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Characterization, dynamic modeling, and monitoring of the degradation of hydroelectric production infrastructures

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Hydropower infrastructure globally faces three primary challenges: aging infrastructure, climate change, and hydropeaking. These issues result in increased degradation rates, with a higher degree of associated unpredictability. This preliminary research aims to identify a modeling approach that would inform an optimized maintenance plan within a host organization, to aid in ensuring the availability and good operation of hydropower assets, while balancing strategic production objectives with risks. The methodology for modeling the asset degradation phenomena must leverage how degradation mechanisms evolved historically for critical assets, considering condition monitoring data over time, to recognize trends in their health state and thus optimizing maintenance interventions, minimizing production losses. The work presented in this paper describes an investigation of the existing data and its sources, including experts' feedback, within the host enterprise, a review of the literature on dynamic modeling and the monitoring of degradation mechanisms, and an evaluation of potential degradation modeling methods that could be applied to two distinct assets that were selected as case studies: the spillway gate and the alternator. It is proposed that a model based upon a Bayesian Stochastic Petri Net (BSPN) would meet the desired criteria for a degradation model for asset management, allowing for refinement and adaptation over time as more data becomes available and as variable degradation drivers continue to evolve.

Keywords: Degradation modeling, asset management, maintenance decision-making, hydroelectric powerplant, critical infrastructure.

1. Introduction

The Compagnie Nationale du Rhône (CNR) is responsible for managing the hydropower (HP) infrastructure on the Rhône River in France. As France's largest producer of fully renewable energy, it faces challenges common to the HP industry: aging infrastructure, climate change, and hydropeaking. Much of their infrastructure is displaying age-related degradation. Typically, the highest-yield projects are developed first. Thus, the oldest facilities are also the most productive, exacerbating the risks associated with aging. CNR manages 20 major HP plants. The four oldest are on average 73.7 years old, close to twice the global average, while accounting for 35 percent of the total energy production, according to 2019 figures. Typically, HP facilities are decommissioned after 60 years on average, though some may operate past 100 (IRENA, 2023).

Climate change has disrupted river flows, reducing HP output and increasing the prevalence of extreme floods (CNR, 2019), (RTE, 2022). Additionally, "hydropeaking", used to stabilize grids with increasing wind and solar inputs, accelerates wear on certain assets due to start and stop cycles (Solvang et al., 2009), (Savin, 2022). Together at a time when inflationary pressures are increasingly constraining maintenance budgets, more focus is being put on optimising the asset management (AM) and maintenance decision-making (MDM) processes. Generally, classical reliability analysis techniques are used to derive metrics such as remaining useful life (RUL) to inform AM and MDM. These rely upon robust lifetime data, while assuming that the environmental influences are constant. In the HP industry however, this is typically not the case.

Assets are designed to be highly reliable and rarely allowed to reach failure due to the associated costs, resulting in sparse lifetime data (Si et al., 2011). Historically, record keeping has lacked formalisation and digitisation, further complicating the use of the data that does exist. Accelerated life testing is rarely used in the industry due to the expense (Welte, 2008). When it is, the methods do not necessarily imitate the true failure mechanisms (Nikulin et al., 2010).

As such, often predictive degradation modelling (PDM) techniques are preferred to derive reliability metrics to inform MDM (Sapkota et al., 2022), (Åsnes et al., 2018). PDM's may take many forms and be continuous or state-based. They predict the degradation trajectory based upon the evolution of measurable degradation indicators such as cracking, erosion, or deformation, or use signals derived from condition monitoring data (Yildirim et al., 2019), (Ye and Xie, 2015). These however present their own challenges. Significant limitations exist in quantifying assets' condition (Welte, 2008). Regarding covariate influences, these relationships are rarely well understood and often models mix causal relationships (Si et al., 2011). Finally, difficulties and costs associated with collecting high quality degradation data present modelling challenges (Zhou et al., 2011). However, when this data does exist, PDM's can be used to make robust reliability inferences due to the availability of quantitative measurements on the state of the whole population, even when lacking real failure data (Nikulin et al., 2010).

The objective of this research is to identify methods for improving CNR reliability analysis capabilities, used to inform the MDM process, in the context of the outlined industrial challenges and an evolving data gathering and management environment. The methods must account for sensitivity to operating conditions, environmental factors, and imperfect maintenance. They should integrate data from condition monitoring, expert input, and physical models where possible.

Based on this research, we conclude that a methodology allowing the integration of different sources of data and information into the degradation modelling dynamics, such as enabled by a BSPN method, would be suitable. This would aid in tackling the issue of data deficiencies, and enable model adaptation over time, thus tackling the described existing challenges. The approach addresses both technological and natural risks to aid in informing a complex, multi-stakeholder decision process by optimally leveraging the available data to predicatively model the asset degradation. This is outlined in the context of two different use cases with varying degrees of data availability.

The paper is structured as follows: Section 1 serves as an introduction to the problem and its context, while outlining the research objectives; Section 2 describes the analysis of the assets that will be focused upon; Section 3 consists of a review of the existing methods; Section 4 describes the methodology selected and section five covers the discussions and perspectives at this stage of the research.

2. Analysis of Selected Assets

At this stage, two assets were selected for analysis: the radial spillway gate and the turbine alternator. The associated mechanical, hydraulic and electrical characteristics provide a juxtaposition of possible degradation phenomena to be considered. Degradation mechanisms with suitable data and behaviour for modelling were identified.

2.1. *Spillway gate*

Spillway gates control the discharge from dam reservoirs, particularly during extreme flood events. By releasing excess water during periods of high discharge they ensure the reservoir capacity is not exceeded, or result in flooding upstream. This throttling can also dampen flooding downstream, by reducing peak discharge and dissipating it over a longer period. They are designed to handle long return-period floods, however, climate change has made them vulnerable to extreme events that are increasingly common (Le Delliou et al., 2013).

Their failure can have devastating consequences, including damage to property, agricultural land, and the environment, loss of life, and in extreme cases catastrophic dam failure due to exceeding the reservoir capacity inducing a loss of structural stability and/or overtopping induced erosion or scouring. As such, this system is essential not only to HP but also flood management. Mechanical installations in HP facilities, such as spillway gates, have typical expected technical service lives of 25 to 50 years and remain economically viable for 25 to 40 years (IRENA, 2023).

Failure corresponds to the gate being unable to regulate discharge adequately. Due to the catastrophic consequences of failures, they are designed with a high degree of redundancy. The most significant source of risks identified include improper maintenance, poor operation, extreme flood events, as well as seismic events (Le Delliou et al., 2013), (Faridmehr et al., 2020), (Shi et al., 2023). The enigmatic fluid-induced vibration effect has also received significant attention in the literature, with a few spillway gate failures having been attributed to this phenomenon (Xu et al., 2023), (Bower et al., 1994).

2.2. *Alternator*

Alternators are core components in power generation systems. In the HP context, they convert the mechanical (potential and kinetic) energy of the discharge harnessed by the turbine into electrical energy. Here, the term alternator will refer to grid-connected, 3-phase synchronous salient pole alternating current generators associated with reaction turbines. In this configuration, the turbine blade rotation applies a torque to a shaft that spins a rotor surrounded by a stationary armature coil, the stator. The rotor is magnetized by the exciter, inducing an alternating current in the stator which is processed before being supplied to the electrical grid (EN13306, 2001).

Two classes were considered: those associated with horizontal Bulb units and vertical Kaplan units. Bulb units are more compact, with the turbine and alternator being combined into a single unit upstream of the impeller, while Kaplan units have separate alternators (Thirriot, 1987). HP alternators typically have technical service lives of between 30 to 60 years, with economically viable service lives between 25 to 40 years (IRENA, 2023).

Alternators have intricate and interdependent components, with demanding operating conditions in a harsh environment. This results in a high prevalence of wear-out failures driven by extreme vibrations and mechanical stresses, overloading, part-load operation, start-up cycles, and high operating temperatures (Solvang et al., 2009), (IEEE, 2011). Their maintainability is inhibited by factors such as their inaccessibility and the prohibitive cost of downtime for preventative maintenance. It is thus often preferable to limit maintenance and inspections periodically to low production periods.

3. Review of existing methods, approaches, and standards

A review of industry standards, the existing literature, and industrial practices was conducted. Assets were analyzed as systems of components, each affected by various degradation processes, potentially leading to failure (IEEE, 2011). Modelling can be used to predict failures to inform MDM. In practice, modelling approaches are simplifications of the real process. However, decision quality is limited by the suitability of approach, and thus it must be adequately representative (Rausand and Høyland, 2004). MDM must weigh the risks of failure against downtime losses (Kumar and Saini, 2022).

3.1. *Monitoring*

CNR uses a four-level asset health rating system to assess their condition on five dimensions: general state, operation behavior, functional adaptation, maintainability, and regulatory conformity. Static and semi-static structures such as spillway gates rely on visual inspections, which are limited by subjectivity. Data takes the form of maintenance intervention logs, specifically renewal data. These are used as an analogue to failure time data to infer reliability metrics, although it is not true failure time data and so the input and results should be scrutinised. Data verification is also vital due to factors such as data-age and subjective interpretability of the logs. The dynamic assets, such as turbine alternators, increasingly use sensor data to track health state parameters like temperature and vibration (Amadi-Echendu et al., 2012). Compared with past trends in data, health state parameters and predictions can be assessed (Zhang et al., 2019), (Welte, 2008).

3.2. *Modeling*

Using a multi-dimensional health state definition that characterizes failure modes beyond a simple technical failure to inform MDM, the PDM must then account for the factors influencing each dimension, beyond simply the technical state. Integrated degradation models enable accounting for multiple covariant influences simultaneously driving the health state evolution. Independent variables may include time, environmental conditions, and performance indicators.

PDM's are typically data-driven for complex systems as the underlying degradation mechanisms have multiple drivers, with poorly understood relationships making mechanistic models impractical (Savin, 2022). Hybrid models combining elements of the two are possible, which is desirable when a greater degree of certainty is required (Stetter and Witczak, 2014). By defining observable states for the system, the random evolution paths between the defined states can be described with stochastic processes, when sufficient data is available (Rausand and Høyland, 2004). Several limitations exist for purely data-driven methods however and as such, significant care must be taken to ensure their validity (Si et al., 2011).

4. Development: A Selected Methodology

This section outlines the features of the chosen PDM, for future development and implementation as a tool to inform MDM within CNR. Consideration was given to what condition monitoring data was present in CNR, the input of experts, data on the operating and environmental conditions of the system, maintenance history, incident reports, and other pertinent information to the degradation mechanisms being investigated, including the physical state of the system and components, performance metrics, system maintainability, and operating thresholds. These factors will be used to inform characterizations of the global health state of the system at a later stage of this research.

A first consideration was the identification of the level of detail of interest. System-level analyses with a top-down view are simpler to implement, but in complex electromechanical systems they can have limited utility. Thus component level, bottom-up approaches are often necessary. As a first step, the effect of a single failure mechanism on a single component would be focused upon. This has the efficiency advantage of enabling building complexity step-wise as necessary. It may however present difficulties in propagating the effects up to determine the system level reliability, based upon PDMs for each component.

A further perspective was the ultimate use of the model outputs. It is intended that the model would eventually be used as an input to MDM models for maintenance scenario evaluation and the development of AM plans, for a portfolio of different facilities. As such, the result should be quantitative and unambiguous, with the uncertainty as well defined and understood as possible. It should also be easily interpreted and accessible. It should thus have the capacity to both accurately represent the trend of the degradation processes on the global health state and to predict the RUL distribution for the system in the form of a prediction of the time expected until an unacceptable health state has been reached.

4.1. *Spillway gate methodology analysis*

The first step involves the component selection. To inform this, a frequency analysis of the historical maintenance logs for 85 radial spillway gates was carried out to identify components subject to suitable degradation phenomena, that had a reasonable base of data to work with and had a relatively high level of criticality. The majority of gates are decomposed into ten components, with some exceptions, resulting in 842 components considered. The time range varies by component and facility, with the log covering a period of 72 years from 1952 to 2024 inclusive. Based on the analysis, one strong candidate is the gate seals. It was found to have a short service life, a high frequency of interventions overall, and a relatively high criticality rating. It should be noted there is significant subjectivity in the assessment of the state of this component according to CNR's experts and is not well covered in the literature.

For the spillway gate, and by extension assets of a similar nature, a survival analysis using a probability density function (PDF), to model the time to failure distributions, would be suitable based upon the nature of the available data and may be adequate to improve the existing maintenance planning. The PDF may be fitted to the components that have failure data available or use historical maintenance data as an analogue for the observed lifetimes of the components. As a first iteration, all spillway gates of the same type on the Rhône would be assumed to be comparable, to ensure so far as possible the conditions are kept constant while maintaining a statistically significant population. Future research may seek to add a Cox model to the PDF and identify a small number of sub-classes for which individual covariates may be applied. The PDF may be used to derive useful statistics about the defined population which could inform AM strategies and more optimally allocate maintenance resources.

A possible choice may be a Weibull model, which can be fitted using the shape and scale parameters, determined using the maximum likelihood method. The more data that this is based upon, the closer these two variables will cause the trend to converge on the true values, if the data is of high quality and genuinely representative. This has been selected as an example on the basis that it has been used successfully in similar applications, although it has not yet been tested against other models at this stage (Savin, 2022). For application in the methodology, the PDF should be validated against other distributions such as Gompertz, by comparing their AIC to determine the best fitting solution, as although it is often the best adapted, this is not always the case (Nikulin et al., 2010).

A Bayesian modeling framework could be developed to build on this, to create an integrated model combining the outputs of the component level models, updated in conjunction with expert input and monitoring data as it becomes available. This may also incorporate the outputs of physics-based material fatigue models, such as crack propagation models, as have been developed for similar applications (Mahmoud et al., 2018). Bayesian statistics allows subjective observations to be updated in a rational manner, as new observation data becomes available over time (Taleb-Berrouane et al., 2020). This is particularly useful here due to the reliance on maintenance data as an analogue for service lives, in the absence of "true" failure data, by aiding in quantifying the uncertainty. This has also been shown to be very effective method of improving the Weibull parameters (Nikulin et al., 2010). Furthermore, this would enable the input of other sources of data, in anticipation of the improvement of direct condition monitoring for these assets and Bayesian methods generally have been shown to be strong at handling complex degradation models (Nikulin et al., 2010).

4.2. *Alternator methodology analysis*

For the alternators, more comprehensive data sets enabled a greater degree of granularity in the analysis relative to the spillway gates. Many of these components had their first intervention very shortly after their initial installation. This may be due to manufacturing defects that resulted in infant mortality or other wear-in issues. The stators notably had a high frequency of maintenance, close to double the interventions for the rotors. When analyzed by component, the horizontal stator components in Bulb units, such as the stator windings and magnetic circuits, received more frequent maintenance than their vertical counterparts. This is possibly a result of the integrated Bulb configuration motivating maintenance overlapping of different components to minimize long term downtime losses and failure risks.

For the alternators, and comparatively dynamic assets, a similar approach would be developed as proposed for the semi-static assets. However, considering the existence of more extensive condition monitoring data, more complexity can be introduced from the outset. By defining global asset health state ratings based on the existing CNR health classification system, using expert assessments and quantifiable degradation indicators, a stochastic process model using Petri nets could be developed to describe the progression of a component or system through these discrete health states. This would enable a more granular view of the system than the binary state model proposed for semi-static assets. Stochastic Petri Nets (SPN) are an effective way of modeling the nature of this phenomenon, while a Bayesian Stochastic Petri Net (BSPN) would combine this capability with the data updating capabilities of Bayesian updating (Taleb-Berrouane et al., 2020).

Due to its dynamic nature, there is greater variance in its degradation evolution, with the possibility of rapid deterioration. Understanding these failure trajectories is necessary for their safe and effective operation. Furthermore, this solution grants a few other useful capabilities. The ability to update the model enables adaptation to changes in the drivers of degradation and the current global health state over time, to update degradation trajectories predictions. Meanwhile, the SPN provides a means to represent maintenance interventions within the model, to reverse the health states by varying degrees, depending on the effectiveness of the intervention, which may itself be imperfect and have associated uncertainty (Chahrour et al., 2019), (Chahrour et al., 2021).

For the development of a BSPN for a single component, the component health states would be characterized as described previously. The transition firing probabilities between health states may be represented using a suitable PDF, describing its probability of transitioning to an advanced degradation state, remaining in its current state, or potentially undergoing maintenance, as a function of time. The specific selection requires further data analysis, validation, and expert opinion, with the selected distributions chosen based on the fit of available operating data, which may be updated over time as more data becomes available.

The triggering of transitions to maintenance interventions would be determined by maintainability data with factors including the availability of manpower and replacement components. Maintenance is treated as imperfect. The intention is to return the system to a state virtually, ”as-good-as-new”. However, this is not always accomplished in practice. There is a probability that preventive maintenance may be completely unsuccessful, resulting in no change in the health state, while corrective maintenance, such as replacement, will always improve the health state. The probability of success for each maintenance intervention type could also be represented by a PDF based on maintenance data and updated with expert opinion, as well as new monitoring data as it becomes available.

The incorporation of the binary Bayesian network to the SPN would be carried out as described in (Taleb-Berrouane et al., 2020). As the system's health evolution is described stochastically, using discreet states, a Monte Carlo simulation could be used to create large data sets, from which statistical information regarding the overall distribution of the results can be derived for the development of maintenance scenarios and AM planning.

5. Discussions and perspectives

The selected BSPN methodology meets the predefined criteria and theoretically has the capacity to adapt predictions both in the short term, through Bayesian updating of health states, and in the long term, by accounting for evolving degradation drivers such as aging, climate change, operating policies, and maintenance interventions, based upon its application in other contexts. Future research will focus on developing and testing this methodology, starting with a meta-analysis of existing data, and defining objective health state characterizations and indicators.

Currently, a significant limitation in CNR towards the development of a model using this methodology is in the identification of quantitative measures that can be used to define objectively the health states to represent the degree of degradation, as currently this process lacks formalism. Ongoing research to this affect is underway within the company.

A validation plan for the methodology after its development will involve the comparison of its predictive performance with those made by a digital twin simulation of the assets, emulating the conditions. Based upon the results of this, it may be implemented on a localised scale, perhaps in a single facility for a defined set of assets, to compare in parallel its predictions with in-situ conditions. An aim of the selected methodology was that it would have broad applicability due to the need to work for various HP facilities under CNR's remit. The selected methodology is expected to accomplish this due to its basis in fundamentally robust statistical principals and its adaptive nature, although this can not be stated definitively at this stage prior to validation.

Handling imperfect information, either from sensors or experts, is a key challenge. The innovation here is in the implementation of a dynamically adaptive capability that adjusts predictions over time in light of new information and changes in conditions, which are vital capacities in the modern HP context. This approach would enable CNR to leverage the data and expertise they currently have at their disposal to improve their reliability analysis capabilities, while remaining adaptable to improvements in data gathering and management techniques, as well as evolving degradation drivers.

The intention is that these models will act as one input for general MDM's within CNR that will be used broadly across assets of various types. By using the improved asset RUL predictions to develop scenarios that allocate maintenance resources optimally to find the balance between maximising the intervals between interventions, or allocating them to low-production periods, and minimising failure risks, thus theoretically reducing unexpected failures, improving availability and minimising maintenance costs as well as downtime losses. Fundamentally, when preemptive interventions can be carried out as close to functional failure as possible, without failure occurring or compromising other safety or environmental constraints, costs are minimised.

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