p)$.

For this paper, the influence of duty cycle, operating environment and regular maintenance actions were not considered.

- Assumptions on target state occurrence

Failure mechanisms are considered to be in competition. The first failure mechanism to reach a target 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. This maintenance task M_n could be considered specific to a physical state occurrence v^{ei} and is denoted $v_{M_n}^{ei}$. The maintenance task $v_{M_n}^{ei}$ must be performed before the occurrence of a related failure mode v^{Fb} .

Based on these assumptions, the causal graph G introduced by Amyot et al. (Amyot et al., 2014) could be considered as a PN where physical states are *places* (also called *vertices* (V)) identified by specific detection algorithms, and *transitions* are the different stochastic transition times $T_{FM^j}^{eu, ev}$. A colored PN can be considered a generic model for the fleet. This type of PN makes it possible to represent all possible failure mechanisms FM^j in a causal graph which is a specific path from one root cause v^{RCa} to a failure mode v^{Fb} .

To simplify the graph in the proposed approach, visual representations of PN will not illustrate transition nodes as rectangles as defined in PN formalism.

2.4. Diagnostic Algorithm

2.4.1. Fault Detection: Active Physical State Detection Algorithms

Fault detection consists of detecting physical state evidence ε at a discrete time of prediction k_p , denoted as $v_{\varepsilon}^{ei}(k_p)$. For each physical state, a detection algorithm has been defined by experts using a rule-based combination of symptoms. A physical state can be identified as unknown, inactive or active. If the physical state is detected as active, an activation interval $v_{\varepsilon_{KE}}^{ei}(k_p)$ is estimated based on the measurement or inspection interval that can detect the physical state. Figure 3 presents the physical state detection algorithm. The detection algorithm is performed for each prediction date required. In this paper, the detection approach is similar to the one described by Blancke et al. (Blancke, Tahan, et al., 2018).

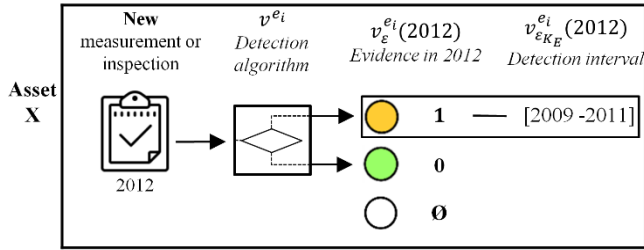


Figure 3. Physical state detection algorithms based on symptom analysis (Blancke, Tahan, et al., 2018)

2.4.2. State Estimation: Active Failure Mechanism Detection Algorithm

Following fault detection, the state estimation consists of estimating the actual state of the system for a specific prediction date k_p . In our case, the state estimation consists of identifying active failure mechanisms ($FM_{\varepsilon}^j(k_p) = 1$) based on active and inactive physical states and in estimating their propagation through the PN. In this paper, Algorithms 2.4.2.a and 2.4.2.b are also similar to the algorithm introduced by Blancke et al. (Blancke, Tahan, et al., 2018).

The failure mechanism detection algorithm analyzes each physical state sequence. If at least one physical state is active, the failure mechanism is detected as active. However, if inactive physical states are located before some active physical states in the sequence, the whole failure mechanism is detected as inactive in order to eliminate incoherent failure mechanisms.

Algorithm 2.4.2.a

Active failure mechanism detection for a discrete time of prediction k_p (Blancke, Tahan, et al., 2018)

- 1: **Input:** $k_p, [FM^1, \dots, FM^j], [v_{\varepsilon}^{e1}(k_p), \dots, v_{\varepsilon}^{ej}(k_p)], [FM_{\varepsilon_x}^1(k_p), \dots, FM_{\varepsilon_x}^j(k_p)]$
- 2: **Output:** $[FM_{\varepsilon}^1(k_p), \dots, FM_{\varepsilon}^j(k_p)]$
- 3: **for** $a = 1$ to j **do:**
- 4: **if** $v_{\varepsilon}^{eu}(k_p) = 1$ **not exist in** FM^a **and** $v_{\varepsilon}^{ev}(k_p) = 0$ **not exist in** FM^a **then**
- 5: $FM_{\varepsilon}^a(k_p) = \emptyset$
- 6: **else if** $v_{\varepsilon}^{eu}(k_p) = 1$ **exist in** FM^a **and** $v_{\varepsilon}^{ev}(k_p) = 0$ **with** $\text{rank}(v) < \text{rank}(u)$ **not in** FM^a **then**
- 7: $FM_{\varepsilon}^a(k_p) = 1$
- 8: **else**
- 9: $FM_{\varepsilon}^a(k_p) = 0$
- 10: **end if**
- 11: **end for**

State isolation relies on the assumption that the last active physical state of active failure mechanisms defines that state. As the last active physical state has been detected based on periodic measurement or inspection, its detection date is considered interval-censored. Thus, state isolation of an active failure mechanism is also considered interval-censored and follows a specific distribution. Algorithm 2.4.2.b presents the state estimation algorithm based on detected active failure mechanisms ($FM_{\varepsilon}^j(k_p) = 1$) and active physical states ($v_{\varepsilon}^{ei}(k_p) = 1$) at a discrete time of prediction k_p .

Algorithm 2.4.2.b

Active failure mechanism state isolation for a discrete time of prediction k_p (Blancke, Tahan, et al., 2018)

- 1: **Input:** $k_p, [FM_{\varepsilon_x}^1(k_p), \dots, FM_{\varepsilon_x}^j(k_p)], [v_{\varepsilon_{KE}}^{e1}(k_p), \dots, v_{\varepsilon_{KE}}^{ej}(k_p)], [FM_{\varepsilon}^1(k_p), \dots, FM_{\varepsilon}^j(k_p)]$
- 2: **Output:** $[FM_{T_x}^1(k_p), \dots, FM_{T_x}^j(k_p)]$
- 3: **for** $a = 1$ to j **do:**
- 4: **if** $FM_{\varepsilon}^a(k_p) = 1$ **then**
- 5: $FM_{T_x}^a(k_p) \sim \text{distribution}(FM_{\varepsilon_x}^a(k_p) [v_{\varepsilon_{KE}}^{e_x}(k_p)])$
- 6: **end if**
- 7: **end for**

In Figure 4, physical state and failure mechanism detection and isolation algorithms have been performed for the prediction dates $k_p=2015$ and $k_p=2016$. In 2015, based on available symptoms of asset X, one physical state was detected as active (orange node) and four as inactive (green nodes). Thus, three failure mechanisms were detected as active. In 2016, three physical states were detected as active and four as inactive. Thus, nine failure mechanisms were detected as active. The state estimation is shown in Figure 4. The path of the active failure mechanisms is represented in

bold. It is possible to see how far failure mechanisms have progressed for each prediction date.

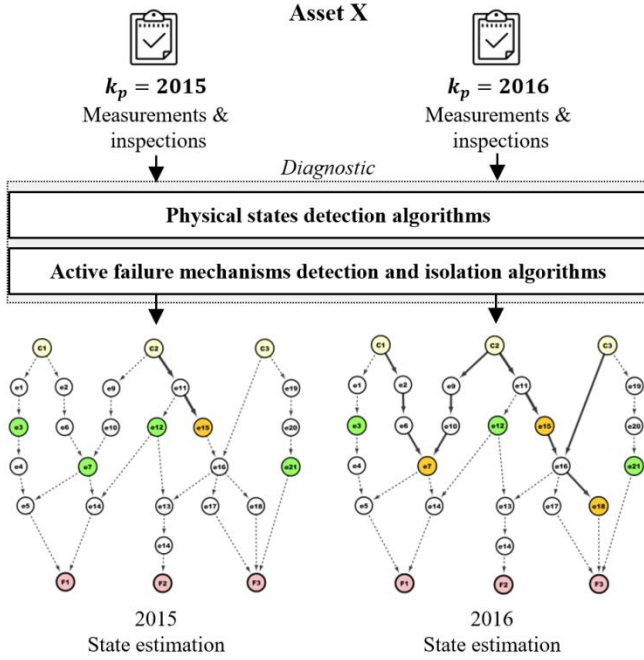


Figure 4. Asset-specific state estimation process based on active failure mechanism detection and isolation algorithms

2.5. Failure Mechanism Propagation Algorithm

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

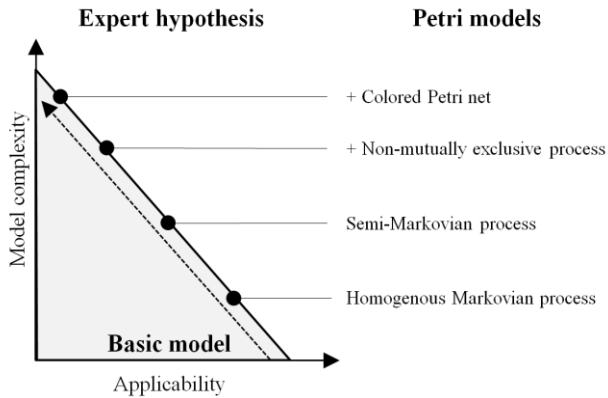


Figure 5. From basic Petri Net model to complex PN model satisfying expert assumption

Transition times $T_{FM^j}^{e_u, e_v}$ from physical state v^{e_i} to another physical state v^{e_j} in a specific failure mechanism FM^j have been defined by experts as Weibull distributions. Thus, the

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

2.5.1. Failure Mechanism Propagation to a Target State

The first resulting algorithm independently propagates any active failure mechanisms to the target state. A variable denoted $v^{e_{target}}$ is defined to store the target state for which we wish to predict the occurrence over a discrete time of prediction $v_{CDF}^{e_{target}}(k_p)$. As defined in the diagnostic algorithms, the state of an active failure mechanism $FM^j_x(k_p)$ at a discrete time of prediction k_p is defined by the activation interval of the last active physical state $FM^j_{e_x}(k_p)$ as the propagation start date. Then, the stochastic PN propagates through the remaining states of the failure mechanism to the target state $v^{e_{target}}$. To sum the different remaining time transitions, a Monte Carlo simulation is used for a specific number of iterations denoted $numIter$ in Algorithm 2.5.1. Algorithm 2.5.1 presents failure propagation through the PN.

Algorithm 2.5.1	Failure mechanism propagation algorithm for a discrete time of prediction k_p to target states contained in $Target$
-----------------	--

```

1: Input:  $k_p, numIter, [FM^1_{e_x}(k_p), \dots, FM^j_{e_x}(k_p)], [FM^1_{e_x}(k_p), \dots,$ 
    $FM^j_{e_x}(k_p)], [FM^1_{T_x}(k_p), \dots, FM^j_{T_x}(k_p)], [FM^1, \dots, FM^j],$ 
    $[T_{FM^1}^{e_1, e_2}, \dots, T_{FM^j}^{e_u, e_v}], v^{e_{target}}$ 
2: Output:  $[FM^1_{v^{e_{target}}}(k_p), \dots, FM^j_{v^{e_{target}}}(k_p)]$ 
3: for  $a = 1$  to  $j$  do
4:   if  $FM^a_{e_x}(k_p) = 1$  and  $v^{e_{target}}$  in  $FM^a$  then
5:     for  $c = 1$  to  $numIter$  do
6:        $X \sim FM^a_{T_x}(k_p)$ 
7:        $rank = rank(FM^a_{e_x}(k_p))$ 
8:        $FM^a_{v_c^{e_{target}}}(k_p) = X_c$ 
9:       while  $rank \neq rank(v^{e_{target}})$  do
10:         $Y \sim T_{FM^a}^{e_{rank}, e_{rank+1}}$ 
11:         $FM^a_{v_c^{e_{target}}}(k_p) = FM^a_{v_c^{e_{target}}}(k_p) + Y_c$ 
12:      end while
13:    end for
14:  end if
15: end for
    
```

* $FM^a_{v_c^{e_{target}}}(k_p), X_c, Y_c$ realization c of distribution $FM^a_{v^{e_{target}}}(k_p), X, Y$.

Figure 6 shows the propagation of each active failure mechanism to the target state $v^{e_{14}}$. In 2016, even though nine failure mechanisms were detected active, only two of them

led to the v^{e14} state. So only two failure mechanisms were propagated: FM^1 and FM^2 . The Cumulative Density Function (CDF) of these two failure mechanisms is shown in Figure 6. Those CDFs, $FM_{v^{e14}}^1(2016)$ and $FM_{v^{e14}}^2(2016)$ illustrate the probability predicted in 2016 that each failure mechanism FM^1 and FM^2 reached the state v^{e14} .

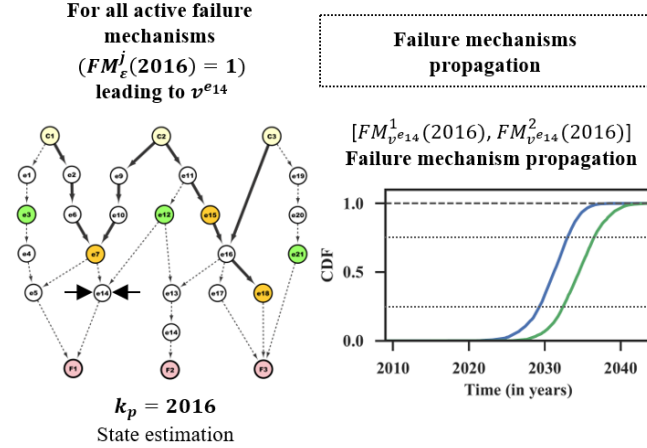


Figure 6. Illustration of the algorithm for failure mechanism propagation to a target state

2.5.2. Failure Mechanism Propagation to Failure Modes

Based on the same assumptions, a second resulting algorithm independently propagates any active failure mechanisms that contain the target states $v^{e_{target}}$ from their state estimation $FM_{T_x}^j(k_p)$ at the date of prediction k_p to the resulting failure modes v^{F_b} . This algorithm is slightly different from the one proposed by Blancke et al. (Blancke, Tahan, et al., 2018) because it propagates only failure mechanisms that relate to the target state $v^{e_{target}}$. Thus, this algorithm (see Algorithm 2.5.2) will be used to identify failure mechanism propagation leading to failure modes related to the target state $v^{e_{target}}$.

Algorithm 2.5.2. Failure mechanism propagation algorithm for a discrete time of prediction k_p to failure modes v^{F_b} related to the target state $v^{e_{target}}$

- 1: **Input:** $k_p, numIter, [FM_{e_x}^1(k_p), \dots, FM_{e_x}^j(k_p)], [FM_{\varepsilon}^1(k_p), \dots, FM_{\varepsilon}^j(k_p)], [FM_{T_x}^j(k_p), \dots, FM_{T_x}^j(k_p)], [FM^1, \dots, FM^j], [T_{FM^1}^{e_1, e_3}, \dots, T_{FM^j}^{e_u, e_v}], v^{e_{target}}$
- 2: **Output:** $[FM_{EOF}^1(k_p), \dots, FM_{EOF}^j(k_p)]$
- 3: **for** $a = 1$ to j **do:**
- 4: **if** $FM_{\varepsilon}^a(k_p) = 1$ and $v^{e_{target}}$ in FM^a **then**
- 5: **for** $c = 1$ to $numIter$ **do**
- 6: $X \sim FM_{T_x}^a(k_p)$
- 7: rank = rank($FM_{e_x}^a(k_p)$)
- 8: $FM_{EOF_c}^a(k_p) = X_b$
- 9: **while** rank \neq rank(v^{F_b}) **do**
- 10: $Y \sim T_{FM^a}^{e_{rank}, e_{rank+1}}$
- 11: $FM_{EOF_c}^a(k_p) = FM_{EOF_c}^a(k_p) + Y_c$
- 12: **end while**

13: **end for**
14: **end if**
15: **end for**

* $FM_{EOF_c}^a(k_p), X_c, Y_c$ realization c of distribution $FM_{EOF}^1(k_p), X, Y$.

Figure 7 shows the propagation of each active failure mechanism to the failure modes that relate to the target state v^{e14} . In this case, the two active failure mechanisms related to the target state end at one failure mode: v^{F1} . In 2016, these two failure mechanisms have been propagated: FM^1 and FM^2 . Their CDF is shown in Figure 6. CDFs $FM_{EOF}^1(2016)$ and $FM_{EOF}^2(2016)$ represent the probability predicted in 2016 that each failure mechanism FM^1 and FM^2 reached the End of Function (EOF). In other words, $FM_{EOF}^2(2016)$ is the probability of occurrence of the failure mode resulting from propagation of the failure mechanism FM^2 for the 2016 date of prediction.

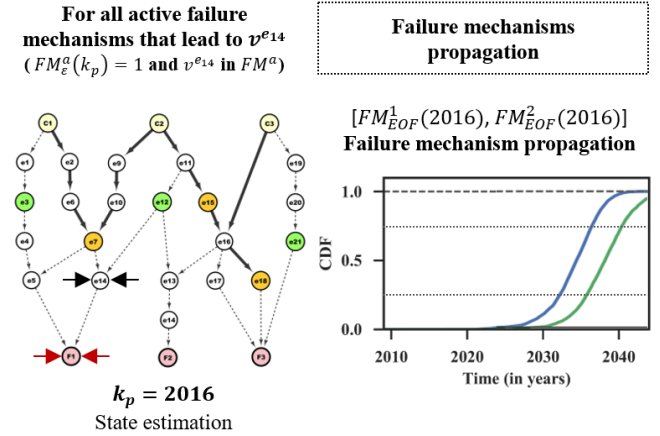


Figure 7. Illustration of the algorithm for failure mechanism propagation to a target state

2.6. Target State and Failure Mode Occurrence Prediction

The last step consists of aggregating failure mechanism propagation in order to estimate the occurrence of the target physical state $v^{e_{target}}$ and the related failure modes v^{F_b} for a time of prediction k_p . Based on the assumption that failure mechanisms are in competition, their occurrence has been defined as the envelope of all CDF functions. Equation 1 presents the two aggregated functions.

$$v_{CDF}^{e_{target}}(k_p) = \text{Max_envelope}(FM_{v^{e_{target}}}^j(k_p)) \quad (1)$$

$$v_{EOF}^{F_b}(k_p) = \text{Max_envelope}(FM_{EOF}^j(k_p)) \quad (2)$$

3. FROM FAILURE MECHANISM PROPAGATION TO PREDICTIVE MAINTENANCE

The algorithm is used to estimate the state of the system for different discrete times of prediction k_p and to propagate

detected active failure mechanisms until target physical states $v^{e_{target}}$ or failure modes v^{F_b} are reached. Predictive maintenance is aimed at predicting and suggesting maintenance actions based on prognostic algorithms. 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 target physical states are reached, specific maintenance actions will have a positive effect on the system. Thus, maintenance actions can be attributed to target physical states of the PN and are denoted $v_{M_n}^{e_{target}}$. Experts have the knowledge to suggest the possible expected effects. For example, those effects could work to:

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

The predicted maintenance tasks will allow the organization to plan the work ahead. However, maintenance planning generally faces many operational and organizational issues. For an organization, it is more convenient to have an applicability interval for each maintenance task in order to more easily prioritize different tasks with regard to operational and organizational constraints.

In the nuclear industry, the concept of maintenance interval applicability (or admissible tolerance of the maintenance interval) has already been discussed. An EPRI report (EPRI, 2002) defined a time range in terms of the inspection interval for a specific maintenance task. This timeframe is defined between two limits applied to the inspection interval (T_o): $0.9T_o$ and $1.125T_o$. In this paper, we chose to apply those factors to the time necessary to reach the target states $v_{TTE}^{e_{target}}(k_p)$. This time is defined in equation 3 as the difference between the predicted occurrence date of the target state $v_{k_E}^{e_{target}}(k_p)$ and the prediction date k_p . To define the date of occurrence $v_{k_E}^{e_{target}}(k_p)$, the $q_{75\%}$ percentile rank of the predicted occurrence of the target state $v_{CDF}^{e_{target}}(k_p)$ for a specific date of prediction k_p is used.

$$v_{TTE}^{e_{target}}(k_p) = v_{k_E}^{e_{target}}(k_p) - k_p \quad (3)$$

Equation 4 presents the applicability interval K_E of a specific maintenance task M_n attributed to a target state e_{target} at a discrete time of prediction k_p .

$$v_{M_n[K_E]}^{e_{target}}(k_p) = [0.9 v_{TTE}^{e_{target}}(k_p); 1.125 v_{TTE}^{e_{target}}(k_p)] \quad (4)$$

However, a maintenance action must be performed before a failure mode is reached. Propagation Algorithm 2.5.2 is used to inform decision makers of the occurrence of potential failure modes. If the $q_{25\%}$ percentile rank of one related failure mode occurrence is lower than the upper bound of the applicability interval, the applicability interval will be

replaced by the $q_{25\%}$ rank of one related failure mode occurrence.

As a result, Figure 8 illustrates an example of predictive maintenance M_n attached to a state $v^{e_{14}}$. The predicted time to reach $v^{e_{14}}$ for the prediction date 2016 is 17 years. The suggested applicability interval for the maintenance task is between 2031 and 2035. Lubrication of the shaft bearing can be done in 2031 if the expected effect on the equipment is desired. However, it has to be done before 2035 in order to mitigate the risk of failure

Asset X	Predicted time to targeted state $v^{e_{14}}$	Associated maintenance task	Potential effect on system	Predicted applicability interval
$k_p = 2016$	$v_{TTE}^{e_{14}}(2016)$	$v_{M_n}^{e_{14}}$		$v_{M_n[K_E]}^{e_{14}}(2016)$
	17 years	Lubrication of shaft bearing	Slow failure mechanism	[2031-2035]

Figure 8. Illustration of the failure mechanism propagation algorithm

4. CASE STUDY: HYDRO-GENERATORS

4.1. Industrial Context

The proposed case study is based on the real historical data for a hydro-generator from Hydro-Quebec's generating fleet. Hydro-generators are heavy electro-mechanical rotating machines. Figure 9 shows a hydro-generator in a power plant.



Figure 9. Hydro-Québec generating unit

Groups of experts have been involved in identifying possible failure mechanisms for the stator part of hydro-generators. In this case, three failure modes and over one hundred failure mechanisms have been identified. Seventy different physical states have been defined and the causal graph representing all those stator failure mechanisms is illustrated in Figure 10.

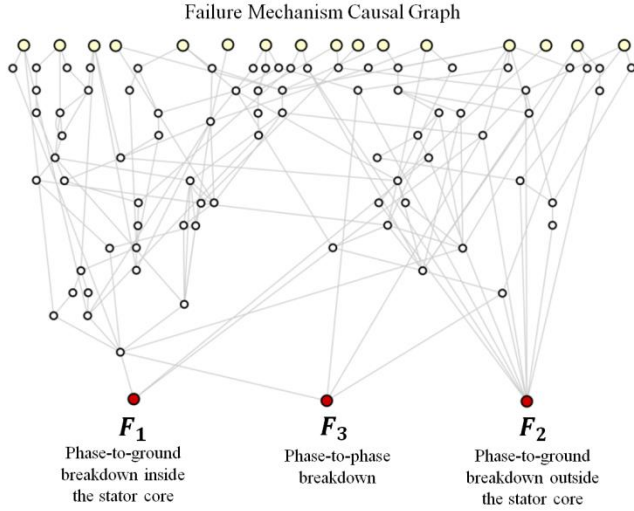


Figure 10. Hydro-generator stator causal graph representing failure mechanisms leading to three failure modes

At Hydro-Québec, a web-based application that gathers symptoms from diagnostic tools was implemented in 2008. The case study proposed in the following section is based on the historical data obtained from this application.

4.2. Associated Maintenance Task

In this case study, a brief analysis of available data has been carried out to identify target physical states that have possible maintenance actions associated with them. Four physical states have been targeted and are presented in Table 1.

Table 1. Target physical states $v^{e_{target}}$

ID	Physical states
v^{t_6}	Thermal aging of groundwall insulation
$v^{m_{31}}$	Stator lamination insulation wear
$v^{m_{21}}$	Mechanical erosion of groundwall insulation inside the stator core
$v^{e_{12}}$	Erosion of the semiconducting coating

Based on expert knowledge, maintenance tasks have been associated with the target physical states, and their potential effects on the system have been estimated. Results are presented in Table 2.

4.3. Application of Prognostic Model

In this case study, a hydro-generator (referred to as hydro-generator A) for which several measurements and inspection data were available is used to illustrate the methodology. Table 3 presents the list of historical diagnostic data and maintenance actions carried out on hydro-generator A.

Five dates of prediction k_p have been chosen: one for each year between 2010 and 2015. The prediction date 2012 is described in detail in the case study. The occurrence of target physical states as well as the timeframe when their associated maintenance tasks will be applicable are presented below.

Table 2. Associated maintenance tasks $v_{M_n}^{e_{target}}$ and their potential effect on the system

ID	Associated maintenance task $v_{M_n}^{e_{target}}$	Potential effect on system
v^{t_6}	Stator rewinding (replacement)	Reset stator winding failure mechanisms
$v^{m_{31}}$	Stator lamination epoxy injection	Slow down associated failure mechanisms
$v^{m_{21}}$	Replacement of a few stator bars	Reset local failure mechanisms (extend the average useful life of the entire winding)
	Stator rewinding (replacement)	Reset stator winding failure mechanisms
$v^{e_{12}}$	Painting of stator semiconducting insulation	Inhibit failure mechanisms associated for a period of time

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 & 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	Semiconducting coating 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	Semiconducting coating assessment
2016-07	DC Ramp test (DCRT)

• State estimation in 2012

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

Table 4. Active physical states in 2012 on hydro-generator A and their activation intervals K_E

Hydro-generator A ($k_p = 2012$)		
ID	Active physical state appellation	Activation interval $v_{\epsilon_{K_E}}^{e_i}(2012)$
v^{a_1}	Conductive contamination on coil ends or end-winding	[1996; 2010]
v^{a_3}	Presence of dust	[2002; 2010]
$v^{e_{21}}$	Iron core hotspot due to eddy currents	[2002; 2010]
v^{t_2}	Thermal shield	[2006; 2010]
$v^{m_{34}}$	Buckling of stator iron core	[2009; 2010]

For the activation intervals K_E , the upper limit corresponds to the detection date k_E and the lower limit to the last date on which the physical state was detected inactive. Based on those results, the failure mechanism detection algorithm (Algorithm 2.4.2.a) and the failure mechanism state isolation (Algorithm 2.4.2.b) were performed. Results are illustrated using graphic visualization of the PN in Figure 11.

In 2012, five physical states were detected as active and 28 as inactive. A total of 30 failure mechanisms were detected as active. In Figure 11, target physical states $v^{e_{target}}$ are identified with a cross in the middle of their nodes. Fourteen of the active failure mechanisms led to the target state v^{t_6} , six to target state $v^{m_{31}}$ and only three to target state $v^{e_{12}}$ in 2012.

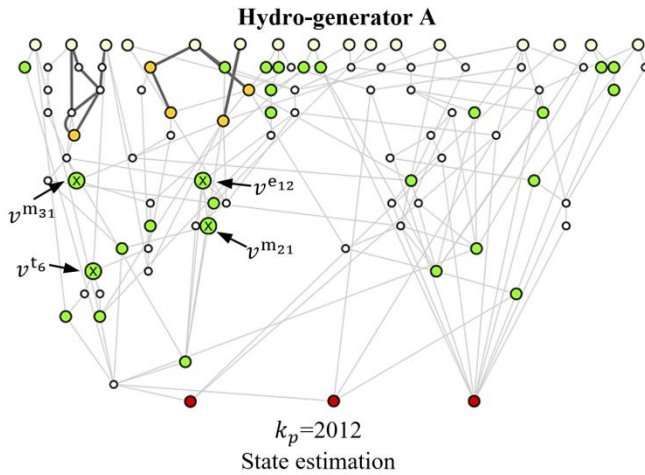


Figure 11. State estimation of hydro-generator A in 2012

• Failure mechanism propagation in 2012

All active failure mechanisms leading to the target physical states were propagated using the failure mechanism propagation algorithm (Algorithm 2.5.1). Transition times have been estimated based on elicitation process. Different expert estimations have been aggregated for this purpose. Their level of confidence has been taken into account in the aggregation process. Figure 12 presents results for the failure mechanism propagations and occurrence probabilities for the target physical states.

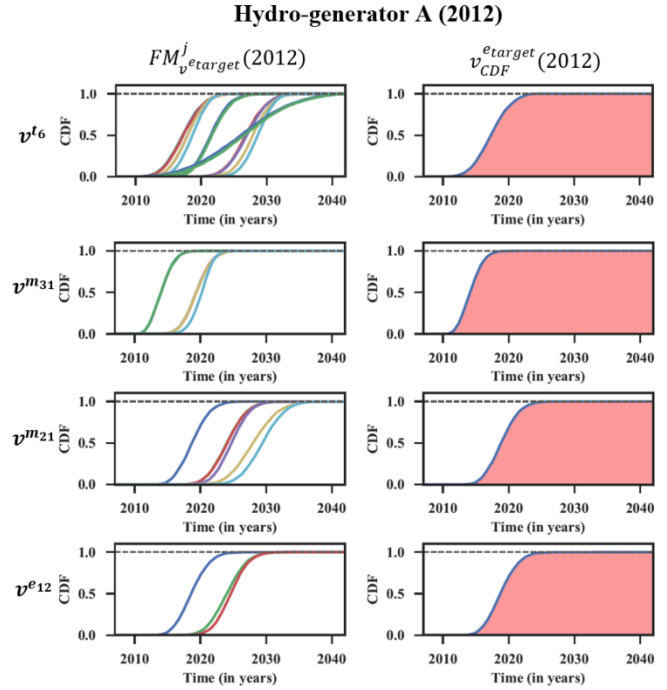


Figure 12. Failure mechanism propagation of hydro-generator A to target states in 2012

The predicted 50% confidence intervals for each target physical state are presented in Table 5.

Table 5. Prediction confidence intervals and time to reach TTE for each target physical states in 2012.

Hydro-generator A ($k_p = 2012$)			
ID	State appellation	Predicted confidence Interval $v_{CDF}^{e_{target}}(2012)$	Predicted time to event (years) $v_{TTE}^{e_{target}}(2012)$
v^{t_6}	Thermal aging of groundwall insulation	[2015; 2019]	7
$v^{m_{31}}$	Stator lamination insulation wear	[2012; 2015]	3
$v^{m_{21}}$	Mechanical erosion of groundwall insulation inside the stator core	[2017; 2020]	8
$v^{e_{12}}$	Erosion of the semiconducting coating	[2017; 2020]	8

The second failure propagation algorithm (Algorithm 2.5.2) was computed to predict the time to failure (TTF) for each failure mechanism related to each target physical state. Results for failure mechanism propagation and occurrence probabilities for the failure modes are presented in Figure 13.

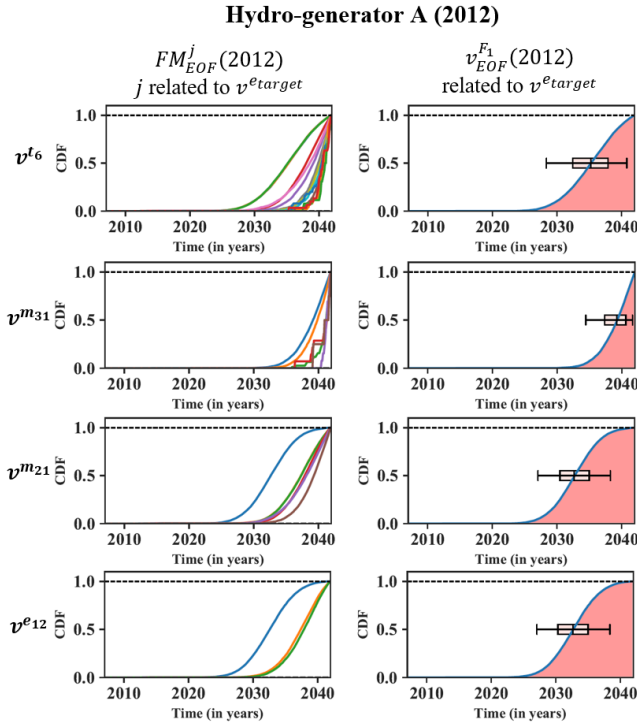


Figure 13. Failure mechanism propagation of hydro-generator A to failure modes related to target states in 2012

In all active failure mechanisms, only the failure mode v^{F_1} is found in failure mechanisms where the target physical states are present. The prediction for a 50% confidence interval for failure mode v^{F_1} is presented in Table 6.

Table 6. Prediction confidence intervals and related TTF to target states in 2012

Hydro-generator A ($k_p = 2012$)				
ID	Target state appellation	Related failure mode	Related predicted failure confidence interval $v_{EOF}^{F_1}(2012)$	Predicted time to failure (years) $v_{TTF}^{F_1}(2012)$
v^{t_6}	Thermal aging of groundwall insulation	v^{F_1}	[2032; 2037]	[20; 25]
$v^{m_{31}}$	Stator lamination insulation wear	v^{F_1}	[2037; 2040]	[25; 28]
$v^{m_{21}}$	Mechanical erosion of groundwall insulation inside the stator core	v^{F_1}	[2030; 2035]	[18; 23]
$v^{e_{12}}$	Erosion of the semiconducting coating	v^{F_1}	[2030; 2035]	[18; 23]

• Predictive maintenance suggested in 2012

Based on the predicted occurrence of the target physical states and related predicted failure occurrence, maintenance

tasks $v_{M_n}^{e_{target}}$ and their predicted dates of applications K_E were proposed in 2012 (see Table 7). As no failure is predicted in the proposed maintenance interval, the failure occurrence has no impact on the proposed intervals.

Table 7. Predicted and suggested maintenance tasks and related dates of application

Predicted interval for maintenance applicability $v_{M_n[K_E]}^{e_{target}}(2012)$	Predicted failure confidence interval $v_{EOF}^{F_b}(2012)$	Suggested maintenance task $v_{M_n}^{e_{target}}$	Potential effects on system
[2015; 2015]	[2037; 2040]	Stator lamination epoxy injection	Slow down associated failure mechanisms
[2018; 2020]	[2032; 2037]	Stator rewinding (replacement)	Reset stator winding failure mechanisms
[2019; 2021]	[2030; 2035]	Replacement of a few stator bars	Reset local failure mechanisms (extend the average useful life of the entire winding)
		Stator rewinding (replacement)	Reset stator winding failure mechanisms
[2019; 2021]	[2030; 2035]	Painting of stator semi-conducting insulation	Inhibit associated failure mechanisms for a period of time

4.3.1. Validation of the Prognostic Algorithm

In order to validate the prognostic algorithms, the activation date of the target physical states have been identified from historical diagnostic data. The historical detection states of the target physical states resulting from the symptom analysis for each measurement date are presented in Table 8. The symbol 0 means that the target states were detected as inactive at that date. The symbol 1 means that they were detected as active; x means that the measurement or inspection data at that date does not allow to detect the state, which can therefore be considered as unknown. For example, in 2016-03, the Polarization/Depolarization Current test (PDC) detected $v^{m_{21}}$ as active but was unable to detect v^{t_6} , $v^{e_{12}}$ and $v^{m_{21}}$.

Table 8. Historical detection state of target physical states on hydro-generator A

Hydro-generator A				
Symptom analysis date (k_p)	$v_{\varepsilon}^{t_6}(k_p)$	$v_{\varepsilon}^{m_{31}}(k_p)$	$v_{\varepsilon}^{e_{12}}(k_p)$	$v_{\varepsilon}^{m_{21}}(k_p)$
2010-05	0	×	×	×
2010-05	×	0	0	0
2010-05	×	0	0	0
2011-04	×	×	×	×
...
2014-02	×	×	×	×
2014-02	×	×	×	×
2014-04	×	×	×	×
2015-10	×	×	×	×
2016-03	×	×	×	×
2016-03	×	1	×	×
2016-06	×	×	1	1
2016-07	1	×	×	×

Based on these results, the observed activation interval K_E for the target physical states is found in Table 9. All target physical states were detected as active in 2016, and the last date when they were all detected as inactive was 2010.

 Table 9. Observed detection dates K_E of target states from historical data

Hydro-generator A ($k_p = 2018$)		
ID	State appellation	Historical activation interval $v_{\varepsilon_{K_E}}^i(2018)$
v^{t_6}	Thermal aging of groundwall insulation	[2010; 2016]
$v^{m_{31}}$	Stator lamination insulation wear	[2010; 2016]
$v^{m_{21}}$	Mechanical erosion of groundwall insulation inside the stator core	[2010; 2016]
$v^{e_{12}}$	Erosion of the semiconducting coating	[2010; 2016]

Figure 12 shows the validation of the prognostic algorithm for the date of prediction k_p from 2010 to 2015. Results show the evolution for each time prediction. As new diagnostic data becomes available, the algorithm updates predictions by computing the diagnostic and prognostic algorithms again.

Hydro-generator A (2010 to 2015)

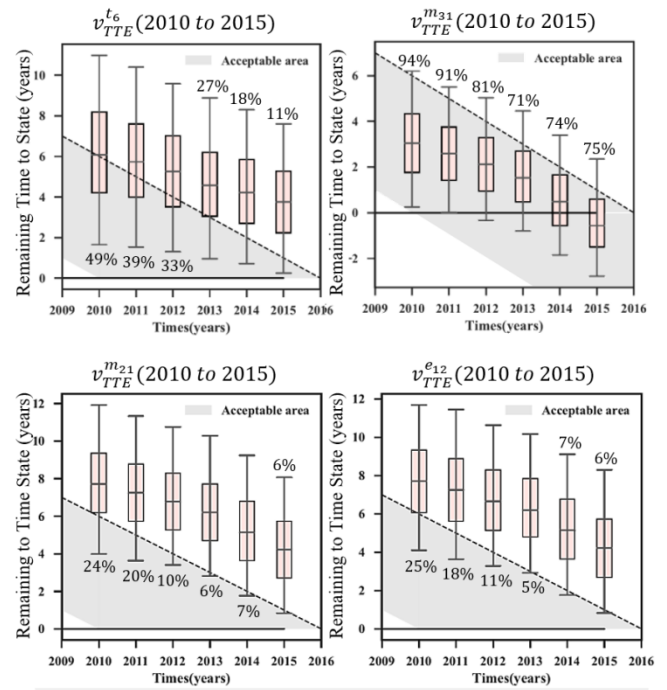


Figure 14. Observed activation intervals (Boxplot) vs. predicted activation intervals for target states. Dotted lines illustrate the observed detection date and the grey area the observed possible activation interval. Percentages represent the ratio of the probability mass of the prediction that stays within the acceptable area.

Results show that all predictions stay within the observed activation intervals for a 90% confidence interval. More than 70% of the probability mass of the predictions stayed within the acceptable zone from 2010 to 2015 for physical state $v^{m_{31}}$ and more than 25% for physical state v^{t_6} until 2013. From a general perspective, predictions are closer to the detection dates from 2010 to 2012. The uncertainty range of predictions goes from approximately 9 years to 6 years for an 80% confidence interval (2 to 4 years for a 50% confidence interval).

As this study was conducted in 2018, the hydro-generator is still in operation and no failure mode has been reached so far. In addition, no maintenance actions have been carried out since 2010. So far, the prognosis of failure modes related to the target physical states is in line with these last available observations.

5. DISCUSSION

From the standpoint of predictive maintenance, results seem consistent with the observed behavior of hydro-generator A from 2017 to 2018. Indeed, in 2012, the model suggested that a minor maintenance action was planned in 2015 and major maintenance actions are expected in 2019. The generator did not experience any failures to date in 2018. In addition,

according to the maintenance action history, no major maintenance has been carried out since 2010. With 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. For example, the model could have extended the life of the equipment by suggesting an epoxy injection into the stator laminations in 2015. In this case, when a suggested maintenance action is performed, the state of the system will be affected, and suggested further maintenance actions become irrelevant. Future studies may be considered to estimate more accurately how maintenance actions affect the system in order to suggest further maintenance scenarios.

The model proposed in this paper is able to calculate an applicability interval for a specific maintenance action by taking into account the prognosis for possible related failures. It enables the organization to prioritize and plan maintenance actions efficiently while being aware of the failure risk. Prioritization requires several years to allow for adjustment, but an organization must be able to plan a prioritized maintenance action within a year. Otherwise, it will be considered inefficient.

Regarding prognostic algorithm results, the width of uncertainty ranges stems from two factors: estimation of the physical state of the system (state activation intervals) and propagation of the failure mechanisms (range of transition time uncertainties). First, as the inspection intervals for the different diagnostic tools are significant and are carried out once a year or after several years, the potential activation intervals for physical states are quite large. This makes for considerable uncertainty regarding system state estimation. For example, in Table 4, based on 2012 data, physical state $v^{e_{21}}$ has a potential activation interval of 8 years which is quite large.

Then, because transition times were estimated based on an elicitation process, various biases such as overconfidence may have induced transition times that do not completely represent the realities of the generation fleet.

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 is associated with discretized degradation states, the graph shows dynamic data. In order to develop the prognostic model, assumptions were first defined based on expert knowledge. Thus, a customized PN model has been defined to propagate active failure mechanisms from their initial states to some target physical degradation states with which maintenance tasks are associated. Once target physical states are predicted, the application interval of maintenance tasks can be predicted for these physical states. A second propagation algorithm is used to propagate failure

mechanisms up to failure modes. This makes it possible to factor the failure risk into decision planning. Results show that the model makes it possible to predict specific maintenance actions based on failure mechanisms detected as active by the diagnostic tools. In addition, the model predicts a timeframe when maintenance actions may be applicable in that they will begin affecting the system. It is also found that the prognostic model quickly adapts to new diagnostic data. Moreover, the model accounts for the uncertainties contained in both the state estimation and the propagation of the mechanisms. Some research perspectives have been identified, such as estimating the effect of maintenance on prognostic outcomes or evaluating prognostic performance for repairable equipment.

ACKNOWLEDGEMENTS

The 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.

NOMENCLATURE

G	causal graph or directed acyclic graph (DAG)
V	finite set of distinct vertices
E	finite set of distinct edges
v^{e_i}	physical state vertex i
v^{RC_a}	physical root cause vertex a
v^{F_b}	failure mode vertex b
FM^j	failure mechanism j
v^{target}	specific target physical state
$T_{FM^j}^{e_u, e_v}$	transition times between physical state u and v align with failure mechanism sequences FM^j
$v_\varepsilon^{e_i}(k_p)$	physical state i evidence ε at discrete time of prediction k_p
$v_{\varepsilon k_E}^{e_i}(k_p)$	discrete date k_E at which the physical state i evidence ε has been detected for discrete time of prediction k_p
$v_{\varepsilon K_E}^{e_i}(k_p)$	physical state i possible detection event interval K_E of the evidence ε for discrete time of prediction k_p
$FM_\varepsilon^j(k_p)$	failure mechanism j evidence ε at discrete time of prediction k_p
$FM_{e_x}^j(k_p)$	failure mechanism j active physical state e_x closest to the failure mode at discrete time of prediction k_p
$FM_{T_x}^j(k_p)$	failure mechanism j estimated state of propagation T_x at discrete time of prediction k_p
$FM_{EOF}^j(k_p)$	end of function predicted EOF of the system based on the propagation of failure mechanism j at discrete time of prediction k_p

$FM_v^{j e_{target}}(k_p)$ predicted time to reach the target state $v^{e_{target}}$ of the system based on the propagation of failure mechanism j at discrete time of prediction

$v_{CDF}^{e_{target}}(k_p)$ predicted cumulative density function of the time to reach the target state $v^{e_{target}}$ at discrete time of prediction

$v_{EOF}^{F_b}(k_p)$ end of function predicted EOF of the system based on the predicted occurrence of failure mode v^{F_b} at discrete time of prediction k_p

$v_{TTF}^{F_b}(k_p)$ time to failure predicted TTF of the system based on the occurrence of failure mode v^{F_b} at discrete time of prediction k_p

$v_{TTE}^{e_{target}}(k_p)$ time to reach the target physical state e_{target} at discrete time of prediction k_p

$v_{M_n}^{e_{target}}$ specific maintenance task M_n related to the target physical state $v^{e_{target}}$

$v_{k_E}^{e_{target}}(k_p)$ predicted date k_E of the time to reach the target state $v^{e_{target}}$ at discrete time of prediction k_p

$v_{M_n[k_E]}^{e_{target}}(k_p)$ predicted interval K_E of application of the specific maintenance task M_n related to the target physical state $v^{e_{target}}$ at a discrete time of prediction k_p

REFERENCES

- Ammour, R., Leclercq, E., Sanlaville, E., & Lefebvre, D. (2016). Faults prognosis using partially observed stochastic Petri nets. Paper presented at the Discrete Event Systems (WODES), 2016 13th International Workshop on.
- Amyot, N., Hudon, C., Lévesque, M., Bélec, M., Brabant, F., & St-Louis, C. (2014). Development of a Hydrogenerator Prognosis Approach. CIGRE.
- Atamuradov, V., Medjaher, K., Dersin, P., Lamoureux, B., & Zerhouni, N. (2017). Prognostics and health management for maintenance practitioners - review, implementation and tools evaluation. *International Journal of Prognostics and Health Management*, 8, 31.
- Blancke, O., Amyot, N., Hudon, C., Lévesque, M., & Tahan, A. (2015). A New Generic Approach to Convert FMEA in Causal Trees for the Purpose of Hydro-Generator Rotor Failure Mechanisms Identification. Paper presented at the Annual Conference of the Prognostics and Health Management Society, San Diego, CA, US.
- Blancke, O., Combette, A., Amyot, N., Komljenovic, D., Lévesque, M., Hudon, C., . . . Zerhouni, N. (2018). A Predictive Maintenance Approach for Complex Equipment Based on Petri Net Failure Mechanism Propagation Model. Paper presented at the PHM Society European Conference.
- Blancke, O., Tahan, A., Komljenovic, D., Amyot, N., Lévesque, M., & Hudon, C. (2018). A holistic multi-failure mode prognosis approach for complex equipment. *Reliability Engineering & System Safety*, 180, 136-151. doi:https://doi.org/10.1016/j.res.2018.07.006
- Chemweno, P., Pintelon, L., Muchiri, P. N., & Van Horenbeek, A. (2018). Risk assessment methodologies in maintenance decision making: A review of dependability modelling approaches. *Reliability Engineering & System Safety*, 173, 64-77.
- Chiachío, J., Chiachío, M., Sankararaman, S., Saxena, A., & Goebel, K. (2015). Condition-based prediction of time-dependent reliability in composites. *Reliability Engineering & System Safety*, 142, 134-147. doi:https://doi.org/10.1016/j.res.2015.04.018
- Chiachío, M., Chiachío, J., Sankararaman, S., Andrews, J., & Target, P. (2017). Integration of prognostics at a system level: a petri net approach. Paper presented at the Annual Conference of the Prognostics and Health Management Society.
- Corbetta, M., Sbarufatti, C., Manes, A., & Giglio, M. (2014). On dynamic state-space models for fatigue-induced structural degradation. *International Journal of Fatigue*, 61, 202-219.
- Elattar, H. M., Elminir, H. K., & Riad, A. M. (2016). Prognostics: a literature review. *Complex & Intelligent Systems*, 2(2), 125-154. doi:10.1007/s40747-016-0019-3
- EPRI. (2002). *Reliability and Preventive Maintenance: Balancing Risk and Reliability: For Maintenance and Reliability Professionals at Nuclear Power Plants (1002936)*. Retrieved from Palo Alto, CA:
- Goebel, K., Daigle, M., Saxena, A., Sankararaman, S., Roychoudhury, I., & Celaya, J. (2017). *Prognostics: NASA*.
- Gu, J., & Pecht, M. (2008, 28-31 Jan. 2008). Prognostics and health management using physics-of-failure. Paper presented at the 2008 Annual Reliability and Maintainability Symposium.
- IAM. (2015). *Asset Management - an anatomy V3*. Retrieved from
- ISO. (2014). *ISO 55000, 55001 and 55002 Asset Management Standards*. In: BSI Standards.
- Javed, K., Gouriveau, R., & Zerhouni, N. (2017). State of the art and taxonomy of prognostics approaches, trends of prognostics applications and open issues towards maturity at different technology readiness levels. *Mechanical Systems and Signal Processing*, 94, 214-236.
- Kulkarni, C. S., Biswas, G., Celaya, J. R., & Goebel, K. (2013). Physics based degradation models for electrolytic capacitor prognostics under thermal overstress conditions. *International Journal of Prognostics and Health Management*, 825.
- Kwon, D., Hodkiewicz, M. R., Fan, J., Shibutani, T., & Pecht, M. G. (2016). IoT-Based Prognostics and Systems Health Management for Industrial Applications. *IEEE*

Access, 4, 3659-3670.
doi:10.1109/ACCESS.2016.2587754

Murata, T. (1989). Petri nets: Properties, analysis and applications. *Proceedings of the IEEE*, 77(4), 541-580.

Peterson, J. L. (1981). Petri net theory and the modeling of systems.

Petri, C. A. (1966). *Communication with automata*.

Zhouhang, W., Maen, A., & H., K. A. (2014). Coloured stochastic Petri nets modelling for the reliability and maintenance analysis of multi-state multi-unit systems. *Journal of Manufacturing Technology Management*, 25(4), 476-490. doi:doi:10.1108/JMTM-04-2013-0045

Biographies



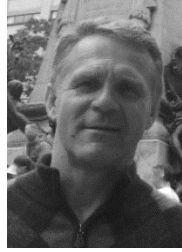
Olivier Blancke received a Master's degree in Mechanical Engineering from the École de Technologie Supérieure de Montréal (Canada) in 2015. His M. Eng. project was done in collaboration with Hydro-Québec's research institute (IREQ) on failure mechanism identification of hydroelectric rotors. He is currently pursuing a Ph.D. on the development of a prognostic approach for complex equipment to support asset management. In 2018 he joined IREQ, where he currently works as a research scientist.



Amélie Combette received a degree in Mechanical Engineering from the National Institute in Mechanics and Microtechnologies (Besancon, France) in 2017. Her final research project was done in collaboration with Hydro-Québec's research institute (IREQ) on development prognostic algorithms based on Petri Nets. She is currently an application engineer at ALTEN S.O.



Normand Amyot received B. Eng. and M.A.Sc. degrees in Physics Engineering from École Polytechnique de Montréal in 1987 and 1990, respectively. He taught Physics for one year at the Université des Sciences et Techniques (USTM) de Masuku in Gabon. In 1991, he joined Hydro-Québec's research institute (IREQ), where he currently works as a research aging and characterization, diagnostic techniques, condition-based maintenance and prognostics. He is currently the leader of the Hydrogenerator Prognostics Project at IREQ. He is an active member of the CIGRÉ working group and a senior member of the IEEE. He is also active in the SCC, ISO and is a member of the PHM Society. He is the author and co-author of more than 50 scientific papers.



Dragan Komljenovic received B.Sc. from the University of Tuzla, a Master's degree from the University of Belgrade, a first Ph.D. from Université Laval (Canada), and a second Ph.D. from the Université du Québec à Trois-Rivières (Canada). He works as a researcher at Hydro-Québec'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 Hydro-Québec's Gentilly-2 nuclear generating station. He is an Adjunct Professor and Industrial Research Chair of "Risk-Based Life Cycle Management of Engineering Systems" at the University of Waterloo (Canada). He also teaches Mining Engineering at Université Laval (Quebec). He has published more than 70 refereed journal and conference papers. He has worked in the mining industry and has been a researcher and lecturer at the University of Tuzla and Université Laval. Dr. Komljenovic is a Fellow of the International Society of Engineering Asset Management (ISEAM).



Mélanie Lévesque received a Ph.D. in Electrical Engineering from Montréal's École de Technologie Supérieure (ÉTS) in 2012. Her Ph.D. work was done in collaboration with Hydro-Québec's research institute (IREQ). She is currently working at IREQ as a research scientist focused on generator diagnostics and prognostics.



Claude Hudon received a Ph.D. in Engineering Physics from the 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 currently works 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.



Antoine Tahan received a Ph.D. in Electrical Engineering from Université Laval (Canada) and a Master's degree in Mechanical Engineering from the same institution. He spent ten years working as a consulting engineer in the aerospace industry and joined Montréal's École de technologie supérieure (ÉTS) Canada as a professor in the department of Mechanical Engineering in 2004. His research interests are in the area of industrial

statistics and include productivity improvement, quality control, metrology and probabilistic approaches.



Noureddine Zerhouni received an Engineering degree from the National Engineers and Technicians Institute of Algiers, Algeria, in 1985, and a Ph.D. 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 Micro Mechatronic Systems at the FEMTO-ST Institute in Besançon. He has been involved in various European and national projects on intelligent maintenance systems. His current research interests include intelligent maintenance, prognostics and health management.