A New Generic Approach to Convert FMEA in Causal Trees for the Purpose of Hydro-Generator Rotor Failure Mechanisms Identification

Olivier Blancke[1], Normand Amyot[2], Claude Hudon[2], Mélanie Lévesque[2], Antoine Tahan[1]

[1]*École de technologie supérieure, Montréal, Québec, QC H3C 1K3, Canada*

olivier.blancke.1@ens.etsmtl.ca
antoine.tahan@etsmtl.ca

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

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

ABSTRACT

At Hydro-Québec (HQ), an integrated diagnostic system (MIDA) is currently used to assess hydro-generators health index. This system gives the global health index but does not propose any understanding of active failure mechanisms. At this point, this work needs to be done by experts after analysis of the diagnostic data in MIDA.

To relieve the expert from part of this work, a prognostic tool, that uses a Failure Mechanisms and Symptoms Analysis (FMSA), is under development. The approach is based on the understanding of the evolution of degradation processes for each failure mechanism. Failure mechanisms are structured as causal trees and defined as a sequence of physical states starting from a root cause and ending with a failure mode. A physical state corresponds to characteristic degradation condition of a component of the generator. Each physical state being defined by a unique combination of symptoms as measured with diagnostic tools. After consigning all possible mechanisms occurring in both the rotor and the stator, the symptoms logged into a database can be read to automatically identify all active physical state and active failure mechanisms. This approach has been under development in HQ for the stator for a number of years and is now extended to the rotors of hydro-generators.

The purpose of this paper is to present the structured method used to build the failure mechanisms from bits and pieces of information (sub-mechanisms) found in the literature and from discussions with experts. This new methodology is based on a two steps process. First, sub-mechanisms were extracted from FMEA in the literature. Then, an algorithm was used to generate a set of causal trees from these sub-mechanisms. The generated results then had to be validated by experts to make sure that automatically generated mechanisms were logical and plausible. The resulting extended failure mechanisms trees built can then be used for the purpose of Root Cause Analysis (RCA), model-based diagnostics and prognosis. This method was developed to be as generic as possible so it could be applied to any complex system.

1. INTRODUCTION

Significant improvement has been done on fault detection and diagnosis during the last decade (Schwabacher and Goebel 2007). Many tools such as condition monitoring systems have been developed for this purpose in various industries to improve health management of complex and critical systems. However, the large amounts of data generated by those systems are rarely used for prognosis.

One of the key issues of condition-based prognostic approaches is to develop a model providing an identification of degradation processes and their future evolution based on historical data such as symptoms obtained from measurements and observations. Several examples of prognostic approaches based on historical data and symptoms resulting from diagnostic tools can be found in the literature; namely an approach based on Bayesian networks (Medina-Olivier et al. 2012), approaches based on Fault Trees (Junjie et al. 2011; Sun et al. 2012) and an approach based on Decision Trees structure (Lee et al. 2005). In this paper, the proposed approach uses another model to analyze symptoms and historical data.

At Hydro-Québec, different diagnostics tools have been developed and implemented to evaluate the condition of hydro-generators using a web-based application called MIDA (Vouligny et al. 2009), which gives the global health index of generators. In order to structure and take advantage of diagnostic data, a damage propagation model has been proposed. It is the backbone of a prognostic model based on a Failure Mechanism and Symptoms Analysis (FMSA). This approach has been detailed elsewhere (Amyot et al. 2013).

The FMSA identifies and structures all possible failure mechanisms occurring in a system of causal trees using successions of physical state starting from root causes and ending with failure modes, as shown in Figure 1. A physical state corresponds to a characteristic degradation condition of a component of the generator. By defining such physical states it becomes possible to discretize each failure mechanism in order to track their progression. In the example in Figure 1, four failure mechanisms are represented and discretized using physical states (e_i). For example, the failure mechanism starting from the Root cause C_1 and ending on the failure mode F_2 is discretized by 4 successive physical states (e_1, e_2, e_3, and e_4).

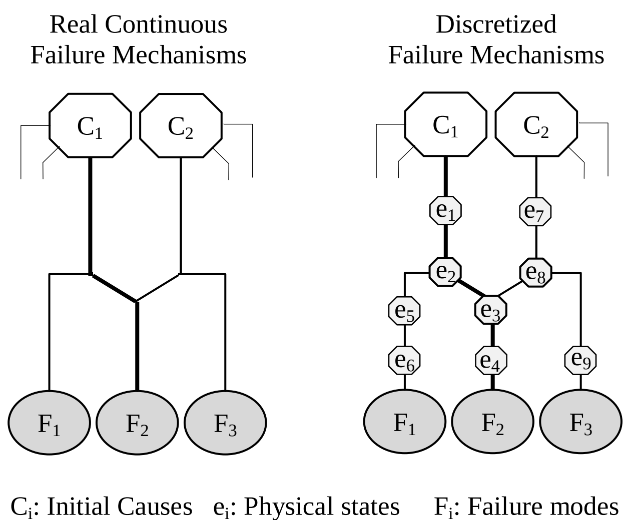


Figure 1. Four active failure mechanisms from root causes to failure modes before and after discretization by physical states.

Each physical state corresponds to a unique combination of symptoms with threshold values associated to the recorded diagnostic data and visual inspection observations. An example of threshold definition is given in Figure 2. The degradation symptoms of a generator are automatically retrieved from the diagnostic database, and compared with the individual thresholds defined by the experts. This makes it possible to identify active physical states and consequently all active mechanisms in the system.

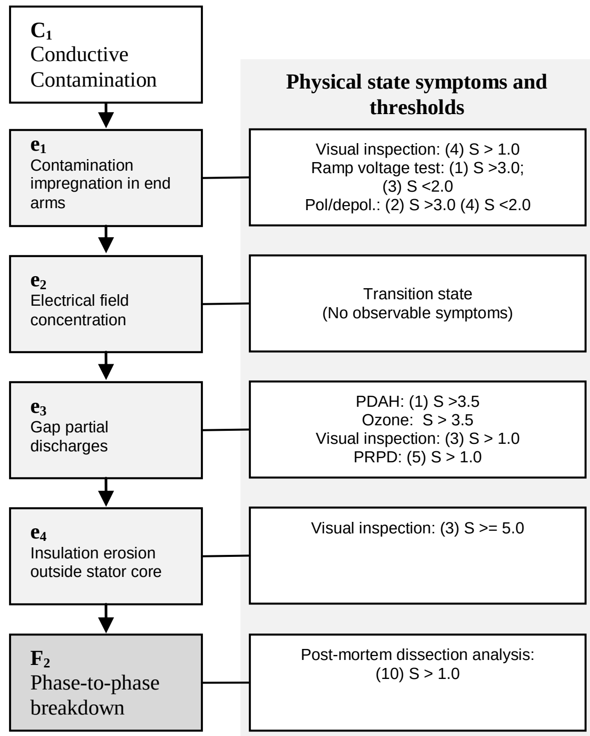


Figure 2. Failure mechanism with symptoms and thresholds defining physical states. Between parentheses are symptoms specific to each diagnostic tool. S is the severity ranging from 1 to 5. (Amyot et al. 2013)

It is then possible to monitor failure mechanisms progression using physical states activation time as shown in the Figure 3. Based on historical data and probabilistic approach a prognosis can be performed. Moreover, some targeted maintenance tasks will eventually be proposed by the system.

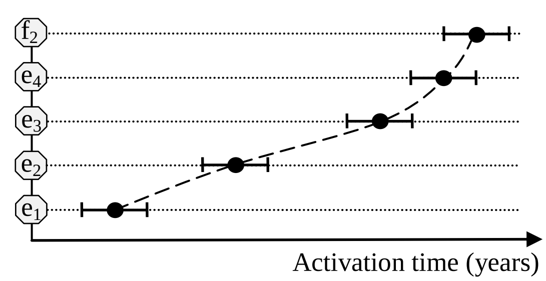


Figure 3. Discretized Failure Mechanism time evolution

As defined in the review of Schwabacher and Goebel on intelligent prognostic approach (Schwabacher and Goebel 2007), the FMSA is based on a damage propagation model and a data driven model (expert system, knowledge-based).Table 1 present the categorization proposed by Schwabacher and Goebel in 2007.

Table 1. Possible models (rows) to address specific problems (columns) (Schwabacher and Goebel 2007)

	Fault detection	Diagnostics	Prognostics
Physic-based	System Theory		Damage propagation models
AI- Model based	Expert systems	Finite state machines	
Conventional numerical	Linear regression	Logistic regression	Kalman filters
Machine learning	Clustering	Decision trees	Neural networks

In complex systems such as hydro-generators, failure mechanisms evolve in all system components. To build a list of all possible failure mechanisms is a complex task; it requires many areas of expertise. After several experts' interviews, it was noticed that they usually have a clear view of failure sub-mechanism but have more difficulty in building complete complex failure mechanisms longer than 5 successive physical states. This is especially true when multiple side branches split from a main common branch. Even in the literature, failure mechanisms are indirectly described as degradation progress and symptoms but report or papers seldom present them in a logical succession of physical state. A methodological approach is thus needed to build failure mechanisms in a causal tree structure.

In the literature, some methods and models are already used for Root Cause Analysis (RCA) which shows similarities with Failure Mechanism Analysis (FMA). A paper written by (Medina-Olivier et al. 2012) proposed a survey on reliability and risk analysis main approach for RCA. Five methods such as Causes and Effect analysis, Hazard and operability studies (HAZOP), Bayesian Networks, FMEA and Fault tree are compared according to different criteria (experience dependence, time and resource consumption, providing a path to root causes…). The author concludes that a single method does not allow characterizing all causal relationship of the degradation process of a system but they all give parts of information about it. For complex systems, those methods give essential information on degradation mechanism allowing fault detection and probable root causes categories. However, they do not allow defining the failure mechanism from a root cause to a failure mode. The authors suggest that the best way to perform a Failure Analysis is to combine information from different approaches such as FMEA and Fault Tree.

The approach we propose is doing exactly this by using information captured from literature such as FMEA and expert knowledge to build structured causal trees step by step. As information available only contains parts of failure mechanisms, we have built an algorithm to assemble those sub-mechanisms into complete failure mechanisms. Once a complete set of detailed causal trees have been built, it can be used to perform Condition Based Maintenance (CBM) and improve asset management. This is true for any industry. In our case, it serves as the premise for the implementation of a FMSA-based prognostic approach.

A statistical analysis of hydro-generator failures performed by CIGRE in 2003 (CIGRE 2003) revealed that stator failures represent 70% of generator failures and the rotor, bearings and the excitation system represent all together approximately 25% of all failures. As the FMSA of the stator has already been performed, this paper will focus on hydroelectric rotor failure mechanisms.

2. METHODOLOGY

The following section will describe step by step the methodology developed to generate a structure causal tree from FMEA and from sub-mechanisms found in the literature.

2.1. System definition & delimitation

The first step is to define and delimitate the scope of the work. Each component of the system has to be defined precisely by a unique appellation in order to avoid miss-understanding between experts. A universal terminology has to be defined for physical state naming such as System/Components/Sub-component/Part/ physical state. The system has to be delimitated and external components which will interact with the system as input or output on failure mechanism should be identified.

2.2. Sub-failure mechanisms analysis based on FMEA interpretation

Once the system is defined, a survey on its failure mechanisms has to be performed by gathering FMEA, technical papers, accident reports, RCA… The methodology proposed can be defined as a "*Bottom Up*" strategy. At first, failures modes and sub-mechanisms leading to failure have to be identified by interpreting the FMEA results. It creates a work base. The next step is to identify and build all possible logical successions of physical states called sub-mechanisms (*i.e.* sets of a few successive physical states) of the system by interpreting the information from scientific literature and expert knowledge. The analysis can be carried out on individual components or on the entire system.

All sub-mechanisms interpreted have to be listed in a database, like the one shown in Figure 4. For example, it was found that the rotor degradation state e_4 (ex: Rotor Interpol connection cracking) is caused by the degradation e_3 (ex: Rotor Interpol connection mechanical fatigue stress) and can induce e_5 (ex: Rotor Interpol connection failure). In this first rough analysis, all lines are independent and yet no links between sub-mechanisms exist.

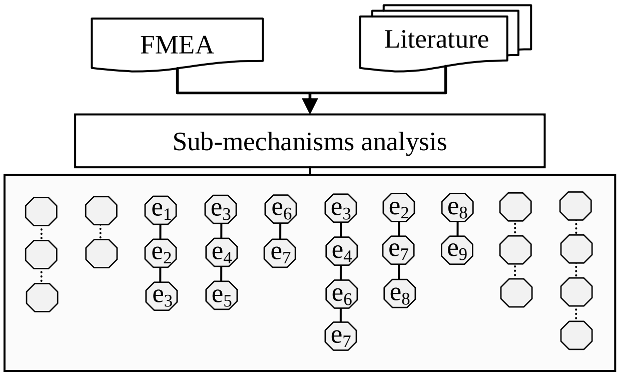
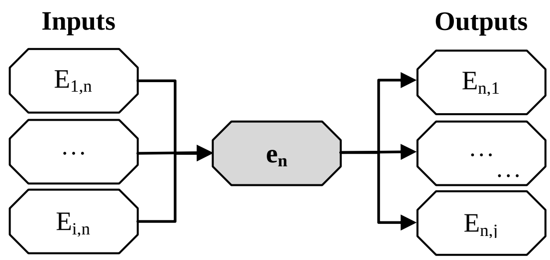


Figure 4. Example of database sub-mechanisms

2.3. Causal Trees structure assumptions

A physical state can be represented as a node which has inputs and outputs as shown in the Figure 5.



$E_{i,n}$: Physical state input i of the physical state n
$i \in \mathbb{N}$
$E_{n,j}$: Physical state output j of the physical state n
$j \in \mathbb{N}$

Figure 5 Physical state properties

Some assumptions have been proposed in order to generate causal trees from the sub-mechanisms in Eqs. (1, 2, 3, 4):

- Root Causes (C) are physical states which do not have any input:

$$e_n \in C \text{ if } \forall i \; E_{i,n} = \emptyset \quad (1)$$

- Failure Modes (F) are physical states which do not have any output:

$$e_n \in F \text{ if } \forall j \; E_{n,j} = \emptyset \quad (2)$$

- All outputs of a physical state are independent of its inputs:

$$\forall i,j \;\; E_{i,n} \nvDash E_{n,j} \quad (3)$$

- All inputs of a physical state are independent of its outputs.

$$\forall i,j \;\; E_{n,j} \nvDash E_{i,n} \quad (4)$$

2.4. Causal tree generation algorithm

Based on those assumptions, an algorithm has been developed in order to assemble sub-mechanisms retrieved from the literature into a structured causal tree. The causal tree generation methodology is presented in the Figure 6.

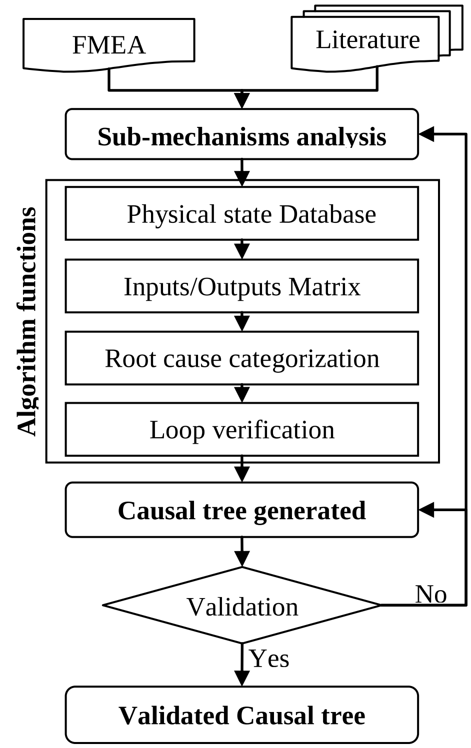


Figure 6. Causal Tree generation methodology

Once the Sub-failure Mechanisms Analysis database has been finalized, the algorithm scans all sub-mechanisms and identifies inputs and outputs of each physical state in a matrix. For example, using the fictive sub-mechanisms in Figure 4, the resulting input/output matrix is presented in the Table 2.

Table 2. Input/Output Matrix

	Input (i)									
Output (j)	$E_{i,j}$	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8	e_9
	e_1	0	**1**	0	0	0	0	0	0	0
	e_2	0	0	**1**	0	0	0	**1**	0	0
	e_3	0	0	0	**1**	0	0	0	0	0
	e_4	0	0	0	0	**1**	0	0	0	0
	e_5	0	0	0	0	0	0	0	0	0
	e_6	0	0	0	0	0	0	**1**	0	0
	e_7	0	0	0	0	0	0	0	**1**	0
	e_8	0	0	0	0	0	0	0	0	**1**
	e_9	0	0	0	0	0	0	0	0	0

The physical state e_2 have one input e_1 and two outputs e_3 and e_7 as shown in Eqs. (1, 2):

$$E_{i,2} = (e_1) \tag{5}$$
$$E_{2,j} = (e_3, e_7) \tag{6}$$

The algorithm will assemble physical states together independently of previous sub-mechanisms. Thus, generating a large amount of new combinations.

Based on the proposed assumptions, the algorithm is able to identify the root causes and failure modes of the system. In our example there is only one root cause e_1, and two failure modes e_5 and e_9. Once the root causes are all identified, they need to be classified into categories in order to structure the causal trees and to allow advanced root cause analysis. The categorization chosen has been taken from a report of the US. Nuclear Regulatory Commission (Nuclear Regulatory Commission 2003). This report proposed more than 20 sub-categories originating from 7 main categories such as Design/Construction/Manufacture or Operation/Human Error. In order to categorize identified root causes, each corresponding categories should be added as input. The algorithm will take the categories into account during the tree generation. Our root cause e_1 has been affected to the fictive root cause category Cat_3 as shown in Figure 7.

To generate a structured causal tree, the algorithm calls each root cause and scans the input/output database. Then a “While” loop is initiated generating failure mechanisms by adding each physical state output by output from a root cause up to failure modes. Still based on the same fictive example shown in Figure 4 and Table 2, a structured causal tree has been generated in the Figure 7. An important remark is that this logic can be easily reversed for root cause analysis.

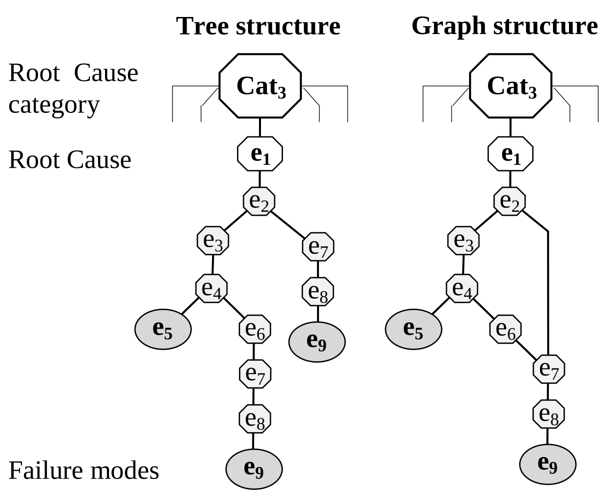


Figure 7. Causal tree generated

Next, the algorithm initiate a loop test verifying that each physical state appears only once in each failure mechanism.

The main goal of the algorithm is to allow the transition from a simple structure composed of sub-mechanisms to a complex structure of all mechanisms.

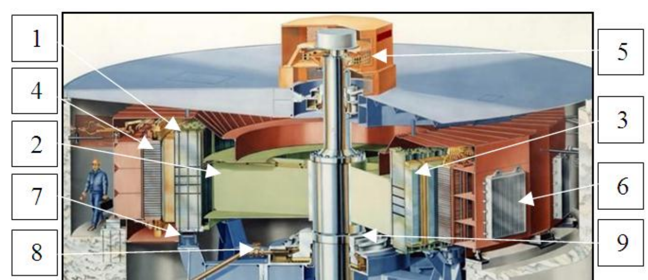
2.5. Expert validation process

A validation process has to be done on each failure mechanism generated. This is one of the most important and complex part of the process. For this, two methods were used: a validation process based on sub-mechanisms and one on the complete causal tree generated as shown in the Figure 6.

3. HYDRO-GENERATOR ROTOR APPLICATION:

3.1. Hydro-generator Rotor definition & delimitation:

Hydro-generators are large machines which can measure over 12 meters in diameter. They are composed of three main components, the stator, the rotor and the excitation system. In the current case, the system studied has been defined as the rotor. As shown in the Figure 8, the rotor is composed of three main internal components which are themselves composed of sub-components and parts. Six external components related to our main component have been identified, such as the stator and the excitation system. They may interact with the rotor as input or output in some failure mechanisms.



Rotor Components	External Components
1 : Rotor rim	4 : Stator
2 : Rotor spider	5 : Excitation system
3 : Rotor pole	6 : Cooler
	7 : Rotor brake pad
	8 : Thrust bearing
	9 : Guide Bearing

Figure 8. Rotor definition & delimitation

3.2. Hydro-generator Rotor Failure mechanisms analysis

A literature review has been done on hydro-generator rotor failure mechanisms. Using FMEA such as those from the Electric Power Research Institute (EPRI 1999) and other sources (Calleecharan and Aidanpa 2011; EEA 2013; EPRI 2009; Hydro-Québec 2007; Walker 1981), failure modes and sub-failures mechanisms leading to them have been identified. Then an interpretation of the literature review and expert knowledge lead to the creation of 108 rotor sub-mechanisms based on the combination of 110 physical states. Those sub-mechanisms have an average of 3 successive physical states. They are listed in a structure similar to the one presented in the Figure 4.

3.3. Hydro-generator Rotor Causal Tree generation

Based on the 108 sub-mechanisms, an input/output analysis has been done and 24 root causes have been identified. These causes have been associated with 5 main categories. Then, by assembling the sub-mechanisms, a structured causal tree has been generated comprising a total of 294 rotor failure mechanisms with an average of 10 successive physical states for each failure mechanisms. An example is illustrated in the diagram in Figure 9. In this example, three complete rotor failure mechanisms all originating from the same root cause ("Over speed excursion") lead to two different failure modes ("Half phase current unbalance "& "Rotor guide bearing excessive vibration"). The root cause has been categorized in a sub-category ("Incorrect procedure") belonging to the "Operation/Human error" category. Since each failure mechanism is defined by a unique sequence from a root cause to a series of physical state then to the final failure; as soon as a mechanism differs from another by one single state, it is considered as a separate mechanism. This is the case in figure 9 where two of the mechanisms only differ by the failure mode. This will become important later when the severity (impact) of failures will be considered.

The algorithm developed has allowed us to generate systemically and reliably all possible failure mechanisms in a detailed causal tree structure based on sub-mechanisms interpreted from the literature. This automatic generation makes sure that no possible mechanisms are omitted.

3.4. Validation process

After the tree generation process a validation must be done by experts. All the mechanisms automatically generated by aggregation of sub-mechanisms do not necessarily bare any physical meaning. In some case the algorithm may have assembled sets of physical states into mechanism according to our rules and it is thus mandatory that experts validate all proposed mechanisms. Another aspect of the validation process is related to the scope of our work, aimed at improving preventive maintenance and mainly looks at slow degradation process. Thus any instantaneous failure mechanisms not giving any warning sign, should be discarded by the expert from our analysis. Although these modes will be extracted from the FMEA and are part of the original 294 rotor mechanisms, they will be discarded by the experts, not because they do not exist, but because they are not relevant for the sake of prognosis.

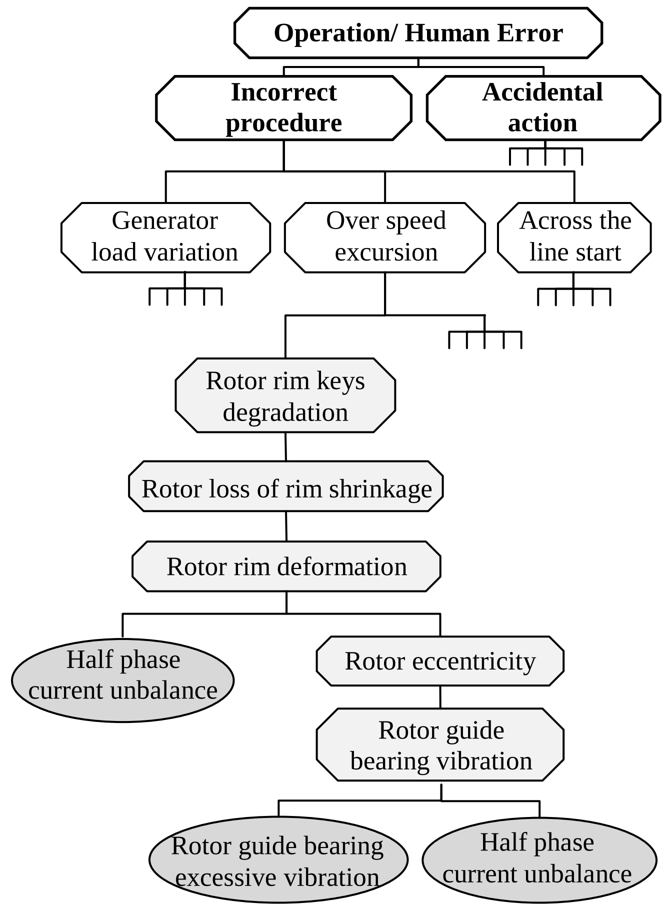


Figure 9. Illustration of the Rotor Causal Tree generated

4. DISCUSSION

Based on assumptions made on sub-mechanisms and physical states input/output analysis, an algorithm has allowed to generate all possible failure mechanisms in a coherent causal tree structure. We believe that it is much easier for expert to discard from all the mechanisms proposed by an algorithm, the ones that are not plausible, than to generate all possible mechanisms one by one without any omission. This constitutes the first step in the rotor FMSA process. The next step will be to combine the final failure tree with the results of diagnostic measurement from rotor using a symptom and threshold analysis. Once this is done, automatic identification of active failure mechanism will be possible. This will eventually lead to identification of personalized maintenance actions suited for each generators' condition and probable timeframes to carry out the maintenance while reducing failure risk. This can be called a prognosis.

5. CONCLUSION

A methodological approach has been developed in order to identify and structure all possible failure mechanisms potentially occurring in a complex system as causal trees. Based on FMEA reports and expert knowledge, a Failure Mechanisms Analysis was built from identification of sub-mechanisms from short sequences of physical states. Then an algorithm has been used to assemble those sub-mechanisms and propose structured causal trees representing all possible failure mechanisms of the system. The proposed causal trees have to be validated to ensure that all failure mechanisms are coherent and real. This approach was used to build a Failure Mechanism Analysis of hydro-generator rotors and causal trees have been generated. The algorithm generated 108 sub-failure mechanisms with an average of 3 successive physical states and 294 complete failure mechanisms with an average of 10 successive physical states. Results have shown that in general generated failures mechanisms are coherent and well structured.

The main advantages of this approach are to help experts to move from a simple system such as sub-failure mechanisms to a complex system (causal trees) using an algorithm to give guidelines to experts by presenting them well-structured causal trees for further validation.

NOMENCLATURE

e_n	Physical state n
$E_{i,n}$	Physical state input i of the physical state n
$E_{n,j}$	Physical state output j of the physical state n
C	Root Cause Domain
Cat_i	Root Cause Category i
F	Failure Mode Domain

REFERENCES

Amyot, Normand, et al. (2013), 'A New Prognostic Approach for Hydro-generator Stator Windings', *Annual Conference of the Prognostics and Health Management Society* (New Orleans, USA).

Calleecharan, Y and Aidanpa, J-O (2011), 'Dynamics of a hydropower generator subjected to unbalanced magnetic pull', *Journal of Mechanical Engineering Science*, Part C.

CIGRE (2003), 'Hydrogenerator Failures - Results of Survey', *International Council on large Electric Systems (CIGRE)*, 129.

EEA (2013), 'Asset Health Indicator Guideline for Generators', (Wellington, New Zealand: Electricity Engineers' Association of New Zealand (Inc.)).

EPRI (1999), 'Advanced Condition Monitoring of Hydrogenerators', (Electric Power Research Institute).

--- (2009), 'Handbook to assess the insulation condition of large rotating machines', (Toronto, Canada: Electric Power Research Institute).

Hydro-Québec (2007), 'Guide d'analyse de la maintenance - Système groupe turbine alternateur'.

Junjie, Zhao, et al. (2011), 'An estimation method of system performance degradation state based on fault tree method', *Quality, Reliability, Risk, Maintenance, and Safety Engineering (ICQR2MSE), 2011 International Conference on*, 132-36.

Lee, C., Alena, R. L., and Robinson, P. (2005), 'Migrating Fault Trees To Decision Trees For Real Time Fault Detection On International Space Station', *Aerospace Conference, 2005 IEEE*, 1-6.

Medina-Olivier, Gabriela, et al. (2012), 'Root cause analysis to identify physical causes', *11th International probalistic Safety Assesment and Management Conference and The Annual European and Safety and Reliability Conference* (Helsinki, Finland).

Nuclear Regulatory Commission, U.S. (2003), 'Common-Cause Failure Event Insights - Emergency Diesel Generators', (Washington, USA).

Schwabacher, Mark and Goebel, Kai (2007), 'A survey of artificial intelligence for prognostics', *Aaai fall symposium*, 107-14.

Sun, Quian, Lu, Chen, and Luan, Jiaui (2012), 'An Intelligent Diagnosis System for Vehicle Chassis', *International Conference on Future Information Technology and Management Science & Engineering Lecture Notes in Information Technology* (14).

Vouligny, L., Hudon, C., and Duc Ngoc, Nguyen (2009), 'Design of MIDA, a Web-Based Diagnostic Application for Hydroelectric Generators', *Computer Software and Applications Conference, 2009. COMPSAC '09. 33rd Annual IEEE International* (2), 166-71.

Walker, J. H. (1981), *Large Synchronous Machines* (Oxford, England: Oxforf University Press) 300.

BIOGRAPHIES

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

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

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

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

Antoine Tahan was born in Aleppo, Syria in 1966. He received his Ph.D. 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. He is a registered professional engineer in Quebec, Canada, and member of the ASME (American Society of Mechanical Engineers), the CMVA (Canadian Machinery Vibration Association), and the ASQ (American Society for Quality). He is the author or co-author of more than 40 scientific papers.