

Dual-Threshold Maintenance Optimisation for Hydraulic Floodgates under Runaway Stochastic Degradation

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ABSTRACT

A stochastic predictive degradation modelling framework for hydraulic floodgates operating with combined environmental and operational influences is presented. A condition-based maintenance approach is optimised for a multi-gate system to identify the most cost effective negative opportunistic preventative replacement policy, in order to minimise concurrent maintenance interventions. Our research focuses on the hydropower context, where evolving operating practices and regulatory constraints have increased exposure to the highly degrading fluid-induced vibration mechanism. A coupled simulation of the system is developed integrating (i) a synthetic hydrological forcing process, (ii) a reservoir-operation control model, and (iii) a stochastic degradation model based on a gamma process with state-dependent parameters. The degradation dynamics capture the interacting feedback loops that connect seal wear, leakage, vibration and erosion, with environmental conditions and operating decisions, leading to a run-away degradation effect beyond critical thresholds. A dual-threshold preventive maintenance policy is implemented using vibration as an observable proxy for a hidden degradation state, considering for inspection intervals, degradation uncertainty, and operational constraints on gate availability. The policy performance is evaluated via long-term Monte Carlo simulation, optimising expected annual cost under variations in conditions. The expected cost is highly sensitive to the lower preventive threshold, which effectively mit-

igates runaway degradation, while the upper threshold shows limited influence due to increasing end-of-life uncertainty. This undermines the effectiveness of negative opportunistic maintenance strategies aimed at avoiding simultaneous interventions for systems with runaway degradation behaviour. The findings emphasise the critical role of degradation non-linearity and information limitations in maintenance decision-making, and indicate that improved monitoring may be necessary to effectively make use of condition-based maintenance policies for similar applications.

1. INTRODUCTION

La Compagnie Nationale du Rhône (CNR) is the largest producer of certifiably renewable energy in France. While they operate and continue to develop a significant portfolio of solar and wind projects, they are primarily and historically a hydropower (HP) operator with 19 facilities dispersed in a cascade dam system along the Rhône River. These are typically medium-head, concrete gravity dams in open channel diversion type, run-of-the-river configurations. The facilities are largely composed of a dam on the original river course, as well as a diversionary open channel containing the HP plant and navigational lock in parallel as seen in Fig. 1.

This modifies the rivers, flattening the water course and creating a differential head pressure across each dam system, storing potential energy which can then be exploited by the production groups within the HP plant. The increased water level upstream is contained by a system of dykes. Fig. 2 illustrates the cascade effect formed by all of CNR's facilities on the Rhône River, forming a multi-tiered course of effectively

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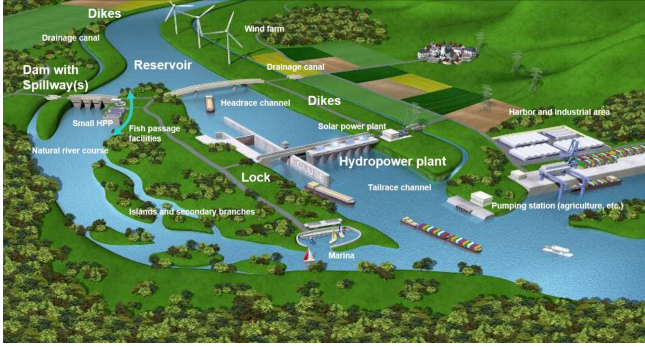


Figure 1. Typical CNR run-of-the-river hydropower development configuration. Source: CNR.

flat runs.

Run-of-the-river HP dams' primary function is the exploitation of the natural river flow for the production of electricity. They accomplish this by harnessing the kinetic energy of flow, augmented by the artificially created head pressure storing potential energy short term in a stored pondage zone. Relative to impoundment dams, that typically have higher head pressures and large reservoirs, run-of-the-river configurations have limited capacity to manage flooding by providing buffer storage to smoothen peak discharges.

As is characteristic of this type of HP development, the production flow throughput was designed to meet the annual low-flow periods so that a nominal output could be maintained continuously, without the need to regularly throttle production groups. Excess flows would be evacuated via auxiliary infrastructure involving systems of hydraulic flood gates and diversionary channels. During flooding, the downstream level rises giving rise to a natural slope forming again in the river. This reduces the head pressure differential, reducing the production output. CNR's dams also play a critical role in agricultural irrigation and enabling navigation in the region, by ensuring a constant level is maintained.

The HP industry is the most mature of the renewable energy sectors. Many of Europe's rivers were developed with HP infrastructure in the early to mid-20th century, as part of the post-war reconstruction. As such, today much of this infrastructure are aging. Globally, the age at which hydropower installations are decommissioned is around 60 years old, however many do remain in service beyond a century when well maintained (IRENA, 2023).

To ensure the continued safe and effective operation of these facilities in Europe, a strategic asset management decision-making perspective is required. The context however is highly complex. There are several different factors that must be considered for capital and operational investment planning, while considering the management of the risks posed.

While HP assets are typically designed to be highly reliable

with long service lives, failures can have significant safety, economic and environmental consequences. As such, although they are already rare, minimising them further must always remain a priority. There are significant costs involved in carrying out maintenance to ensure normal operation, and eventually reinvestment in the replacement or refurbishment of assets at the end of their service lives. Due to this, it is apparent that it is preferable to predict as accurately when to perform replacement and maintenance, in order to maximise the extraction of value from the assets, before sinking further costs into their upkeep or replacement, while minimising the risks associated with an unforeseen failure occurring.

Historically, classical reliability analysis approaches have been used to make these predictions using age-based population approaches. However, today a number of issues have made the adequacy of this approach questionable in this context. These methods typically require failure data to characterise the service life of a particular item. This assumes that the items are identical to be comparable (Rausand, Barros, & Høyland, 2020). As such, their environmental and operating conditions, design, manufacturer and materials should all also be comparable. While in controlled factory contexts this may often be the case, when managing a fleet of HP dams spread across a large geographical region and with numerous sites constructed decades apart making use of different technologies, this assumption does not apply. In fact, often the equipment's are bespoke, designed for the specific hydraulic and geomorphological conditions and as such as not inter-comparable, even controlling for environmental and operating conditions. Further, due to the long service lives, reparability and the criticality of the equipment's, true failures are rare, contributing to data sparsity. High costs also make accelerated life testing undesirable (Welte, 2008).

Regarding data from other sources that may be used, data quality is also often an issue. A lack of formalisation and digitalisation in recording operating and maintenance data limits their utilisation in modelling applications. Climate change has also contributed to this issue. Due to changes in environmental conditions, namely extremes in flow regimes and temperatures, have made it more difficult to compare past trends with the present, and into the future. Similarly, due to the aging of the infrastructure, non-linear degradation evolutions resulting in a higher frequency of incidences requiring maintenance interventions has also affected condition comparability. Finally, changes in the means of operating assets have had notable effects on the degradation rates of these equipment, as they adapt to behaviours for which they were not designed.

The following includes two examples of this. First, the rapidly increasing influx of intermittent renewable energy loads derived from solar and wind resulting in HP being used as a means to balance load to the grid, known as "hydropeaking". Increasing rapidly since the deregulation of the European en-

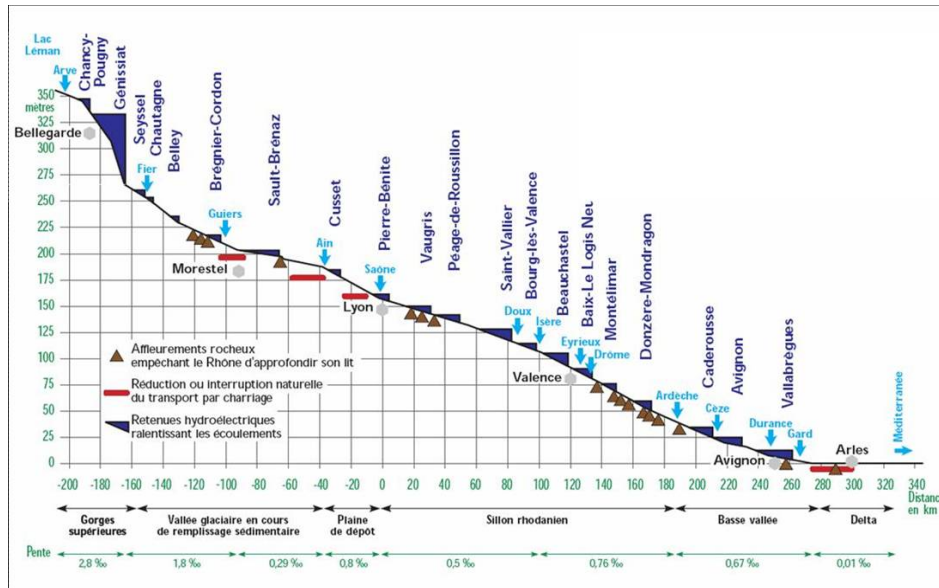


Figure 2. Hydropower developments along the Rhone River.

Source: (Couvert, 2000)

ergy market in 2003 and occurring particularly during peak hours, this involves frequent start-stop cycles in production groups. It is applied particularly in pumped-storage for the medium-term and impoundment dams more so for short-term load management, although large run-of-the-river dams with significant pondage can be used for this purpose for short periods (Savin, 2022). This can also arise in these types of dams due to extreme high and low flow scenarios, which are increasing in prevalence, forcing groups to be throttled or shut down completely.

The second example arose due to increases in the minimum reserved flow that must be maintained in rivers for ecological preservation, mandated in France since 2014 (*LOI N° 2022-271 Du 28 Février 2022 Relative à l'aménagement Du Rhône (1)*, 2022). As a result of this, the minimum flow that was originally designed to be met by the production group throughput was no longer sufficient. In order to meet the difference, a number of different approaches were taken. One of these was by using hydraulic gate structures that had originally been designed for managing flood flows. However, by operating them with small openings, the presence of a fluid-induced vibration (FIV) phenomenon became more prevalent. This complex and poorly understood effect can be highly degrading to the structure, with the capacity to induce cracking and significantly reduce the gate's service life (Xu, Liu, Zhao, Liu, & Wang, 2023).

These factors have motivated the development of a condition-based modelling approach, that would consider the uniqueness of assets and the conditions in which they operate, to aid in maintenance and operation decision-making, as well

as informing in long-term asset management planning. A SINTEF led survey of 15 hydropower companies found that there is significant potential for improvement in the adoption of new condition monitoring methods and leveraging of data, to improve maintenance practices (Solvang, Kagestad, Schjøberg, & Tufte, 2009). In order to select which approach should be taken, a review of the approaches taken in the literature was carried out. Some of the approaches considered are outlined hereafter.

Globally, many industrial contexts are undergoing intense periods of technological evolution and digitalisation, in order to keep pace with and adapt to innovations in domains such as machine learning (ML) and digital twins (DT) that largely characterise Industry 4.0. While in hydropower, as is the case in many industrial contexts, progress is somewhat limited by the data at hand, technological evolution is still required to adapt to climate change, aging assets and changes in operating methods.

ML models have shown great promise in feature extraction and pattern recognition in data analysis in recent years, enabling system states to be linked with health indicators. The drawback of this however is that it requires large data sets, it is a black-box method and poor data quality can cause lead to erroneous predictions (Deng, Khanh, & Medjaher, 2022). This limits its usefulness in HP, where we have seen data is often problematic, and where decision-making involves a significant risk management element where black-box methods are typically not deemed acceptable.

Similarly, true DT models can give valuable insights into the

effects of changes in operating and environmental conditions on expected remaining useful service lives (RUL). However, this requires significant data input, often expensive sensor arrays, a robust understanding of the physics and interactions between the different degradation processes and for a fleet of effectively unique assets, the work involved in developing and initialising the DT's, even for a sub-set of the most critical assets, would be a highly complex and costly process without guaranteed results due to uncertainties around some of the degradation processes, such as in the case of FIV (Fang, Li, Su, & Feng, 2024).

An approach that has been adopted for similar applications requiring a condition-based resolution involves the use of stochastic predictive degradation modelling (PDM) (Welte, 2008). This requires a characterisation of the assets current health and data that represents signals indicative of the rate of evolution of its degradation towards defined failure modes. These signals represent the monitoring of characteristic parameters such as temperatures or vibrations that are commonly used to infer degradation trends (Amadi-Echendu, Willett, Brown, & Mathew, 2012; Zhang, Yu, Dai, & Pan, 2019). This can then be used to determine the link between the predicted failure time distribution, and the underlying degradation process (Ye & Xie, 2015).

In this way, operating and maintenance decisions could be taken to intervene before failures occur, thus managing the risks (Sapkota, Chitrakar, Neopane, & Thapa, 2022; Åsnes, Willersrud, Kretz, & Imsland, 2018). Like all data-driven approaches, this method is also inhibited by the data issues discussed previously, a benefit of this is that it can be developed combining data from multiple sources, including with the aid of expert feedback to characterise the parameters, which can aid in alleviating these deficiencies somewhat. They can also be subsequently improved relatively easily as data collection improves. Furthermore, they may be used to aid in informing how best to invest in monitoring, via sensors or increased inspections for example, by illustrating the value of information with reducing uncertainty.

It should be noted however that in certain context's, gathering useful data may be prohibitively difficult or expensive, due to constraints such as operating conditions, the value of information versus the cost of monitoring or issues regarding the observability of the condition indicator. This results in sparse or fragmented data from which degradation trends cannot be characterised reliably. This poses a significant issue in PDM development (Zhou, Serban, & Gebraeel, 2011). A review paper on data-driven, statistical approaches focusing on RUL highlighted a number of other challenges in the use of PDMs. These include questions regarding how to handle subjective expert input, components with multiple failure modes, the influence of external variables and the means for combining different data sources coherently (Si, Wang, Hu,

& Zhou, 2011). While these factors are significant and must therefore be considered carefully in the development of any PDM, this approach appears to be the best adapted to this context, of those considered.

In this context, a key challenge exists in determining how to optimally manage maintenance for hydraulic floodgates subject to complex, non-linear degradation mechanisms driven by both variable environmental conditions and operating decisions. Traditional reliability-based approaches are inadequate due to asset heterogeneity, data sparsity, and the strong coupling between operation and degradation, while purely data-driven methods are limited by data quality and interpretability constraints. In particular, the presence of degradation processes where observability is major obstacle. For example, wear in sealing systems leading to FIV, introduces significant uncertainty in condition assessment and maintenance timing.

This leads us to the question which we aim to address. How can a condition-based maintenance policy be applied and optimised for hydraulic gate systems exhibiting stochastic, state-dependent degradation with limited observability, while accounting for operational constraints and system-level risks such as reduced evacuation capacity? To address this, we propose a coupled stochastic predictive degradation modelling framework integrated with a dual-threshold maintenance optimisation approach, enabling the evaluation of maintenance strategies under realistic hydrological and operational conditions.

2. SYSTEM AND MECHANISM SELECTION

HP facilities are highly complex infrastructure developments, consisting of many interacting systems working in tandem to carry out its required functions. In order to develop a PDM to aid in the condition-based maintenance (CBM) decision-making, we chose to begin by selecting an equipment family with relevant issues to those that we were seeking to address. This motivated our selection of radial hydraulic flood gates. An example of this equipment is shown in Fig. 3.

These gates work in parallel with other gates along the crest of the retention dam to control the discharge downstream, varying their opening level between accommodating just the minimum ecological reserved flow with a small opening, up to enabling the passage of extremely high discharges during rare flood events in the fully open position.

This decision for this system was based on a number of factors. This equipment influences the production efficiency by maintaining the upstream level and thus the head pressure differential. Similarly, it influences the security and environmental functions via its role in the evacuation of high discharges during flood events and via the maintenance of the minimum flow rate. These gates have also had their operat-



Figure 3. Radial hydraulic gate. Source: CNR.

ing roles changed, as discussed previously, adversely affecting their expected RUL and are directly affected by climate change driven changes in river flow patterns.

Failures of flood gates while very rare can have a very high impact. Meeting evacuation capacity requirements is a regulatory constraint. Additionally, if a flood were to exceed the facility capacity due to gate failures, uncontrolled flooding can occur both downstream as well as upstream, with the possibility for the structural integrity of the dam to be destabilised with catastrophic consequences. A further justification for the section of this system is the cross applicability of potential methods developed. A number of different configurations of hydraulic gates with similar functions are used in HP facilities and so it is hoped that a PDM model developed for these specific assets may eventually be adapted to a broader range of equipment. In CNR, radial configurations represent the most commonly used type of flood gate, and so they were chosen above the rest on this basis.

In CNR and in the literature, a number of different failure modes affecting radial hydraulic flood gates have been identified. In this context, failure typically refers to a functional rather than a structural failure. This is defined as being the point at which their safe operation cannot be ensured and thus they cannot be articulated in order to regulate flow on demand. Some examples include blockages due to corrosion, structural cracking, hoist failures and the aforementioned FIV phenomenon. The failure mode dictates the maintenance action required, and thus impacts materialise in the form of the risk costs associated with downtime when evacuation capacity is reduced and direct costs in the form of maintenance.

We chose to focus upon the FIV phenomenon due to the in-

herent uncertainty that it contributes to maintenance decision-making due to the many different influences that effect it, allowing it to be controlled via the dual levers of operation and maintenance. In our view, this makes it a strong candidate for benefiting from a CBM approach. While FIV is well covered in the literature, the physics of the phenomenon is still not clearly understood. It is thought that it likely arises due the diffusion of flows through small gaps, with the flows adhering and detaching from the proximal materials, forming turbulent vortices (Xu et al., 2023). This creates a coupled fluid-structure interaction which can result in significant vibrations in the gates and may even be observed effecting proximal structures as they approach the natural frequency or harmonics of the structures, inducing resonance (Lian, Chen, Ma, & Liang, 2020; Gebhardt, Göbel, Deutscher, Metz, & Thorenz, n.d.).

Small gaps that result in FIV arise primarily in two cases. The first is due to small gate opening as already discussed, to meet the minimum reserved flow requirements. The second arises due to flow passing through sealing systems, particularly at the base of the gate. This may occur due to the seal design, when the seals are installed improperly, or due to leaks when they have been degraded. Leaks may result in FIV even when the gates are in the closed position. Gate seals are generally considered non-repairable when damaged and may degrade due to a number of environmental conditions, such as via UV exposure, temperature cycling and via erosion due to sediment suspended in the river flow. These links between operating mode, environmental conditions, the condition of the seal sub-component and the system-level degradation mechanism make this an interesting choice for a PDM.

FIV also has the capacity to have significant consequences. Severe vibrations with an amplitude exceeding the elastic limit of the structural materials result in material fatigue and eventually cracking. This links another defined failure mode. Notably a number of dam gate failures have been attributed to this phenomenon including the Wachi Dam, Japan in 1967, the Long-Shan Dam, China in 1971 and the Folsom Dam, USA in 1995 (Xu et al., 2023; Lee, Seong, & Kang, 2018).

In this paper, we outline the most recent developments in our effort to develop a stochastic PDM for this hydraulic gate FIV degradation mechanism, with the aim of adopting a CBM approach for this system. This mechanism is characterised by a set of key influence factors that feed into two intersecting positive feedback loops. The relationships within this mechanism were parameterised based on expert knowledge and our review of relevant literature. This is not intended to be interpreted as representative of the true nature of the system, but rather provide a framework that can be expanded upon with further developments and illustrate the possible approaches that could be taken in terms of maintenance modelling, if and when precise PDM models for the system become available.

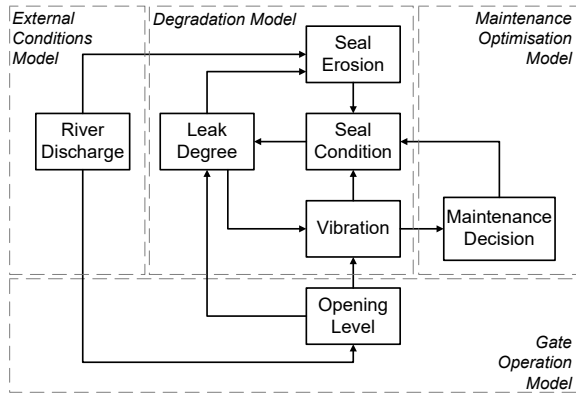


Figure 4. Modelling framework structure.

As such, the units used in the model, particularly those referring to the measurement of the condition, are not physically meaningful and are intended to be considered as relative terms.

The most recent developments involved moving to a multi-gate model while interfacing a simulation of the river and reservoir system interaction. This more realistically dictates the operating requirements of dam gates in response to the river conditions, with the aim of maintaining the upstream level at a constant, optimal level. This allows us to investigate the sensitivities of the gate degradation to external conditions and helps in informing maintenance and operation decision-making.

3. MODELLING DEVELOPMENTS

The modelling framework is primary composed components. The interaction between each of these is illustrated in Fig. 4. The first is the external conditions model. This simulates a river discharge series feeding into a reservoir upstream of the dam, based on characteristic parameters describing the hydrological conditions in the river and the geometry of the reservoir.

The second is the gate operation model. This dictates how a two gate system respond to the external conditions in order to maintain an equilibrium level upstream and simulates how their degradation evolves with respect to their operating and environmental conditions. Thirdly, the stochastic degradation model controls how the varying load on the system due to changes in the environmental and operating conditions effect it's degradation evolution. Finally, the maintenance model applies a set of maintenance policy rules which reset the system conditions when certain thresholds are met.

As we have seen, maintaining small gate openings, although undesirable due to its negative impact on the equipment, is

a regulatory requirement and thus operation-induced FIV is unavoidable. The contribution to the FIV effect derived from leak-induced vibration can be controlled however via seal replacement. This is a relatively inexpensive and simple operation, with a low impact on the gate downtime, and thus risk. Very frequent replacements however would involve sacrificing the remaining useful of the seals unduly, and also compound reducing the gate availability over time and increasing risk. Simultaneous maintenance interventions across gates has an outsized impact on evacuation capacity and should be avoided, unless the risk of true failure is unacceptably high. Finding the correct balance of when to replace the seals, and which should be replaced, is therefore a pertinent question.

A major issue with this however is that it is not possible to quantifiably assess the condition of seals in situ. The seal condition is thus treated as a hidden true state. This state announces itself indirectly in the form of the leak-induced vibrations. This is treated as an observable proxy. The true vibration signal however contains noise from other ambient sources, such as due to the operation of the gate itself. This noise is treated as an exogenous input to the vibration signal.

Thus, for the maintenance modelling, we make the following assumptions. Seal replacement is defined as a perfect preventative maintenance action, which reduces leakage-induced vibrations to zero. Structural maintenance is considered as a perfect corrective maintenance, incurring significantly higher costs involving long downtimes. Maintenance is triggered when predefined thresholds of vibration are reached, from which the component degradations are inferred. The vibrations are measured once annually as part of an inspection and it is assumed that maintenance is carried out immediately, if required. An optimisation is carried out by determining the cost optimal preventative maintenance vibration threshold for the gate seals.

3.1. External condition model

This section of the model defines the environmental conditions that drive the operating and eventually degradation process in later stages. The purposes of this addition was to test the gate operation and degradation model's response to more realistic river flow conditions, considering the response of the dam's upstream level in the pondage zone with the aim of operating the dams gate to maintain the level within an optimal range.

3.1.1. Synthetic river discharge generator

In order to simulate the long-term hydrological forcing effects of the river, a synthetic discharge time series was generated. This approach is commonly taken in risk and reliability analysis (Vogel, 2017). The model is composed of three parts: (i) a seasonal deterministic component, (ii) a stochastic persistence process, and (iii) the occurrence of extreme flood

events.

Seasonal baseline discharge The seasonal flow cycle takes a characteristic baseline flow, Q_i and outputs an annual flow that cycles seasonally represented by a sinusoidal function, with a defined seasonal variation factor, A . This formulation captures the annual hydrological cycle typically observed in river systems.

$$Q_{\text{base}}(t) = Q_i + A \sin\left(\frac{2\pi t}{365}\right) \quad (1)$$

Autocorrelated stochastic discharge Daily discharge variability and persistence are added using a first-order autoregressive process. This modifies the flow generated in the previous step by adding temporal correlation in the discharge while maintaining the seasonality, to produce hydrological behaviour more reflective of reality.

$$Q_r(t) = aQ_r(t-1) + (1-a)Q_{\text{base}}(t) + \sigma\epsilon_t \quad (2)$$

Extreme flood events Rare flood events are introduced using a heavy-tailed peaks over thresholds process. Extreme events occur with probability p_{extreme} per day. This is necessary in order to simulate adequately realistic stresses on the system. When an event occurs, the additional discharge magnitude Q_f is sampled from a generalized Pareto-type distribution:

$$Q_f = \beta \left((1-u)^{-\xi} - 1 \right) \quad (3)$$

where

- $u \sim U(0, 1)$ is a uniformly distributed random variable,
- β is a scale parameter controlling flood magnitude,
- ξ is the shape parameter controlling tail heaviness.

The simulated discharge during an extreme event is then given by

$$Q_r(t) = Q_r(t) + Q_f \quad (4)$$

The events are then injected into the series in the form of a hydrograph. This approach allows the model to reproduce both regular seasonal flow dynamics and rare high-magnitude flood events within long-term Monte Carlo simulations. From this we output a discharge series, that is then used as the input to the reservoir volume buffer upstream of the dam.

3.1.2. Reservoir Storage and Operational Control

The simulated river discharge is translated into an operational mode through its effect on the level upstream of the hydraulic structure. For the safe and efficient functioning of the hydropower production groups, it is desirable to maintain this level constant. As such, the operating objective is to maintain the reservoir close an optimal level while evacuating incoming flow through power production groups and gate discharge.

Reservoir mass balance Reservoir storage is governed by a discrete mass balance equation

$$V(t) = V(t-1) + Q_r(t) - Q_p(t) - Q_e(t-1) \quad (5)$$

where

- $V(t)$ is the stored volume at time t ,
- $Q_r(t)$ is the river inflow,
- $Q_p(t)$ is the flow used for power production,
- $Q_e(t)$ is the discharge evacuated through flood gates.

Reservoir geometry An optimal upstream level, D_{opt} , is set to define the initial condition, along with the reservoir lateral and longitudinal slope coefficients, M_l and M_x respectively. The reservoir cross-sectional geometry is approximated by a trapezoidal channel whose width and length increase with water depth due to lateral and longitudinal slopes. The water surface width w and reservoir length l are defined as:

$$w(d) = W_0 + 2M_l d \quad (6)$$

$$l(d) = L_0 + 2M_x d \quad (7)$$

where

- d is the water depth,
- W_0 is the base width at zero depth,
- L_0 is the reservoir length at zero depth,

Depth–volume relationship The reservoir dimensions change due to the in and outflows. This yields a cubic relationship between stored volume and depth, which after being solved initially for its coefficients, is approximated using Newton-Raphson iteration in each time step to save on computational costs. This allows us to update the depth at each interval, based on the inflows and outflows. In practice, the depth and inflow are the monitored variables.

$$V(d) = W_0 L_0 d + \frac{1}{2} (L_0 M_x + 2 M_l W_0) d^2 + \frac{2}{3} M_x M_l d^3 \quad (8)$$

Hydraulic capacity The evacuation capacity that is possible via the gates is limited by the head pressure, H , above the base of the gates:

$$H(t) = D(t) - H_{\text{base}} \quad (9)$$

The maximum evacuation capacity of each gate is estimated with the following discharge law:

$$Q_{\text{max}}^{(g)}(t) = \begin{cases} 0 & \text{if } H(t) \leq 0 \\ C_d W_g H_{\text{max}} \sqrt{2gH(t)} & \text{otherwise} \end{cases} \quad (10)$$

where

- C_d is the coefficient of discharge,
- W_g is the gate width,
- H_{max} is maximum opening of level of the gate,
- g is acceleration due to gravity,

The total evacuation capacity for each time step is the summed capacity of the available gates:

$$Q_{\text{max}}(t) = \sum_{g=1}^{N_g} Q_{\text{max}}^{(g)}(t) \quad (11)$$

Operating rules Based on the monitored depth, the control system computes the evacuation required, Q_{req} , to correct or maintain the equilibrium within an acceptable tolerance, D_{tol} .

$$Q_{\text{req}}(t) = \begin{cases} 1.2 Q_r(t) & D > D_{\text{opt}} + D_{\text{tol}} \\ \max(Q_{\text{res}}, Q_r(t) - Q_p) & D_{\text{opt}} < D \leq D_{\text{opt}} + D_{\text{tol}} \\ Q_{\text{res}} & D < D_{\text{opt}} \end{cases} \quad (12)$$

We implement a continuous feedback-based evacuation control law using a sigmoid function, $\sigma(K)$, to smoothen gate responses to changes in upstream levels. The flow is allowed to vary between the minimum ecological discharge, Q_{res} , and maximum evacuation capacity, Q_{max} . The harshness of the transitions is controlled by the tolerance variable. From this we compute a target evacuation, Q_{target} . The actual evacuation discharge, Q_e , is determined after applying constraints on the discharge, ensure the required flow is never exceeded and that the minimum flow is always met.

$$K = \frac{D(t) - D_{\text{opt}}}{D_{\text{tol}}} \quad (13)$$

$$\sigma(K) = 2 \left(\frac{1}{1 + e^{-K}} - \frac{1}{2} \right) \quad (14)$$

$$Q_{\text{target}} = Q_{\text{res}} + \sigma(K)(Q_{\text{max}} - Q_{\text{res}}) \quad (15)$$

$$Q_e(t) = \min(Q_{\text{req}}(t), \max(Q_{\text{res}}, Q_{\text{target}})) \quad (16)$$

The model next checks the availability status of each gate, N_{active} , before sharing the discharge demand between those that are operational to derive the per gate demand, $Q_{\text{per gate}}$. The corresponding opening levels for each gate, h_g , are then applied using a variation of the discharge law in Eq. (10). By equating the maximum and actual discharges, the opening level of the gate required relative to its maximum position can be calculated. This is limited by the water level and the maximum opening level.

$$Q_{\text{per gate}} = \frac{Q_e(t)}{N_{\text{active}}} \quad (17)$$

$$h_g(t) = \min \left(H_{\text{max}}, H(t), H_{\text{max}} \frac{Q_{\text{per gate}}}{Q_{\text{max}}} \right) \quad (18)$$

3.2. Degradation model

This portion of the model describes how the targeted degradation mechanism was parameterized for our simulation (Lally, Gigot, Tacnet, & Berenguer, 2026). We have made a number of simplifications and assumptions in our parameterization, due to the complexity of the physics involved and the interactions between different factors. The model describes the links and positive feedback loops between the operating and environmental conditions with formation of vibrations in the structure, the gate seal degradation evolution and eventually structural damage. While there has been significant research completed on the identifying the individual links in this mechanism, clearly quantifying the relationships remains a challenge. As such, the purpose of the research is to put in place a framework capable of investigating the sensitivities between the different variables. The nature of the relationships each component in the model have been assumed based on our review of the literature, expert feedback and knowledge of the physical processes. Work towards improving the accuracy of how these relationships behave in reality is ongoing.

In our model, we consider a simple two gate system. Each gate has two sub-components, the gate seals and the gate structure. We model the gate seals health evolution as being

subjected to three sources of degradation: (1) a minor, base-line aging rate, (2) vibration-induced damage and (3) erosion due to the presence of leaks. Two positive feedback loops exist here. In the first, as seal degradation rises, leak severity increases, which in turn increases leak-induced vibrations, thus adding to the rate of seal degradation. In the second, similarly as seal degradation increases, leak severity increases. This in turn increases the rate of erosion, which then adds to the rate of seal degradation. From this we can see that we expect seal degradation to experience a run-away effect after the point of leak inception.

The structure is considered as only being affected by strong vibrations. Above a fixed damage threshold corresponding to the elastic limit of the structural material, we consider to failure to occur. These failures are self-announcing and require a corrective maintenance intervention to bring them back into service.

Vibration model The total vibration level, $V(t)$, is calculated at each time interval as the superposition of two vibration sources. These are (i) the vibration induced by leakage, V_{leak} , and (ii) the vibration associated with the gate opening level, V_{op} .

$$V(t) = k(h(t)) V_{\text{leak}}(t) + V_{\text{op}}(h(t)) \quad (19)$$

The opening-induced vibration, V_{op} , is assumed to have an inverse-square relationship with respect to opening level, $h(t)$. This aims to reflect the significant vibration responses that arise due to small opening levels

$$V_{\text{op}}(h) = \begin{cases} 0, & h = 0 \\ \frac{V_0}{h^2}, & h > 0, \end{cases} \quad (20)$$

The leak-induced vibration component is modelled as proportional to leak severity, relative to the maximum vibration, V_{max} , that would define the failure condition:

$$V_{\text{leak}}(t) = L(t) V_{\text{max}} \quad (21)$$

This leak-induced vibration is also moderated by the seal utilisation factor, $k(h)$. This represents the effective seal length in use due to the gate opening position. This is maximised in the closed position, and zero when fully opened.

$$k(h) = \frac{2(H_{\text{max}} - h)}{2H_{\text{max}} + W} \quad (22)$$

Seal efficiency and leak modelling The seal condition is modelled as a continuous degradation state variable, $D_s(t)$.

The seal is hydraulically impermeable up to a leak initiation threshold of degradation, D_s^{leak} . As the degradation evolves beyond this threshold, the seal efficiency, $n(t)$, decrease as a function of the seal condition. D_s^{max} denotes the seal degradation corresponding to the maximum possible leakage limited by the gate geometry.

$$n(t) = \begin{cases} 1, & D_s(t) \leq D_s^{\text{leak}} \\ \max\left(0.05, 1 - \frac{D_s(t)}{D_s^{\text{max}}}\right), & D_s(t) > D_s^{\text{leak}} \end{cases} \quad (23)$$

Leak severity, $L(t)$, is the reduction of seal efficiency due to degradation.

$$L(t) = 1 - n(t) \quad (24)$$

Seal degradation The seal condition degradation, $D_s(t)$, is modelled as following a non-stationary stochastic gamma process with shape α and scale β parameters that are dependent on the instantaneous total vibration level (van Noortwijk, 2009). These parameters are updated at each time step. We chose the gamma process to ensure irreversibility in the degradation process, preventing spontaneous reductions in degradation. This process also enabled linking the parameters to the factors influencing the degradation process. The stochastic gamma process for the seal degradation $\{D_s(t), t \geq 0\}$ has the following properties:

- $D_s(0) = 0$;
- $D_s(t)$ has independent increments;
- The degradation increments on Δt are Gamma distributed:

$$D_s(t + \Delta t) - D_s(t) \sim Ga(\alpha_s(t) \cdot \Delta t, \beta_s(t)), \quad (25)$$

where the probability density function of the Gamma law $Ga(\alpha_s(t) \cdot \Delta t, \beta_s(t))$ is

$$f_{Ga}(x; \alpha_s(t) \cdot \Delta t, \beta_s(t)) = \frac{x^{\alpha_s(t) \cdot \Delta t - 1} e^{-x/\beta_s(t)}}{\beta_s(t)^{\alpha_s(t) \cdot \Delta t} \Gamma(\alpha_s(t) \cdot \Delta t)} \quad (26)$$

with $\Gamma(\alpha) = \int_0^{+\infty} x^{\alpha} e^{-x} dx$ is the Gamma function.

Seal condition and vibration level dependence modelling The shape and scale parameters dependence on the vibration level, enable the environmental and operating conditions to influence the rate and variability of the degradation evolution. A vibration threshold, V_s^{el} , corresponding to the elastic limits of the seal material demarcates the separation of two degradation regimes. Below this value, the rate and variability parameters are constant and equal to β_0 and α_0 respectively. In this range, degradation evolves slowly, governed by steady aging process due to environmental exposure. Beyond this level,

these values increase relative to the vibration level. $\beta_s(t)$ increase's are proportional to the vibration increase, where the relationship with $\alpha_s(t)$ is exponential. V_{\max} is the maximum vibration amplitude, which would result in failure.

$$\beta_s(t) = \begin{cases} \beta_0, & V(t) < V_s^{\text{el}} \\ c_s V(t), & V(t) \geq V_s^{\text{el}} \end{cases} \quad (27)$$

$$\alpha_s(t) = \begin{cases} \alpha_0, & V(t) < V_s^{\text{el}} \\ \alpha_0 \exp\left(\frac{V(t)}{V_{\max}}\right), & V(t) \geq V_s^{\text{el}} \end{cases}, \quad (28)$$

Seal degradation and leak dependence modelling Sediment concentration in the flow is modelled as relative to the upstream flow rate, Q_r , above a critical bedload transport threshold Q_{crit} and a scaling factor k_s . After leak initiation, as described previously, the degradation rate is increased via an erosion factor, $s(t)$. This depends on sediment concentration and inverse seal efficiency.

$$s(t) = \begin{cases} 0 & Q_r(t) < Q_{\text{crit}} \\ k_s \left(\frac{Q_r(t) - Q_{\text{crit}}}{Q_{\text{ref}}} \right)^{m_s} & \text{otherwise} \end{cases} \quad (29)$$

$$\beta_s(t) \leftarrow \beta_s(t) \frac{s(t)}{n(t)} \quad (30)$$

Model Behaviour As discussed, a number of different degradation regimes dictate the seal condition evolution. These are largely controlled by the influence of vibration on the degradation covariates, as described above. At low levels of vibration, aging takes place slowly. Above a certain threshold of vibration, defined by V_s^{el} , the degradation trend becomes dependent on the the vibration level. Early in the equipment lifecycle, when the seal condition is robust and remains remains, no leakage and thus no leak-induced vibrations exist. During this period, vibrations arise due to the opening level. This regime is illustrated in Fig. 5.

Here we see how variations in river discharge drive gate operation. Gate operation in turn results in severe vibration responses when forced to operate at small openings. These high levels of vibration translate into higher rates of degradation, with greater uncertainty regarding the evolution trajectory due to increased variance. This is captured by the jumps in degradation of varying magnitudes at the points when the opening level is low, with a slow and steady evolution for higher opening levels.

Beyond a critical threshold of seal degradation, leaks begin to form as the integrity of the material is weakened by cyclical loading resulting in material fatigue above the materials elastic limits. This marks the beginning of the next degrada-

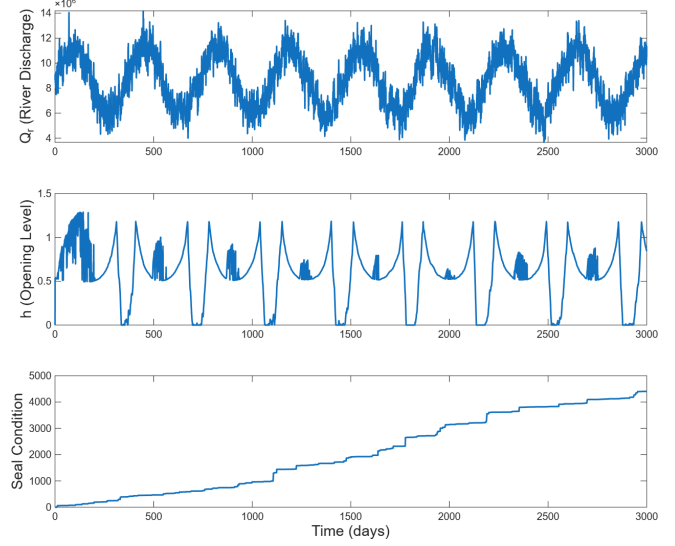


Figure 5. Relationship between river discharge, operating response and degradation evolution.

tion regime, the initiation of the positive feedback loops and the consequently, the beginning of the run-away degradation effect.

In Fig. 6, the casual chain of this relationship and its impact on the degradation covariates is illustrated. We see the leak initiation occur after a certain period, corresponding to the seal degradation threshold being reached. This results in leak-induced vibrations, which rise in relation to the leak severity. In addition to the effect of the vibration, abrasion due to the sediment in suspension also accelerates this process as it passes through small gaps formed by the leaks at high velocities. There is also the link to the opening level, as this controls how much of the gate seals are in contact and thus are effectively in a state in which leaks can have an effect. Combined, this leads to a self-perpetuating cycle where in increases in seal degradation result in more significant leaks, which increase the rate of degradation via higher vibration levels and a greater impact from sediment abrasion.

As this evolves, the two sources of vibration have a combined effect. The first resulting from operation necessary to control the river discharge to maintain the upstream level at a relative equilibrium and the second due to leaks arising from the lost of seal integrity due to degradation. When peaking in tandem, the constructive inference works additively to reach a level capable of exceeding the elastic limits of the structural materials of the gate. When this occurs, material fatigue may begin to accumulate. We treat this as our failure condition. We see a representation of this in Fig. 7. Here the peaks are due to the small opening levels, where as the positive drift over time is due to the leak evolution.

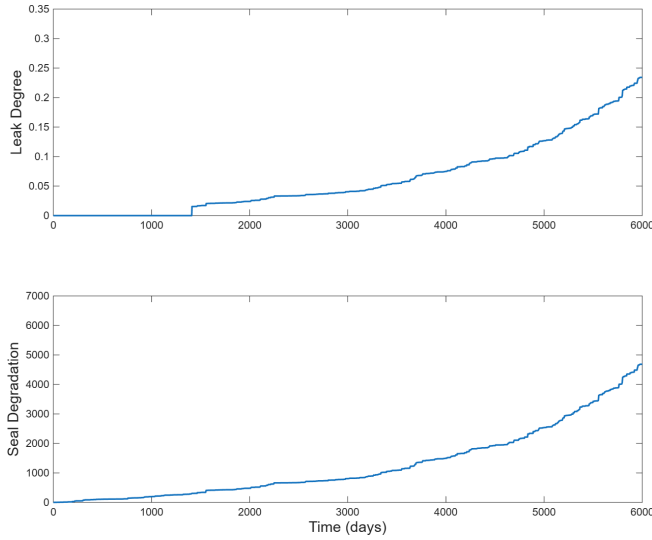


Figure 6. Positive feedback loop initiated by leakage, feeding degradation.

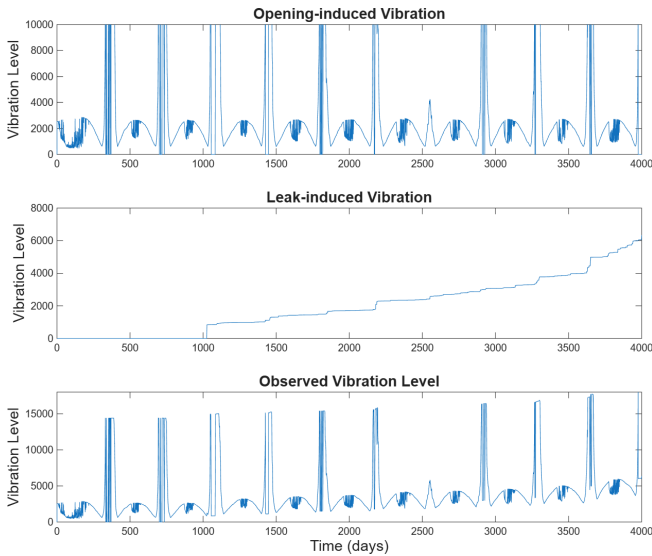


Figure 7. Combination effect of operating and condition-induced vibrations

3.3. Maintenance policy

As discussed previously, hydraulic flood gates are critical to safe hydropower operation. However, in many instances due to changes in operating policies, regulatory changes and climate change's effects on river behaviour, the conditions for which they were originally designed is no longer valid. This has led to case where the redundancy that was designed into these systems to ensure evacuation can be met, even in the most extreme case, has been compromised. Paired with the increasing risk of failures due to aging assets, as well as the other factors discussed, developing a CBM policy that can aid in avoiding simultaneous maintenance interventions, while also minimising the risk of unexpected failures, would be greatly beneficial.

In order to explore a possible approach to this, a dual-threshold CBM policy was implemented in order to optimise the preventative seal replacement for the two gate system. The policy makes use of an upper threshold, PM_U , and a lower threshold, PM_T , where $PM_U > PM_T$. These thresholds are applied to the vibration level, $V_g(t)$ measured during inspections. This condition indicator is a proxy for the hidden true state of the seal, as the seal condition can not be measured directly.

A goal of this policy is to penalise simultaneous replacements, as they overlapping downtime associated with these interventions would significantly compromise the dam's evacuation capacity, leaving it vulnerable in the case of an extreme event. Such simultaneous replacements would only be justified in the event that the expected cost of incurring a failure before the next maintenance opportunity arises outweighs the risk cost associated with replacing both simultaneously.

We assume inspections are carried out periodically. We assume arbitrary cost units. This has led us to define the following rules, which based on the observed vibration, maintenance decisions will be taken after each inspection:

1. If the vibration in both gates exceeds the upper threshold, PM_U , simultaneous preventive replacement is performed. This incurs an additional risk costs, Cr due to concurrent downtime reducing evacuation capacity.
2. If at least one gate exceeds the lower threshold, PM_T , but the previous condition is not met, a selective preventive replacement is performed on the most degraded gate seal.
3. If neither threshold condition is satisfied, no maintenance action is taken.

Additionally, a corrective maintenance policy is triggered when a higher critical vibration threshold corresponding to structural damage is exceeded. This event is assumed to be self-announcing and results in immediate repair and condition reset. This incurs a longer downtime CM_T and higher cost Cc ,

and thus penalises run-to-failure behaviour. Inspections incur cost C_i , regardless of whether or not maintenance is carried out.

The maintenance logic dictates that if both gate's seal's degradation levels had exceeded the upper threshold, it would justify the risk cost of simultaneous replacements, due to the risk of failure that would arise before the next inspection. If one or both of the gate's seal's had exceeded the lower threshold, the more degraded of the two would be replaced. If neither had exceeded the lower threshold, operation was allowed to continue. We assumed the gates are inspected once annually. Inspection involved a measurement of the vibration level. From this, the seal condition is inferred. A higher vibration limit corresponding to the structural damage threshold was set to define the corrective maintenance threshold. This is assumed to be self-announcing. A preventative maintenance has a relatively short downtime PM_T and smaller cost C_p . The corrective maintenance has a relatively longer downtime CM_T and higher cost C_c . Inspections incur cost C_i , regardless of whether or not maintenance is carried out. The cost optimal threshold pair is identified through simulation-based optimisation by minimising the expected average annual cost over multiple system lifetimes under varying environmental conditions.

4. RESULTS

A three hundred year simulation was tested with time increments of 6 hrs, in order to allow for approximately thirty asset lifecycles to be considered. The following is a list of the main parameters used in the final simulation. First, for the external conditions mode the following input parameters were used:

- $Q_i = 100m^3/s$
- $A = 0.3$
- $\sigma = 0.1 Q_i$
- $\alpha = 0.85$
- $p_{\text{extreme}} = 1/365$
- $\beta = 0.25$
- $\xi = 5 Q_i 5$

For the reservoir storage and operational control model, the following input parameters were used:

- $D_{\text{opt}} = 50m$
- $D_{\text{tol}} = 1m$
- $W_g = 5m$
- $H_{\text{max}} = 5m$
- $D_g = 6m$
- $W_0 = 30m$
- $L_0 = 50m$

- $M_l = 10$
- $M_x = 60$
- $Q_p = 0.2 Q_i$
- $Q_{\text{res}} = 0.8 Q_i$

For the degradation model and maintenance optimisation, the following input parameters were used:

- $D_s^{\text{leak}} = 500$
- $\alpha_0 = 0.01$
- $V_s^{\text{el}} = 4000$
- $V_{\text{max}} = 20000$
- $D_s^{\text{max}} = 20000$
- $C_d = 0.7$
- $Q_{\text{crit}} = 0.5 Q_i$
- $k_s = 1$
- $m_s = 2$
- $C_i = 1000$
- $C_p = 10000$
- $C_c = 100000$
- $C_r = 20000$

An initial simulation tested the target ranges for the threshold optimisation using intervals of 1000 units in order to identify the region containing the minimum value. A more refined simulation with smaller target ranges focusing on this region using intervals of 250 units was subsequently used to identify the local minimum corresponding to the optimum cost threshold pair.

The output of our simulation, in terms of the optimisation of the two preventative maintenance thresholds, is illustrated in the heat map in Fig. 8. Here we have the average annual costs associated with each threshold pair that was tested, illustrated by the colour gradient. The relation is characterised by a clear valley, indicating a high degree of sensitivity to the lower threshold, PM_T , relative to the higher threshold, PM_U . The dark blue area to the bottom right represent invalid pairs, in which $PM_U < PM_T$. From this, the following optimal pair way identified, with the corresponding average annual cost of this maintenance policy:

- Upper threshold, $PM_U = 20000$
- Lower threshold, $PM_T = 16500$
- Average annual cost = 3233.33

This is indicative of the nature our system. Due to the runaway degradation effects that occur later in the lifecycle of the system, a high degree of variation exists during this period. While the lower threshold works well at truncating this effect, allowing intervention before the variability and rate

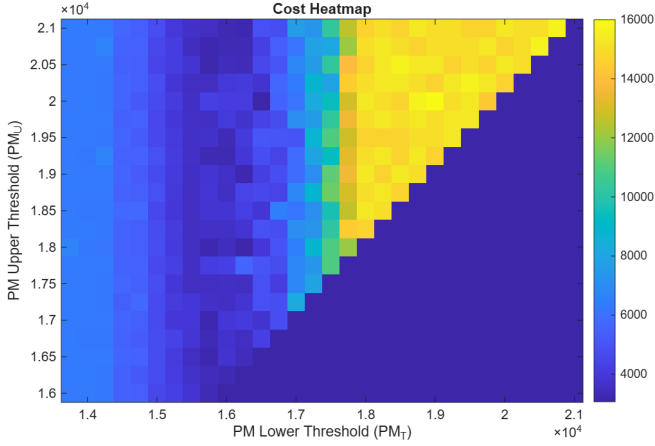


Figure 8. Average annual cost associated with each PM_U - PM_T pair.

become too extreme, identifying a clear upper threshold is more problematic. In fact from this result, it appears that for systems of this nature where degradation rate and variability increase greatly as its RUL decreases, defining a negative opportunistic maintenance policy in this way in order to improve asset availability by minimising simultaneous maintenance interventions is not reliable due to the inherent end-of-life uncertainty.

For the simulation parameters tested, the optimal lower threshold consistently corresponding to the early stage of the run-away degradation regime, while the optimal upper threshold consistently trended towards the failure threshold. The expected cost corresponding to each tested lower threshold varied according to the expected preventative cost optimisation curve behaviour, illustrated in the upper half of Fig. 8. Here, in the early part of the curve, the threshold is too low and thus preventative maintenance is triggered each time there is an inspection, sacrificing the RUL of the sealing system without real risk of failure. As the threshold is increased, the effect of the degraded seals begins to influence the system degradation by initiating the run-away degradation effect. At this stage, preventative replacement becomes cost effective, and thus the cost curve approaches a minimum. After this, as the threshold is increased further, we see run-to-failure scenarios taking hold. Here the costs rise as they become dominated by the corrective maintenance, where the seal condition degrades to the point at which leak-induced vibrations become so severe they contribute to structural damage.

In the graph of the upper threshold costs curve however, no clear trend is visible. This was true for each simulation that was run. In each case, the minimum did indeed trend towards the failure threshold as expected, however the cost-benefit between each threshold was relatively small with respect to the lower threshold.

For the purposes of comparison, the same simulation car-

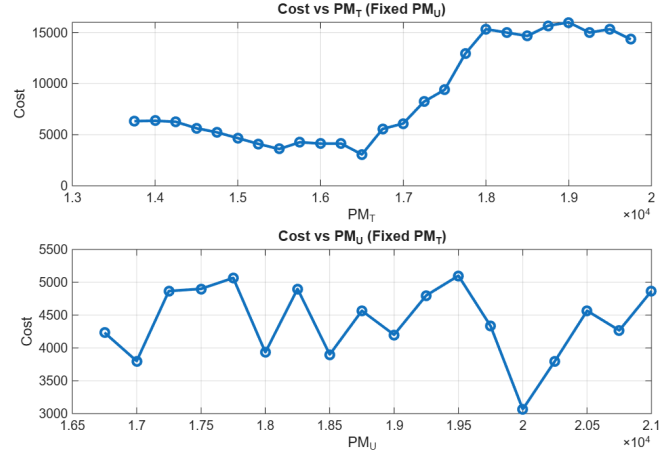


Figure 9. Average annual cost associated with the tested preventative replacement thresholds. Top - PM_T , Bottom - PM_U

ried out, however optimising for a single preventative maintenance threshold, in order to compare the long term average annual costs of both policies. The cost curve derived from this simulation is illustrated in Fig. 10, and the results were as follows:

- Single threshold, $PM = 16250$
- Average annual cost = 3480

Notably, for all simulations that were run with these parameters, the single threshold policy had a marginally high cost, and a more conservative preventative threshold. This indicates that there is still some value in the dual-threshold policy, as it reduces the need to replace as frequently as the single threshold case, while still providing a backstop to prevent simultaneous failures and thus incurring the risk cost.

However, simulations carried out for different risk costs found that the resulting margin were tightly correlated with this value. As the risk cost increased, so did the benefit of dual-threshold policy, as visa versa. Similarly, and as mentioned previously, the variability increases seen at the end of the seal's useful service life was also found to have a significant impact. For lower variabilities, a more reliable upper threshold could be established, improving the desirability of dual threshold policy.

This implies that for certain applications, where end-of-life degradation variability can be controlled or is well understood, or when the consequences of failure are extremely costly or unacceptable, a dual-threshold policy may be more advantageous than a single threshold approach.

5. DISCUSSION AND PERSPECTIVES

This example illustrates the results of a CBM policy that is limited by knowledge of the system condition. One pos-

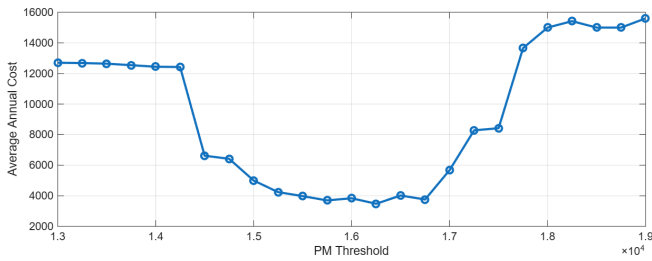


Figure 10. Average annual cost associated with the single preventative threshold optimisation.

sible solution to this would be to increase monitoring frequency, thus improving knowledge of the system. An appropriately optimised monitoring policy would reduce the uncertainty around failure probability between maintenance decision intervals, allowing an upper threshold to be more clearly defined. This hypothesis will be tested in an extension to this work.

While this research represents a significant step in our work towards developing a viable CBM approach for hydraulic floodgates, the current framework is still lacking a number of key features that we intend to address in future developments. Core to this is the improvement of the realism of the PDM. Currently, as discussed, the PDM parametrization is largely estimated qualitatively and uses relative units with fixed threshold values delineating behaviour regimes. Future work will seek to address these deficiencies with subsequent iterations, by calibrating the relationships based on real data if available or through the implementation of more accurate models reflective of the true physics at play. The addition of other degradation mechanisms and their interactions with the modelled components may also be considered. In terms of the environmental and operational aspects of the model, refinements will continue to be made in order to make the behaviour and interactions between the environment and the system, via operational decision-making, closer to reality.

It is hoped that this work can aid in justifying the investment required to improve condition-monitoring for hydraulic gate systems, in order to gather the data necessary for developing practical models for CBM applications. Essentially the question becomes, do the costs associated with monitoring justify the value of information that could be garnered from it, in terms of better decision-making? We believe this is one step towards a tool that may aid in answering that question.

6. CONCLUSION

In summary, the developed model represents a coupled, non-linear stochastic degradation process on a multi-gate system, in which hydrological variability drives reservoir dynamics and operational decision-making. These decisions in turn influence gate degradation and maintenance decision-making, which then impacts gate availability, evacuation capacity and

risk management.

The degradation in this system is complex and is influenced by operating decisions, via the effects of gate opening levels on vibration response, environmental conditions in the form of the flow rates and sediment in suspension and via maintenance decision making, to reset condition states. In the early stage of the asset equipment life cycle aging is slow, mainly driven by environmental exposure. However, once critical thresholds are exceeded, accelerated deterioration takes hold resulting in a self-reinforcing failure mechanism. The framework being developed here provides the foundation of a tool to enable the analysis of system reliability and maintenance strategies under dynamically evolving operating conditions, with the capacity to have its accuracy improved over time with the input of relevant expertise and modelling refinements.

This describes a cascading system, where in gate failures reduce evacuation capacity, which increases the load on the system forcing the remaining gate to articulate to greater extremes in order to maintain reservoir equilibrium. This further increases the rate of degradation within the system. To counter this, a negative opportunistic maintenance policy is applied in which simultaneous maintenance interventions are avoided, in order to maintain the evacuation capacity of the system to handle flooding.

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