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Reliability-based inspection and maintenance planning of a nuclear feeder piping system

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Abstract

Inspection and maintenance (I&M) is essential to ensure the integrity of feeder pipes in a nuclear power plant. The pipes are subject to flow accelerated corrosion (FAC), which can lead to plant malfunction and high associated costs to the operator. We explore the opportunity for improving I&M strategies while ensuring that the system still maintains an acceptable level of reliability. To this aim, a reliability-based planning framework is proposed, where a fixed threshold is imposed on the annual probability that pipes are non-compliant. With this planning framework we can a) evaluate the performance of any I&M strategy constrained to a fixed reliability criterion, without requiring this strategy to be specifically designed for such a criterion; and b) find an I&M strategy optimized for this reliability level using a heuristic description of the strategy space. We demonstrate the framework on a case study, where wall thinning due to FAC of 480 pipes in a feeder piping system is modelled by a Gamma process with uncertain parameters. We compare the expected life-cycle I&M cost of multiple strategies, including one representative of current practice, and assess the efficiency of the rules guiding I&M decisions. The effect of the model assumptions are also investigated.

Keywords: maintenance, flow accelerated corrosion, reliability-based planning

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1. Introduction

Operation and maintenance of a nuclear power plant requires careful planning. Aside from the safety of the plant, which is ensured by a multitude of redundant safety systems, the continued operation of the plant is a major concern of the operator. Regular maintenance of the reactor components is essential to prevent interruptions in energy production, which represent a high loss in revenue.

Flow accelerated corrosion (FAC) is the deterioration phenomenon largely responsible for wall thinning and leakage in the reactor piping system and in particular the feeder tubes, which are steel pipes that contain coolant to cool the nuclear fuel injected into the reactor. FAC affects the wall thickness of the tubes, more precisely at the bends formed by the pipes (see Figure 1). Wall thinning and leakage can have serious consequences, such as accidents during maintenance operations and general malfunction of the plant. In the event of such failure, total interruption of plant activity is typically required, at very high cost. Inspection and maintenance (I&M) planning of feeder pipes is part of the FAC management programme. Such planning is especially complex due to the high number of pipe bends where FAC can occur. Inspecting and/or replacing every single pipe is not economically feasible.

Following a major FAC-related incident at the Surry nuclear power plant (NPP) in 1986 and to address the lack of a unified maintenance practice, guidelines and principles were drafted (Wu, 1989). They are articulated around the following points: (i) piping systems must be inspected regularly; (ii) inspections must measure the wall thickness; (iii) the evolution of the wall thickness must be predicted for every pipe and account for the past inspection outcomes; (iii) pipes that do not comply with a minimum wall thickness must be replaced; (v) pipes selected for the next planned inspection should include pipes never inspected, as well as pipes marked as near-critical during a past inspection (EPRI, 2013).

Good I&M planning controls the risk of an unplanned outage due to pipe failures, while keeping the I&M costs (pipe inspection and replacement costs) low. In the current unified practice, the I&M strategies adopted for FAC management in NPPs do not vary widely and have been adapted from past practice. These strategies have not been explicitly optimized to comply to a certain reliability level. Such a level is also not quantified in the guidelines. Therefore, there is an opportunity to optimize the I&M costs while maintaining a specified level of reliability. This paper proposes a reliability-based planning framework to improve current I&M practice and to quantify the potential reduction in I&M costs.

With this planning framework, a plant operator can a) evaluate the performance of any I&M strategy constrained to a fixed reliability criterion; and b) find an I&M strategy optimized for this reliability level. In this framework, the proposed reliability criterion is formulated as a threshold p_0 on the annual system failure rate (see Section 3.3). A heuristic approach to the reliability-based optimization problem is proposed, whereby the strategies explored in the optimization process are described by a set of rules with flexible parameters (Section 4.2). This heuristic approach notably allows for including eventual operator constraints. Its use has been demonstrated in other I&M planning problems (Luque and Straub, 2019; Bismut and Straub, 2021). With this framework, current I&M practices can be evaluated against different reliability criteria, and optimized I&M rules can be found.

The framework is demonstrated on a 480-feeder piping system subject to FAC. The deterioration process at the pipe level is modelled by a mixed-scale Gamma process (see Section 5). The annual system reliability and failure rate is computed and updated over time by including the pipe inspection outcomes and maintenance actions to check compliance with the reliability criterion (see Section 6). In Section 7, the I&M constrained expected costs of a strategy representative of current I&M practice are evaluated and are compared to the optimized heuristic strategies for different values of p_0. The effect of the prior deterioration model parameters are also investigated.

2. Inspection and maintenance of a piping system

2.1. Piping system

The case study presented in this section is based on a piping system of a Canada Deuterium Uranium (CANDU) power reactor. A CANDU piping system typically consists of different pipe geometries (angle of pipe bend, diameter of pipe, thickness of pipe) (Yuan, 2007), however, to restrict our analysis, the piping system considered here consists of identical $N = 480$ large-bore pipes of 2-inch diameter, with initial nominal thickness $W_0 = 5.5$[mm] (Hazra et al., 2020a).

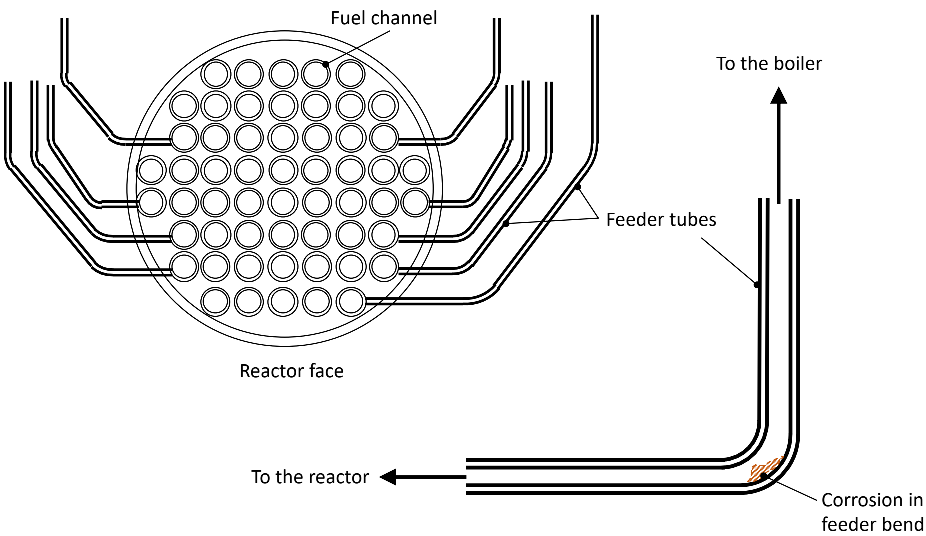


Figure 1: Feeder piping system and corrosion location.

The pipes are indexed by $1 \leq i \leq N$. The thickness of a pipe i at time t is denoted by $W_i(t)$, with $W_i(0) = W_0$. The loss of wall thickness resulting from FAC, $D_i(t)$, is

$$D_i(t) = W_i(0) - W_i(t). \tag{1}$$

To ensure adequate safety and fitness-for-service, the operator must ensure throughout the service life that the wall thickness loss in any of the 480 pipes does not exceed a certain threshold d_{max}. Piping design standards specify this threshold d_{max} to be 40% of the initial thickness W_0 (ASME, 2013; Hazra et al., 2020a). Here, $d_{max} = 2.2$[mm]. Failure to comply with this criterion at time t, indicated by the event $F(t) = \{\max_i D_i(t) > d_{max}\}$, is here called *system failure* at time t. The event $F_i(t) = \{D_i(t) > d_{max}\}$ is called *failure of pipe* i at time t. It is $F(t) = \cup_i F_i(t)$.

The design service life T is measured in effective full-power years (EFPY). For the numerical investigation, we set $T = 25$[EFPY].

2.2. I&M actions and cost model

To ensure compliance with the criterion described above, the plant operator performs inspections of the piping system throughout the service life, by measuring the wall thicknesses at the bend of selected pipes with ultrasonic probes. Based on the inspection results, the operator can choose to replace pipes bends by cutting out the old bend and welding in a new pipe bend. In theory, the operator can decide to inspect or repair the pipes at any point in time. In practice, inspection and repair times are typically synchronized with planned maintenance outages, during which the NPP undergoes different types of checks and maintenance operations.

In a practical setting, the costs of pipe inspection and repair depend on the manner they are scheduled. We outline the I&M scheduling constraints and resulting I&M life-cycle costs in Figure 2. The I&M campaigns occur at times fixed in advance, typically at regular time intervals ΔT. Pipe inspections and maintenance actions are preferably planned one I&M campaign ahead. Certain pipes are labelled 'of interest' (for future inspection). Others are labelled 'critical' (for eventual future maintenance) and form the *PM pool*. Maintenance performed on pipes from the PM pool is called *preventive maintenance*. However, the inspections carried out during an I&M campaign can reveal critical pipes among those that have not been scheduled for maintenance during the previous campaign, which form the *CM pool*; critical pipes in the CM pool warrant *corrective maintenance*. This happens for example when an inspected pipe is deemed to deteriorate too fast so that their replacement cannot be postponed until the next outage. The corrective maintenance cost per pipe is typically higher than the cost of preventive maintenance. It is therefore advantageous to plan preventive maintenance well, so that a minimal amount of corrective maintenance is required. However labelling too many pipes as critical can result in an unnecessarily large number of inspections.

Note that we do not consider the possibility that maintenance actions occur outside of the predetermined campaign times, for instance during unplanned outages to maintain other parts of the NPP. This also means that what here is labelled as corrective pipe maintenance does not include maintenance actions that occur outside of the planned maintenance times, such as emergency repairs due to an unexpected pipe failure or other incidents. As we discuss in Sections 3 and 4, system failure is only considered through the system reliability.

The following costs are considered. The cost of launching an I&M campaign is c_C. It includes mobilisation costs and other overheads. The cost of inspecting one pipe is c_I. It accounts for the time needed for one inspection. A unit cost c_{PM} is incurred for each pipe repaired as planned. The corrective maintenance cost per pipe is c_{CM}, which is larger than c_{PM}.

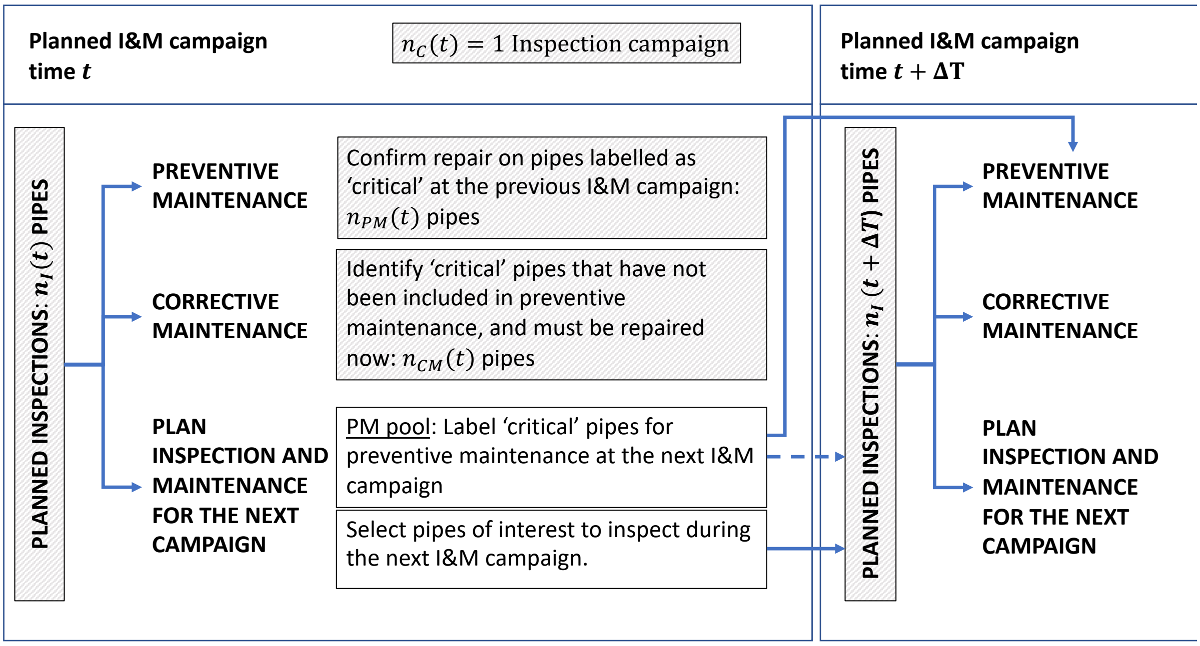


Figure 2: Overview on I&M planning. Inspection and maintenance actions occurring at time t are indicated by lightly hatched boxes. Planning of I&M actions for the next I&M campaign are indicated by unhatched boxes. The PM pool consists of the the pipes pre-selected for preventive maintenance for the next campaign, the CM pool consists of all other pipes. The plain arrows indicate a scheduling imperative. The dashed arrow indicates possible influences, but does not constrain the I&M strategies to follow them. For instance, preventive maintenance or corrective maintenance can be performed on pipes that have not been inspected during the campaign, but might have been in the past. This means that the pipes in the PM pool can be, but not necessarily are, inspected at the next campaign, as indicated by the arrow. $n_C(t)$ records the times of I&M campaigns. During a I&M campaign at time t, $n_I(t)$, $n_{PM}(t)$ and $n_{CM}(t)$ are the total number of pipes inspected, and replaced for preventive and corrective maintenance, respectively.

3. Reliability-constrained I&M strategy

3.1. I&M strategies

A strategy $\mathcal{S}$ is the set of rules (policies) that governs at any time the decision process based on the information available at that time. When considering a deteriorating multi-component system, the rules take as input all or part of the current knowledge on the state of the system, and give the answer to the questions 'Inspect?' {yes, no}, 'Where?' {component i, j, ...},'What to look for?' {corrosion, fatigue,...} ,'How?' {visually, ultrasonic inspection, thickness measurements, ...}, 'Repair?' {yes, no, how}. The system knowledge includes the history of inspection outcomes, monitoring data, repairs and eventual component failures. A formal description of I&M strategies is given by Bismut and Straub (2021).

For the I&M planning problem considered in this paper, a strategy defines at which time step the inspection outage takes place, how the PM pool is composed, which pipes are of interest and which pipes are preventively (or correctively) maintained.

A history $\boldsymbol{M}$ contains all the information gathered during the lifetime of the structure, including inspection outcomes, pipe replacements and eventual system failure. $\boldsymbol{M}_{0:t^-}$ is the I&M information collected up to time t, and $\boldsymbol{M}_{i,0:t^-}$ is the information collected on pipe i.

3.2. Evaluating a strategy under a reliability criterion

The efficiency of a strategy can be assessed with different metrics. One metric is the total life-cycle expected cost, adding the I&M action expected costs (see Equation (7)) to the lifetime risk of failure. This is the risk-based assessment of a strategy. The risk of failure considers explicitly the consequences of failure. These consequences include the cost of an accident (or failure), which entails replacing ruptured feeders but also loss of revenue due to unplanned outage, loss of life, and any other type of financial penalty imposed by the regulator. As an example, the loss incurred after the 1986 Surry NPP incident mentioned in Section 1 above amounted to tens of millions of dollars (EPRI, 2013). Correctly appraising the consequences of failure is crucial for a meaningful result using the risk-based approach. Due to the high uncertainty on the magnitude of the consequences of failure, a risk-based assessment is not further pursued here.

One could also simply assess the life-cycle I&M expected cost (see Equation (7) below), but this assessment presents an obvious flaw: if the strategy considered prescribes no inspections and no repairs during the entire service life, this cost is simply zero, hence this ‘do-nothing’ strategy would always be the one with minimal cost, even if this strategy is clearly undesirable. In real-life, the current I&M practice implicitly leads to a certain level of reliability. Most I&M strategies in the nuclear industry are, however, defined in a rule-based approach, without quantifying the system reliability (e.g., EPRI, 2013), and they do not explicitly guarantee a reliability level.

Here, we propose a method to assess any given I&M strategy, such as those described in guidelines, by assessing the life-cycle I&M expected cost associated with this strategy while constraining the system to a fixed reliability level. This method is illustrated by the diagram of Figure 3.

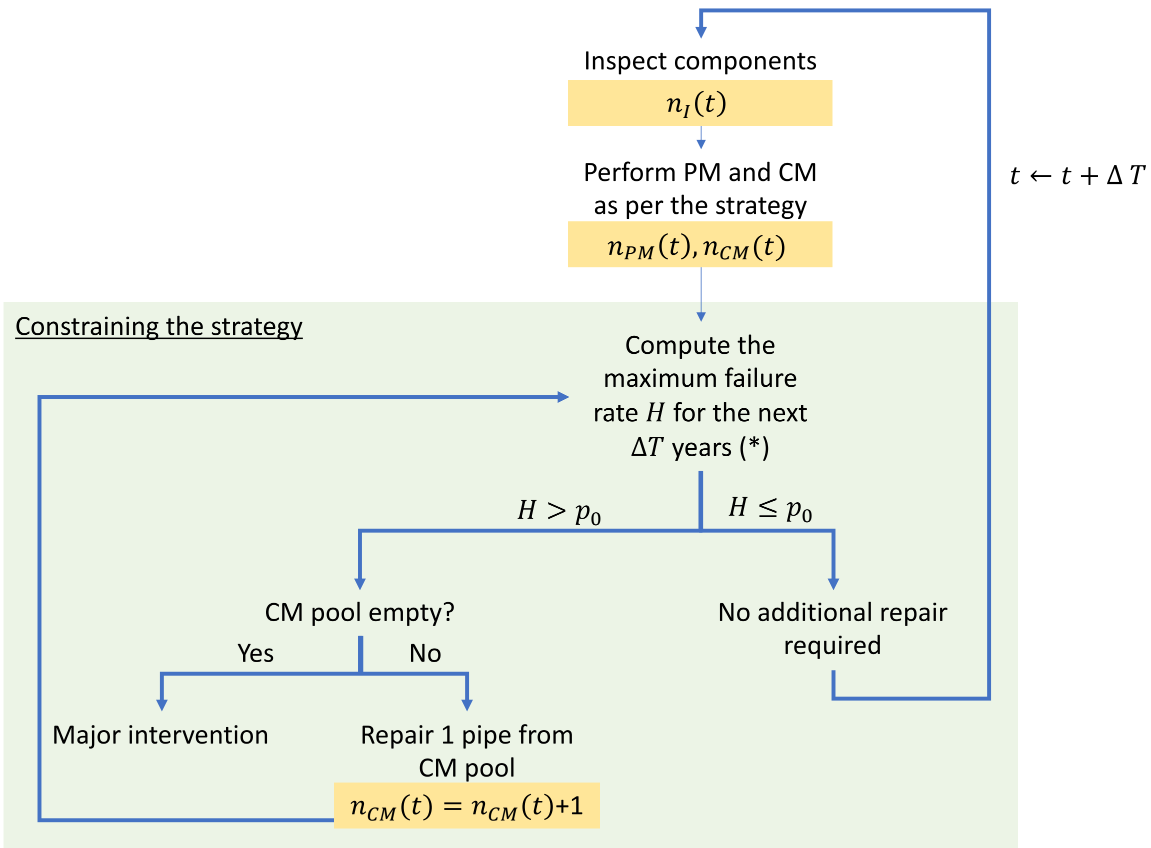


Figure 3: Simulation of an I&M history following a given strategy $\mathcal{S}$ constrained to reliability criterion p_0. The definition of H is given in Section 3.3 and Equation (2).

The I&M campaigns occur at times prescribed by the considered strategy, for example at regular intervals ΔT. The rules for selecting pipes for inspection, for planning the PM pool and for performing preventive (and eventually corrective) maintenance are applied as prescribed by the strategy.

Then, the reliability criterion is evaluated for the time period until the next campaign and is compared against the required reliability level. If the criterion is violated, maintenance actions are performed such that the piping system is brought to a compliant state. Here, additional pipes are replaced one by one until the annual failure rate of the system falls under a certain value (see Section 3.3). The pipes selected for corrective maintenance to satisfy the criterion are those with the highest probability of pipe failure. Since these repairs occur after all I&M actions prescribed by the strategy have taken place, they are accounted for as corrective maintenance, with unit cost c_{CM}.

The eventuality that all pipes are replaced and the system is still not compliant corresponds to a failure event, which requires a major intervention. As explained above, we do not consider explicitly any costs or further I&M action resulting from system failure.

3.3. *Defining the reliability criterion*

In this study, we express the reliability criterion as a threshold p_0 on the annual system failure rate at time t[EFPY] conditional on past I&M outcomes and actions $\boldsymbol{M}_{0:t^-}$, which in turn depend on the chosen I&M strategy $\mathcal{S}$. The annual failure rate at year t[EFPY] must be such that

$$H(t, \boldsymbol{M}_{0:t^-}) = \frac{\Pr\left[F_{cumu}(t+1)|\boldsymbol{M}_{0:t^-}\right] - \Pr\left[F_{cumu}(t)|\boldsymbol{M}_{0:t^-}\right]}{1 - \Pr\left[F_{cumu}(t)|\boldsymbol{M}_{0:t^-}\right]} [EFPY^{-1}] \leq p_0. \tag{2}$$

$\Pr(F_{cumu}(t)|\boldsymbol{M}_{0:t^-})$ is the cumulative filtered probability of system failure at time t, verifying $F_{cumu}(t) = \bigcup_{\tau \leq t} F(\tau)$ (Straub et al., 2020). $\Pr(F_{cumu}(t+1)|\boldsymbol{M}_{0:t^-})$ is the cumulative predictive probability of system failure at time $t+1$.

The value attributed to p_0 can be prescribed explicitly by the regulator. In most situations, such a value is not given as such, but is implied by current regulations and constraints. Therefore, a value of the reliability criterion could be extracted from I&M plans that are considered acceptable by the practitioners and the regulators.

In the numerical investigation, we evaluate the expected life-cycle I&M cost of a given strategy constrained to different levels p_0.

3.4. *Life-cycle I&M cost*

For an I&M history $\boldsymbol{M}$ following a strategy $\mathcal{S}$, the life-cycle cost is calculated by recording the times and numbers of inspection and repair actions during the lifetime, and aggregating their cost. To account for the time-value of money, an annual discount rate r is considered, such that all costs incurred at time t are discounted at time 0 by a factor $1/(1+r)^t$. The components of the life-cycle cost are

$$C_{I,T}(\boldsymbol{M}) = \sum_{t=1}^{T} (c_I n_I(t) + c_C n_C(t)) \frac{1}{(1+r)^t} \tag{3}$$

$$C_{PM,T}(\boldsymbol{M}) = \sum_{t=1}^{T} c_{PM} n_{PM}(t) \frac{1}{(1+r)^t} \tag{4}$$

$$C_{CM,T}(\boldsymbol{M}) = \sum_{t=1}^{T} c_{CM} n_{CM}(t) \frac{1}{(1+r)^t}, \tag{5}$$

where $C_{I,T}(\boldsymbol{M})$, $C_{PM,T}(\boldsymbol{M})$ and $C_{CM,T}(\boldsymbol{M})$ are respectively the total life-cycle inspection costs (including I&M campaign costs and pipe inspection costs), the total preventive maintenance costs and the total corrective maintenance costs. $n_C(t) = 1$ if an I&M campaign takes place at time t, 0 otherwise. All unit costs c_C, c_I, c_{PM} and c_{CM} are constant throughout the service life, their values for the numerical investigation are given in Table 2.

The life-cycle I&M cost for history $\boldsymbol{M}$ is therefore

$$C_T(\boldsymbol{M}) = C_{I,T}(\boldsymbol{M}) + C_{PM,T}(\boldsymbol{M}) + C_{CM,T}(\boldsymbol{M}). \tag{6}$$

Before the execution of a strategy, the observation outcomes and eventual maintenance actions are uncertain. Therefore one can compute the expected life-cycle I&M cost associated with a strategy $\mathcal{S}$ as

$$C(\mathcal{S}) = C_{I,T}(\mathcal{S}) + C_{PM,T}(\mathcal{S}) + C_{CM,T}(\mathcal{S}), \tag{7}$$

where $C_{I,T}(\mathcal{S})$, $C_{PM,T}(\mathcal{S})$ and $C_{CM,T}(\mathcal{S})$ are the expected life-cycle inspection, preventive and corrective maintenance costs, respectively.

3.5. Computing the expected cost of a strategy

In I&M planning, it is typically not possible to obtain an analytical form of the distribution of the observation histories $\boldsymbol{M}$ for a given strategy $\mathcal{S}$. This is because the vector of varying dimension $\boldsymbol{M}$ is generated sequentially with time from the strategy $\mathcal{S}$. Luque and Straub (2019) propose to approximate the distribution of $\boldsymbol{M}$ and evaluate the expected life-cycle I&M cost in Equation (7) by sample averaging the I&M costs (Equation (6)) associated with $1 \leq k \leq n_{MC}$ Monte Carlo (MC) sample observation histories $\boldsymbol{M}^{(k)}$ following strategy $\mathcal{S}$, as

$$C(\mathcal{S}) \simeq \sum_{k=1}^{n_{MC}} \left[C_{I,T}\left(\boldsymbol{M}^{(k)}(\mathcal{S})\right) + C_{PM,T}\left(\boldsymbol{M}^{(k)}(\mathcal{S})\right) + C_{CM,T}\left(\boldsymbol{M}^{(k)}(\mathcal{S})\right) \right]. \tag{8}$$

Furthermore, in the presented reliability-based framework each I&M sample history must be generated with an added reliability constraint (see Figure 3). It requires many computations of the annual failure rate in Equation (2) (one at every time step), for which sampling-based reliability methods are not appropriate. In this case, an efficient reliability computation performed sequentially is needed to generate one sample history $\boldsymbol{M}^{(k)}$. Section 6 describes the procedure for evaluating the probabilities of component and system failure conditional on past observations for the deterioration, inspection and maintenance models presented in Section 5.

Additionally, we consider that system failure is a terminal event, which means that a history ends before the design service life if an observation indicates system failure.

4. Reliability-based heuristic planning

4.1. Reliability-based optimization

Optimal I&M planning means finding the solution of a sequential decision problem in the form of a strategy, which tells one what to do (inspect, repair) and when and where to do it. In this context, the optimal strategy is the one that minimizes an objective function, typically an expected cost. We can distinguish three approaches to I&M planning: *rule-based*, *reliability-based* and *risk-based*. All three approaches affect the formulation of the optimization problem and the objective function. The first approach is the one currently recommended by the regulator. Effectively, it constrains the operator to follow certain principles (see an example below in Section 7.2), and leaves little leeway in modifying the prescribed strategy. Risk-based planning prescribes the risk-based assessment of a strategy and, as stated in Section 3.2, is not suitable for the considered application.

We therefore implement a reliability-based approach, which is reflected in the form of the considered objective function. In this approach, the optimal strategy minimizes the total I&M costs, while ensuring that the system always complies with a reliability criterion. The objective function thus excludes any costs associated with all consequences of system failure, as the occurrence of failure is represented through the reliability criterion. The desired I&M strategy $\mathcal{S}^*$ is the solution to this minimization problem:

$$\mathcal{S}^* = \arg\min_{\mathcal{S}} \left[C_{I,T}(\mathcal{S}) + C_{PM,T}(\mathcal{S}) + C_{CM,T}(\mathcal{S}) \right], \tag{9}$$
$$\text{such that } \forall \text{ I\&M history } \boldsymbol{M}, \forall t,\ H(t, \boldsymbol{M}_{0:t^-}, \mathcal{S}) \leq p_0.$$

4.2. Heuristic formulation

The planning problem expressed in Equation (9) is very difficult to solve, in part because it is not feasible to explore the entire space of all possible I&M strategies $\mathcal{S}$. Several methodologies have been developed to address the risk-based I&M planning problem (Yang and Trapp, 1975; Bloch et al., 2000; Durango and Madanat, 2002; Straub, 2004; Nielsen and Sørensen, 2011; Papakonstantinou and Shinozuka, 2014; Nielsen and Sørensen, 2015; Memarzadeh and Pozzi, 2016; Schöbi and Chatzi, 2016; Papakonstantinou et al., 2018). Reliability-based planning has also been investigated (e.g., Frangopol et al., 1997; Barker and Newby, 2009; Faddoul et al., 2018), however these methodologies generally assume a cost of system failure, which we here do not explicitly consider.

The heuristic optimization approach formalized by Bismut and Straub (2021) gives an approximate solution to Equation (9). Its appeal resides in the fact that one can explicitly include operational constraints in the definition of a suitable plan. A heuristic is defined by a set of rules associated to a set of parameters $\boldsymbol{\omega} = \{\omega_1, ..., \omega_n\}$ so that an I&M strategy is fully defined by the heuristic and the values of its parameters. An example rule is that I&M campaigns take place at fixed time intervals and the associated heuristic parameter is the interval ΔT. Another possible rule is to replace a pipe if the inspected wall thickness is lower than a threshold d_C, with d_C being the heuristic parameter. A heuristic strategy is well defined when every decision can be resolved, such that the questions when and where to inspect and repair are clearly answered.

The optimization of Equation (9) is restricted to a chosen heuristic and is thus reduced to an optimization of the parameter values ω_l.

$$\min_{\boldsymbol{\omega}} C_{I,T}(\boldsymbol{\omega}) + C_{PM,T}(\boldsymbol{\omega}) + C_{CM,T}(\boldsymbol{\omega}), \tag{10}$$
$$\text{s. t. } \forall \text{ I\&M history } \boldsymbol{M}, \forall t,\ H(t, \boldsymbol{M}_{0:t^-}, \boldsymbol{\omega}) \leq p_0.$$

The selected heuristic has an effect on how optimal the strategy resulting from Equation (10) is with respect to Equation (9). Choosing the heuristic is in itself an optimization problem. An important aspect is for instance the rules for selecting pipes for inspection and for maintenance. This selection can be random, or guided by a prioritization index of sorts (Bismut et al., 2017). In the heuristic chosen for the numerical investigation (see Section 7.3), we base the pipe inspection prioritization on the potential reduction in uncertainty, linked to the coefficient of variation of the distribution of the pipe thickness at a given time. The selection of the 'critical' pipes (PM pool) is based on the probability of pipe failure.

With the heuristic formulation, the reliability constraint can be integrated directly into the maintenance rules, which results in the modified history diagram of Figure 4, where pipe replacements are carried out specifically to satisfy the reliability criterion. An example of the annual system failure rate, where the I&M history is such that it follows the strategy and the constraint, is shown in Figure 5, for two different strategies. The underlying computations are detailed in Section 6. We note that the life-cycle I&M cost associated with a history, for which the system does not comply with the criterion (i.e., the branch "major intervention" is reached at some point during the service life), is high. This ensures that strategies which lead to a high number of non-compliant histories are avoided during the optimization process explained in Section 4.3 below, without requiring a system failure cost to be defined.

4.3. Heuristic parameters optimization method

We implement the algorithm developed in (Bismut and Straub, 2021) to optimize the heuristic parameters, based on the cross-entropy (CE) method (Rubinstein and Kroese, 2004). An initial sampling density over parameters $\omega_1, \ldots, \omega_n$ is chosen, for instance a Gaussian distribution. At each iteration, n_S sample sets of parameter values are generated from the CE sampling density. For each sample set, the expected cost of the associated strategy is evaluated with n_{MC} samples.

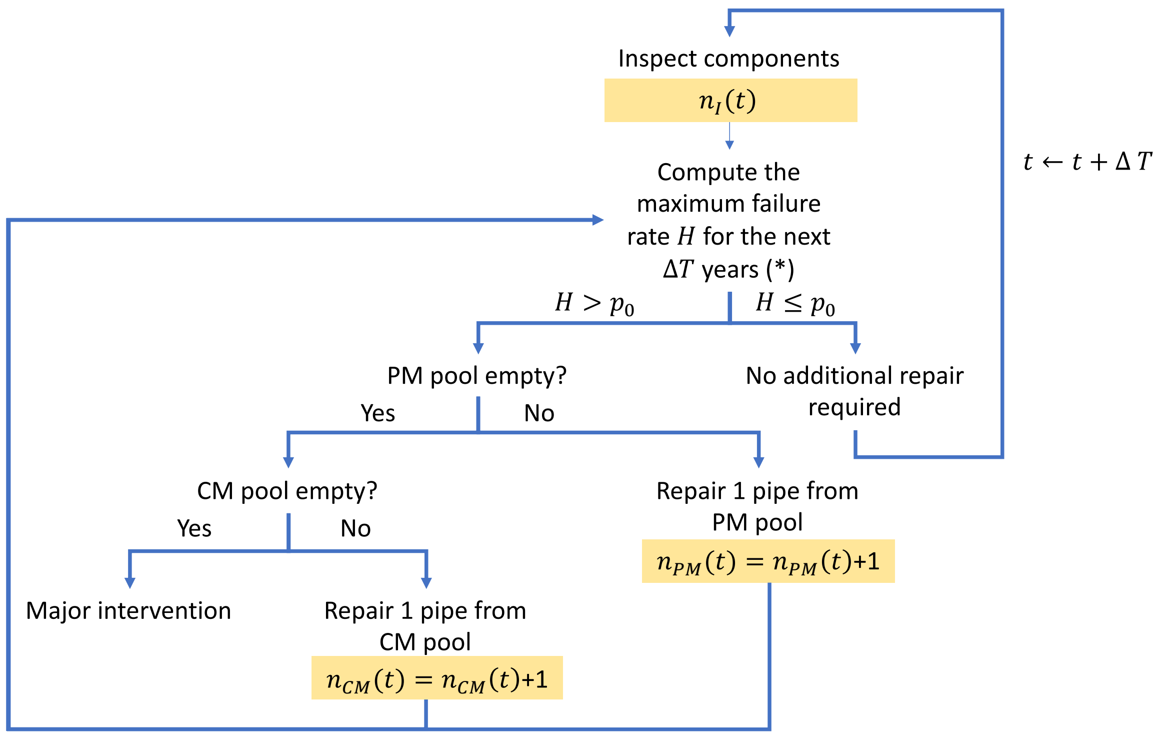
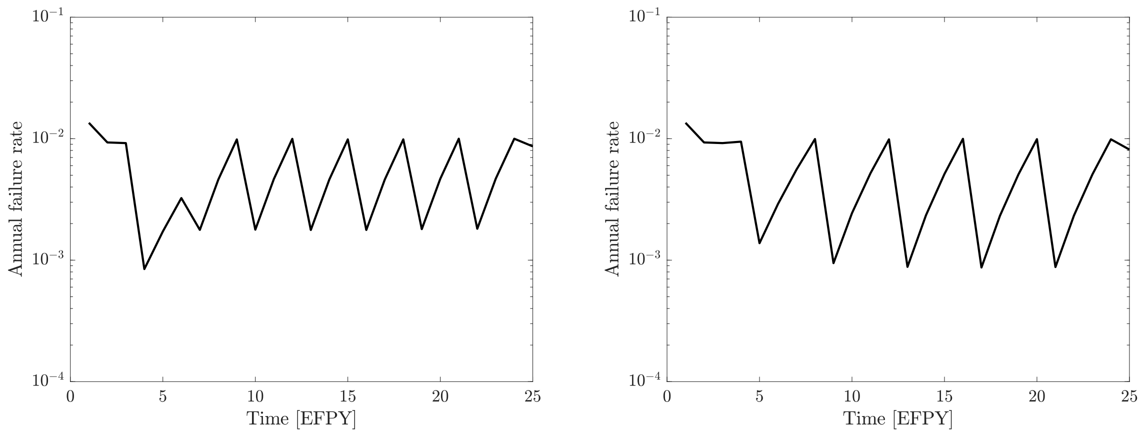


Figure 4: Trajectory simulation for heuristic strategy evaluation under reliability constraint p_0.

The sample sets are ranked in increasing order of expected cost. The CE sampling density for the next iteration is smoothly updated using the parameter values of the top n_{CE} sample sets. In the numerical investigation, we choose $n_S = 100$ and $n_{CE} = 20$. The CE optimization stops after 20 iterations, resulting in a total of 2000 sample strategies. This has proven to allow satisfying convergence of the sampling density. The optimal heuristic parameter values are given by the mean of the final sampling density.

The value of the expected cost evaluated with Equation (8) of a strategy is subject to sampling noise. The accuracy depends on the number of sample histories n_{MC} generated to compute the expected cost. Here, we find that $n_{MC} = 10$ provides suitable results for the CE optimization method. The advantage of assigning a small value to n_{MC} is that little computational effort is spent on non-suitable, i.e., expensive, strategies. Previous works have demonstrated the efficiency of this computational setup (Bismut and Straub, 2021).

Finally, the expected cost associated with the identified optimal heuristic parameters is esti-



(a) (b)

Figure 5: Evolution of the annual failure rate $H(t, M_{0:t^-}))$ for a sample history, following two I&M strategies with different inspection intervals (a) $\Delta T = 3$ and (b) $\Delta T = 4$. In both cases, the strategy ensures that the system complies with the reliability constraint $p_0 = 1.0 \cdot 10^{-2}$, but the second strategy does so in a more efficient manner (see Tables 3 and 4).

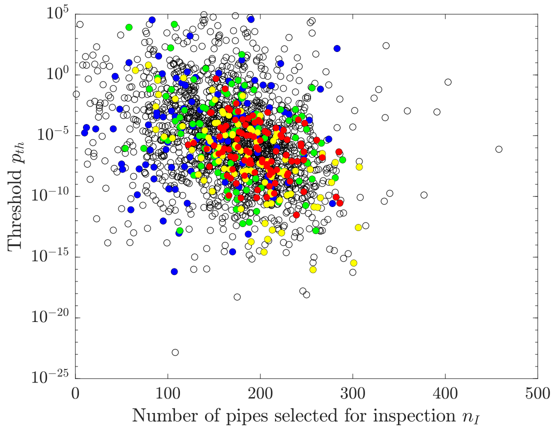
mated with Equation (8) with 2000 MC sample histories.

The convergence of the CE method is illustrated in Figure 6, where the sampling progression is shown for two different initial sampling distributions. There is a variation in the obtained optimal heuristic parameter values, which reflects the higher or lower sensitivity of the objective function to the parameters.

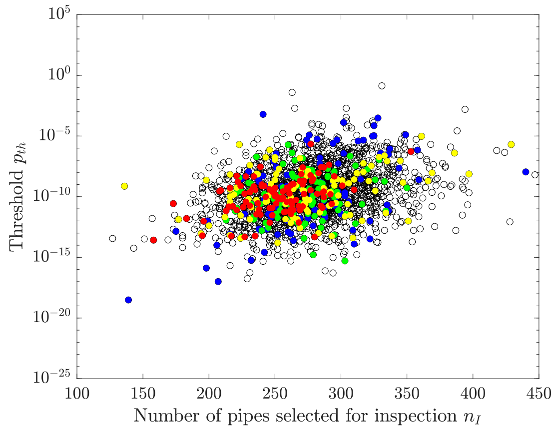
5. Models of pipe deterioration and inspection and repair models

5.1. Modeling FAC with a mixed-scale Gamma process

Mechanistic models of FAC have been developed (e.g., Lister and Lang, 2002), but they require the knowledge of numerous parameters characterizing the operating condition of the operator, such as the chemical environment, temperature and pH levels, which typically fluctuate over time. It is therefore appropriate to model the evolution of FAC with a random process. Here, we model the evolution of FAC in the N pipe bends with a mixed-scale Gamma process (Lawless and Crowder, 2004).



(a)



(b)

Figure 6: 2000 CE samples for the constrained optimization with $p_0 = 1.0 \cdot 10^{-2}$, for two different initial sampling densities. Each point represents a specific I&M strategy, defined by parameters n_I and p_{th}. $\Delta T = 3$[EFPY] is fixed. The expected cost of each strategy is evaluated with 10 sample histories. Samples belonging to CE iterations 5, 10, 15 and 20 are represented with dots of color blue, green, yellow and red, respectively. a) The optimal heuristic strategy obtained from the last iteration is $n_I = 195$ and $p_{th} = 5.6 \cdot 10^{-7}$ with expected cost 379.1 (see Table 3). b) The optimal heuristic strategy obtained from the last iteration is $n_I = 246$ and $p_{th} = 2.5 \cdot 10^{-10}$. The resulting expected cost for this strategy is 388.9, which is close to the cost for the strategy obtained in a).

The service life between time 0 and T is discretized in time steps, corresponding to 1 EFPY. The loss of thickness in one tube i due to corrosion is modelled by a Gamma process with stationary increments ΔD_τ, with strictly positive shape and scale parameters $[\alpha, \beta]^\intercal$ (Hazra et al., 2020b). We denote by $\mu = \alpha\beta$ the mean and by $\nu = \frac{1}{\sqrt{\alpha}}$ the coefficient of variation of these increments. μ and ν are population parameters, common to all pipes.

The wall thinning ΔD in Δt time steps is written as the sum of i.i.d yearly increments ΔD_τ

$$\Delta D = \sum_{\tau=1}^{\Delta t} \Delta D_\tau. \tag{11}$$

ΔD is Gamma distributed with shape and scale parameters $[\alpha \Delta t, \beta]^\intercal$.

$F_{\Delta D, \Delta t}(d)$ and $f_{\Delta D, \Delta t}(d)$ denote the associated cumulative distribution function (cdf) and probability density function (pdf) for a given Δt. It is

$$f_{\Delta D,\Delta t}(d) = \frac{1}{\Gamma(\alpha\Delta t)\,\beta^{\alpha\Delta t}} d^{\alpha\Delta t-1} \exp\left(-\frac{d}{\beta}\right). \tag{12}$$

In the mixed-scale Gamma process, $\nu_i = \nu$ is a known constant and the mean of the yearly increment μ is modelled as a random variable, with an inverse Gamma distribution, here denoted by $IGa(a,b)$, with prior shape and scale parameters $[a,b]$. The inverse Gamma pdf with parameters $[a,b]$ is

$$f(\mu) = \frac{b^a}{\Gamma(a)} \left(\frac{1}{\mu}\right)^{a+1} \exp\left(-\frac{b}{\mu}\right). \tag{13}$$

The distribution of the mean μ is updated through measurements of pipe thicknesses, following Section 6.3.

The choice of the prior distribution in a parameter learning context, performed with Bayesian analysis, becomes less important as more inspection data are gathered. In the context of pre-posterior analysis, where we are interested in computing an expected cost, choosing an appropriate prior has a significant effect on the outcome of the analysis. For a plant-specific optimization, the calibration of the prior distribution of the population parameters can be done by using past inspection data. When no specific information is available, expert knowledge can be a good starting point. The prior parameters a and b of the model are given in Section 7.1 for I&M planning of a new plant.

5.2. *Inspection model*

During a I&M campaign, information is collected on the state of deterioration of the pipes through in-situ inspections. The inspections are carried out with an array of ultrasonic probes to measure the wall thickness. In practice, one probe scan measures the thickness of one quadrant of the pipe bend and four scans are required for full inspection of one pipe bend. The minimum wall thickness from those scans is recorded. The recorded wall thickness at time t of pipe i is $M_i(t)$. For simplicity, we consider the measurement to be perfect, hence

$$M_i(t) = W_i(t). \tag{14}$$

The presented approach can also be used when the observation likelihood includes measurement error. The associated computational aspects are discussed in Section 6.5.

5.3. Repair model

Replacing a pipe at time t sets the wall thinning back to 0, i.e., $W_i(t) = W_i(0)$ and $D_i(t) = 0$ immediately after repair at time t.

6. Piping system reliability

6.1. Probability of cumulative system failure

During the execution of the strategy, the reliability constraint must be met. To verify the criterion, one must compute at each step t the annual failure rate of the system as per Equation (2). As per the definitions given in Sections 2.1 and 3.3, the cumulative system failure at time t is

$$F_{cumu}(t) = \bigcup_{\tau \leq t} F(\tau) = \bigcup_{\tau \leq t} \bigcup_{i} F_i(\tau). \tag{15}$$

The probability of this cumulative failure event must be computed conditional on the inspection outcomes and repair actions up to time t.

We use the notation $D_i(t) = D_{i,t}$, and similarly for all time-variant random variables. At every time t [EFPY] we evaluate the probability $P_{max}(t) = \Pr(F_{cumu}(t)|\boldsymbol{M}_{0:t^-})$. $\boldsymbol{\Theta}$ denotes the model parameters. Here $\boldsymbol{\Theta} = \mu$.

Using Equation (15), one finds

$$P_{max}(t) = 1 - \Pr\left(\bigcap_{\tau \leq t} \bigcap_{i} \{D_{i,\tau} < d_{max}\} | \boldsymbol{M}_{0:t^-}\right). \tag{16}$$

Conditionally on Θ, the deterioration processes and measurements of pipes $i \neq j$ are independent. Conditioning on Θ, one obtains

$$P_{max}(t) = 1 - \int_{\Omega_{\boldsymbol{\Theta}}} \prod_{i} \Pr\left(\bigcap_{\tau \leq t} \{D_{i,\tau} < d_{max}\} | \boldsymbol{M}_{i,0:t^-}, \boldsymbol{\theta}\right) f_{\boldsymbol{\Theta}|\boldsymbol{M}_{0:t^-}}(\boldsymbol{\theta}) \mathrm{d}\boldsymbol{\theta}, \tag{17}$$

where $f_{\boldsymbol{\Theta}|\boldsymbol{M}_{0:t^-}}(\boldsymbol{\theta})$ is the posterior pdf of $\boldsymbol{\Theta}$ conditional on the measurements $\boldsymbol{M}_{0:t^-}$.

The posterior distribution of $\boldsymbol{\Theta}$ is obtained with Bayes' rule:

$$f_{\boldsymbol{\Theta}|\boldsymbol{M}_{0:t^-}}(\boldsymbol{\theta}) \propto \mathcal{L}(\boldsymbol{\theta};\boldsymbol{M}_{0:t^-})f_{\boldsymbol{\Theta}}(\boldsymbol{\theta}). \tag{18}$$

$\mathcal{L}(\boldsymbol{\theta};\boldsymbol{M}_{0:t^-})$ is the likelihood of $\boldsymbol{M}_{0:t^-}$ conditional on $\boldsymbol{\Theta}$. The normalizing constant is $c = \int_{\Omega_{\boldsymbol{\Theta}}} f_{\boldsymbol{\Theta}}(\boldsymbol{\theta})\mathcal{L}(\boldsymbol{\theta};\boldsymbol{M}_{0:t^-})\mathrm{d}\boldsymbol{\theta}$. The measurements are independent conditionally on Θ. This is actually an approximation, due to the selection bias (Nie et al., 2018). We will not correct this bias, as it does not significantly affect our results.

Thus

$$\mathcal{L}(\boldsymbol{\theta};\boldsymbol{M}_{0:t^-}) = \prod_i \mathcal{L}(\boldsymbol{\theta};\boldsymbol{M}_{i,0:t^-}). \tag{19}$$

$\mathcal{L}(\boldsymbol{\theta};\boldsymbol{M}_{i,0:t^-})$ is the likelihood of $\boldsymbol{M}_{i,0:t^-}$ conditional on $\boldsymbol{\Theta}$.

As stated in Section 5.2, we consider that there is no uncertainty in the measurement. Hence for $\tau < T$ we have $M_{i,\tau} = W_{i,0} - D_{i,\tau}$, where the initial thickness $W_{i,0}$ is also known. The conditional probability of pipe failure and the posterior distribution of parameter $\boldsymbol{\Theta}$ are derived in the paragraphs below.

6.2. Conditional probability of cumulative pipe survival

For a fixed time t, we denote by $\mathcal{I}_i = \{t_{I,1} < ... < t_{I,p}\}$ the inspection times and by $\mathcal{R}_i = \{t_{R,1} < ... < t_{R,q}\}$ the repair times of component i up to and not including time t. If no inspection occurred, $\mathcal{I}_i = \emptyset$. If no repair occurred prior to time t, $q = 1$ and $t_{R,1} = 0$.

For a given pipe, the deterioration process is monotonously increasing in the interval between two subsequent replacements. Therefore, the intersection of pipe survival events in Equation (17) is equivalent to

$$\bigcap_{\tau \le t} \{D_{i,\tau} < d_{max}\} = \{D_{i,t} < d_{max}\} \bigcap \{\cap_{1\le j\le q}\{D_{i,t_{R,j}} < d_{max}\}\}. \tag{20}$$

The state of pipe deterioration is furthermore independent of all states and measurements previous to the last repair time. This and the above simplification allow writing the conditional probability of cumulative pipe survival as

$$\Pr\left(\bigcap_{\tau\leq t}\{D_{i,\tau}<d_{max}\}|\boldsymbol{M}_{i,0:t^-},\boldsymbol{\theta}\right)=\Pr\left(D_{i,t}<d_{max}|\boldsymbol{M}_{i,t_{R,q}:t^-},\boldsymbol{\theta}\right)\cdot\prod_{1\leq j\leq q}\Pr\left(D_{i,t_{R,j}}<d_{max}|\boldsymbol{M}_{i,t_{R,j-1}:t_{R,j}},\boldsymbol{\theta}\right), \tag{21}$$

where $t_{R,0}=0$.

The distribution of state $D_{i,\tau}$ at time τ before any repair or inspection is fully determined either by the time of the last repair before τ or by the last measurement, whichever is more recent. Let τ_i be the larger of these times of last repair and last measurement.

– If repair occurred at time τ_i,

$$\Pr(D_{i,\tau}<d_{max}|\boldsymbol{M}_{i,0:\tau^-},\boldsymbol{\theta})=F_{\Delta D,\tau-\tau_i|\boldsymbol{\theta}}(d_{max}). \tag{22}$$

– If a measurement M_{i,τ_i} was obtained at time τ_i,

$$\Pr(D_{i,\tau}<d_{max}|\boldsymbol{M}_{i,0:\tau^-},\boldsymbol{\theta})=\Pr(D_{i,\tau}<d_{max}|\boldsymbol{M}_{i,\tau_i},\boldsymbol{\theta})=F_{\Delta D,\tau-\tau_i|\boldsymbol{\theta}}(d_{max}-(W_{i,0}-M_{i,\tau_i})). \tag{23}$$

The distribution of state $D_{i,\tau}$ after inspection at time τ, $M_{i,\tau}$ is simply the Dirac density in $M_{i,\tau}$.

$$\Pr(D_{i,\tau}<d_{max}|M_{i,\tau},\boldsymbol{\theta})=\mathbb{1}_{W_{i,0}-M_{i,\tau}\leq d_{max}}, \tag{24}$$

where $\mathbb{1}_{W_{i,0}-M_{i,\tau}\leq d_{max}}$ takes the value 1 if $W_{i,0}-M_{i,\tau}\leq d_{max}$, 0 otherwise.

6.3. Likelihood and posterior distribution of deterioration parameters

Using the chain rule and the Markovian assumption, the likelihood $\mathcal{L}(\boldsymbol{\theta};\boldsymbol{M}_{i,0:t^-})$ can be computed sequentially. For each $t_j\in\mathcal{I}_i$, we compute the time interval $\Delta t_j=min(t_j-t_k,\ s.t.\ t_k\in\mathcal{R}_i\ and\ t_k<t_j)$ between inspection time t_j and the time of last repair (0 if the pipe has never been repaired). The likelihood describing measurements on pipe i is

$$\mathcal{L}(\boldsymbol{\theta};\boldsymbol{M}_{i,0:t^-})=\prod_{j\in\mathcal{I}_i}f_{\Delta D,\Delta t_j|\boldsymbol{\theta}}(W_{i,0}-M_{i,t_j}). \tag{25}$$

The rate parameter $1/\beta = 1/(\mu\nu^2)$ of the Gamma process (see Section 5.1) is also Gamma distributed. Making use of the self-conjugacy of the Gamma distribution (Robert, 2007), the posterior (filtered) distribution of $\Theta = \mu$ can be obtained by updating the parameters of the inverse gamma distribution with the (perfect) measurements $\boldsymbol{M}_{0:t^-}$, such that $\Theta|\boldsymbol{M}_{0:t^-} \sim IGa(a_{post}, b_{post})$, with

$$a_{post} = a + \frac{\sum_{j\in\mathcal{I}_i} \Delta t_j}{\nu^2}, \tag{26}$$

$$b_{post} = b + \frac{\sum_{j\in\mathcal{I}_i} (W_{i,0} - M_{i,t_j})}{\nu^2}. \tag{27}$$

6.4. Posterior distribution of pipe deterioration state

The scaled deterioration state at time t conditional on past history $\boldsymbol{M}_{0:t^-}$, $(D_{i,t} - d_M)/\xi$, with $\xi = \frac{b_{post}(t-\tau_i)}{a_{post}}$, follows the Fisher–Snedecor distribution with degrees of freedom $\frac{2(t-\tau_i)}{\nu^2}$ and $2a_{post}$ (Lawless and Crowder, 2004; Yuan, 2007). The cdf of this distribution is denoted by $F_{\frac{2(t-\tau_i)}{\nu^2},2a_{post}}(\cdot)$. τ_i is defined as in Section 6.2 above as the larger of the times of last repair and last measurement before the considered time t and $d_M = 0$ if repair occurred at τ_i, $d_M = W_0 - M_{i,\tau_i}$ otherwise.

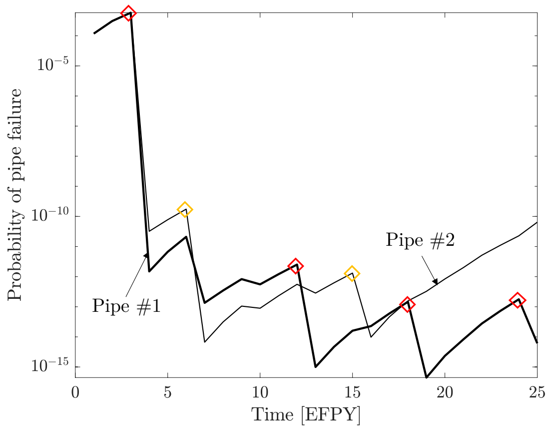
The posterior distribution of $D_{i,t}$ is characterized by its mean $\frac{b_{post}(t-\tau_i)}{a_{post}-1} + d_M$ and its standard deviation $\frac{b_{post}(t-\tau_i)}{a_{post}-1}\sqrt{\frac{\frac{(t-\tau_i)}{\nu^2}+a_{post}-1}{\frac{(t-\tau_i)}{\nu^2}(a_{post}-2)}}$. The associated coefficient of variation is

$$c.o.v.(D_{i,t}|\boldsymbol{M}_{0:t^-}) = \frac{1}{1+\frac{d_M(a_{post}-1)}{b_{post}(t-\tau_i)}}\sqrt{\frac{\frac{(t-\tau_i)}{\nu^2}+a_{post}-1}{\frac{(t-\tau_i)}{\nu^2}(a_{post}-2)}}. \tag{28}$$

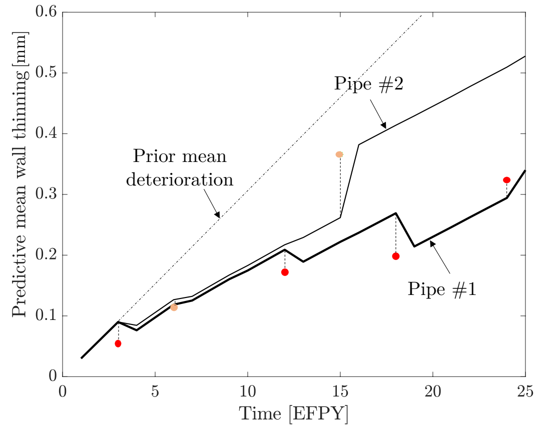
The probability of pipe failure is

$$\Pr(D_{i,t} > d_{max}|\boldsymbol{M}_{0:t^-}) = 1 - F_{\frac{2(t-\tau_i)}{\nu^2},2a_{post}}\left((d_{max} - d_M)/\xi\right). \tag{29}$$

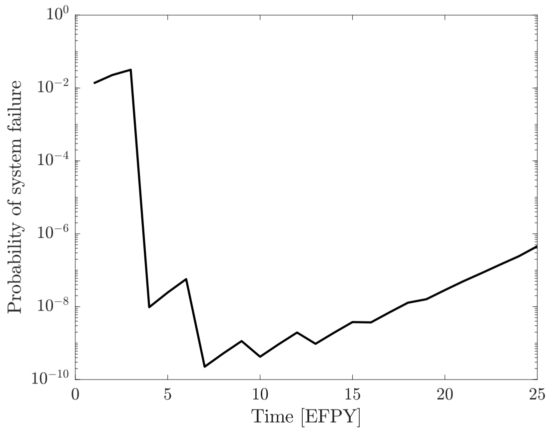
The evolution of probability of pipe failure and expected value of pipe thickness and the resulting system probability of failure and annual failure rate are depicted in Figure 7 for sample histories.



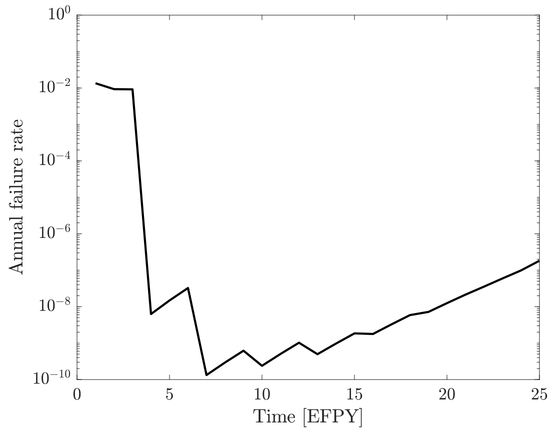
(a)



(b)



(c)



(d)

Figure 7: a) Filtered probability of pipe failure $\Pr(D_{i,t} > d_{max}|\boldsymbol{M}_{0:t^-})$, for pipes number 1 and 2. The diamonds on each curve indicate when the pipes were inspected. b) Evolution of the mean wall thinning D_i for pipes number 1 and 2. The dots represent the measurements reported for the pipes. c) Filtered cumulative probability of system failure $P_{max}(t)$. d) Annual failure rate.

6.5. Computation details

When the observation likelihood does not include measurement error, the integrand of Equation (17) has a closed form and a numerical integration is appropriate to evaluate $P_{max}(t)$.

On the contrary, if a measurement error is included in Equation (14), the product of conditional probabilities of pipe survival in Equation (17) is a product of integrals which do not have a closed form. Equation (17) is an integral in high-dimensional space involving complex pdfs, for which adapted integration methods must be considered; for instance a dynamic Bayesian network model where each random variable is discretized is suitable for performing Bayesian inference in large systems (Luque and Straub, 2016; Bismut and Straub, 2021).

7. Numerical investigation: I&M planning at the beginning of service life.

We apply the framework to evaluate I&M strategies for the piping system in a new NPP, at the beginning of its service life.

7.1. Planning setup

The model used for simulating sample histories for evaluating strategies is described in Section 5. Its prior parameters are summarized in Table 1. The costs are found in Table 2 below.

Table 1: Prior deterioration model parameters

Parameter	Type	Value / Distribution	Unit
μ	Random variable	$IGa(a,b)$	mm
ν	Deterministic	2	
a	Deterministic	3	
b	Deterministic	0.06	
W_0	Deterministic	5.5	mm
$D_i(0)$	Deterministic	0	mm
d_{max}	Deterministic	2.2	mm

The prior expected value of μ is 0.03[mm/EFPY] and the c.o.v. 100%. The choice of this prior model is based on the analysis of historical events: Lister et al. (1997) states that wear rates at 0.02[mm/EFPY] are "acceptable". There is however a high variability in the wear rate. Indeed, wear rates between 0.07[mm/EFPY] and 0.2[mm/EFPY] have been recorded (Lister et al., 1997; Hazra et al., 2020a). Usually, the reported wear rates in the literature are obtained from

Table 2: Cost model

Campaign	c_C	1
Pipe inspection	c_I	0.1
Preventive maintenance	c_{PM}	1
Corrective maintenance	c_{CM}	5
Discount rate	r	0.05

"lead feeders", i.e., feeders which experience larger rate of degradation than an average feeder in the population, and are therefore not representative of the average degradation rate. This high uncertainty in the prior FAC wear rate is here reflected in the high c.o.v. This may be a pessimistic assumption about the state of knowledge about the deterioration process in NPP piping systems. The probability that the mean wear rate exceeds 0.08[mm/EFPY] is 5%. The value of $\nu = 2$ is such that the probability of pipe failure at the end of service life is $4 \cdot 10^{-2}$. The resulting annual failure rate of the system for the non-maintained system is shown in Figure 8.

We investigate the following reliability criteria: $p_0 \in \{0.1, 0.5, 1.0, 1.5, 5.0\} \cdot 10^{-2}$.

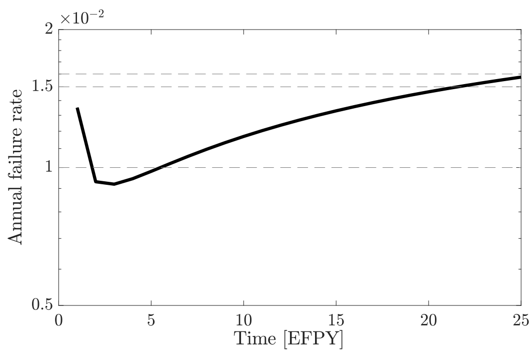


Figure 8: Annual failure rate for the non-maintained, non-inspected system. The levels $\{0.5, 1.0, 1.5, 1.6\} \cdot 10^{-2}$ are also indicated.

7.2. Constrained representative strategy $\mathcal{S}_{REP}$

7.2.1. Description of the strategy and associated FAC prediction model

To test the reliability-constrained strategy approach of Section 3, we consider a strategy $\mathcal{S}_{REP}$ representative of the current I&M practice. (EPRI, 2013; Walker, 2017) provide guidelines for implementing I&M programs specifically targeted to avoid FAC-related failures. The current approach to I&M of piping system typically assumes deterministic prediction models models for FAC. The inspection data is processed with basic statistical tools. Uncertainty is addressed in a semi-probabilistic manner, with safety factors applied to the predicted wear rate.

The inspection plan follows the logic of inspecting critical pipes, which have a small predicted remaining service life, as well as pipes that have not yet been inspected (EPRI, 2013; Walker, 2017). At each I&M campaign, 30% of pipes are inspected, here 140 pipes. As previously stated, this I&M strategy does not allow for I&M campaigns outside of the fixed times. The maintenance interval is fixed at 3 years. Preventive and corrective maintenance prescribed by the strategy are only carried out on pipes which have been inspected.

The strategy is summarized below.

Strategy $\mathcal{S}_{REP}$ - 140 pipes are inspected at each campaign and $\Delta T = 3$[EFPY] is fixed.

- The interval between I&M campaigns is $\Delta T = 3$ [EFPY].
- Pipe inspections: Inspect pipes that have been labelled 'of interest' and those labelled as 'critical' for preventive maintenance at the previous I&M campaign. The two groups of pipes are not necessarily mutually exclusive.
- Preventive maintenance: pipes that have been previously labelled critical and therefore have just been inspected are considered. The pipes i for which the predicted thickness at the next I&M campaign $W_{i,pred}(t+\Delta T) < W_{accept}$ are repaired, at a unit cost c_{PM}.
- Corrective maintenance: the predicted wall thickness $W_{i,pred}(t+\Delta T)$ at the next I&M campaign at time $t+\Delta T$ is computed for each inspected pipe (which has not been already repaired during preventive maintenance) i. All pipes for which $W_{i,pred}(t+\Delta T) < W_{accept}$ are replaced now (at time t).

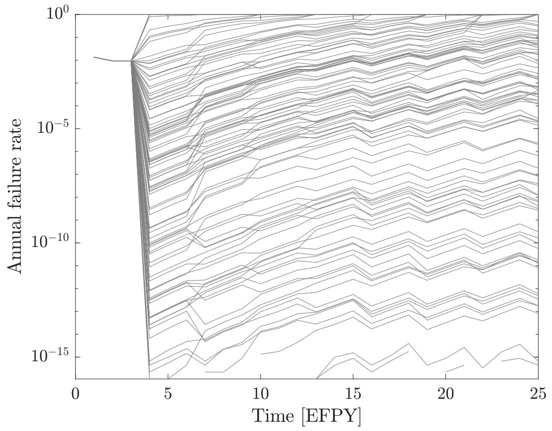
<u>Planning for the next campaign</u>

- Plan predictive maintenance for campaign at time $t+\Delta T$: Pipes for which $W_{i,pred}(t+2\Delta T) < W_{accept} < W_{i,pred}(t+\Delta T)$ are labelled as 'critical' for the next I&M campaign.
- Plan inspections for next campaign: 140 pipes are selected for inspection. A proportion of 70%, i.e., 98 pipes, are selected in decreasing order of time to last inspection, and the remaining 30%, i.e., 42 pipes, are selected according to their estimated remaining service life (Equation (A.3)).

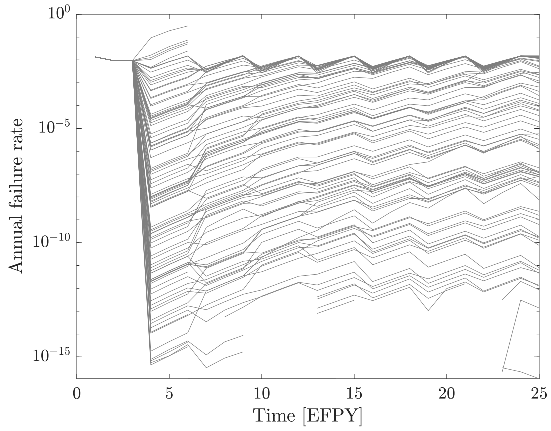
$W_{i,pred}$ is computed using the FAC-predictive model (see Appendix A) and $W_{accept} = W_0 - d_{max}$.

7.2.2. Unconstrained vs constrained strategy

Figure 9a depicts samples of the evolution of the annual failure rate H following the unconstrained strategy $\mathcal{S}_{REP}$. It is clear that for a fixed reliability level, say $p_0 = 1.5 \cdot 10^{-2}$, many trajectories exceed the threshold. On the other hand, for the trajectories that do comply with the criterion, it is possible that superfluous inspections or pipe replacement have taken place, in terms of maintaining the reliability level. Figure 9b shows samples of the evolution of the annual failure rate following the constrained strategy. Only the histories which would have exceeded the criterion are affected by the reliability constraint.



(a)



(b)

Figure 9: a) Annual failure rate $H(t, \boldsymbol{M}_{0:t^-})$, following unconstrained strategy $\mathcal{S}_{REP}$ for 100 sample I&M histories. b) Annual failure rate following the strategy $\mathcal{S}_{REP}$ constrained to $p_0 = 1.5 \cdot 10^{-2}$.

7.3. Heuristic investigated

For the reliability-based heuristic planning, we investigate the following Heuristic A. The selection rule for pipe inspection is done by ranking the pipes according to their coefficient of variation of the wall thickness loss. This reflects the primary goal of an inspection, which is to reduce the uncertainty about the state of the system. The PM pool is composed of pipes for which the probability of pipe failure exceeds a fixed threshold. PM and CM actions are furthermore carried out as outlined in Figure 4.

Heuristic A - Parameters ΔT, n_I, p_{th}

- ΔT is the constant inspection interval. The only I&M opportunities are at the planned inspection times.
- Pipe inspection at first campaign: n_I pipes are randomly selected and inspected.
- Pipe inspection at next campaigns: n_I is the number of pipes selected for inspection (labelled 'of interest') at each campaign, according to the prioritization rule (see point below). To these pipes are added those that have been labelled as 'critical' for preventive maintenance [at the previous I&M campaign]. An overlap between these two groups is possible. Hence, there is a minimum of n_I pipes inspected at each campaign.

Planning for the next campaign

- Pipes are selected for preventive maintenance at time $t+\Delta T$ (labelled as 'critical') based on their probability of failure $\Pr(D_i(t+\Delta T) > d_{max}|\boldsymbol{M}_{0:t^-})$ exceeding a threshold p_{th}.
- The pipes are prioritized for inspection as the ones with the highest coefficient of variation of $D_i(t+\Delta T)$, given by Equation (28).

7.4. Results

We evaluate the expected costs of strategy $\mathcal{S}_{REP}$ constrained to the reliability thresholds p_0 and we optimize the heuristic parameters.

First, we fix $\Delta T = 3$[years] to match the I&M campaign interval specified by strategy $\mathcal{S}_{REP}$ above (see Section 7.2). The optimal parameter values obtained for Heuristic A for different values of p_0 are summarized in Table 3. The expected costs of the optimal strategies and of the constrained strategy $\mathcal{S}_{REP}$ are estimated with $n_{MC} = 2000$ MC sample histories. The standard error on the estimation of the expected cost is around $3-4\%$.

We find that the more stringent the criterion is, the higher the expected cost of the optimized I&M plan from Equation (10) and of the constrained strategy $\mathcal{S}_{REP}$. For $p_0 > 1.6\cdot 10^{-2}$, the non-

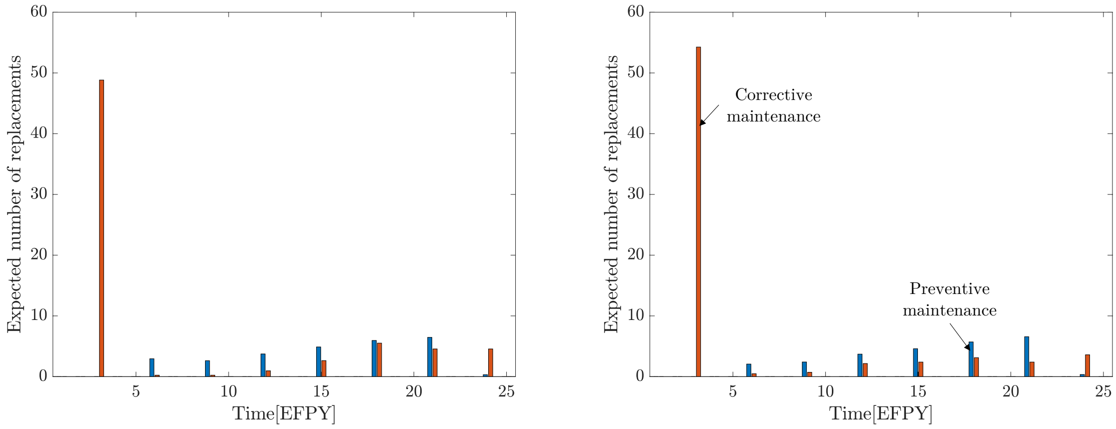
Table 3: Optimized heuristic parameters n_I and p_{th} of Heuristic A (see Section 7.3) for fixed $\Delta T = 3$[EFPY] and associated expected life-cycle I&M cost for different values of p_0. The expected cost of the constrained strategy $\mathcal{S}_{REP}$, for which the total number of inspected pipes per campaign is 140, is indicated for comparison. For p_0 above $1.6 \cdot 10^{-2}$, the best I&M strategy is that which prescribes no inspections or replacements of pipes.

	Optimal heuristic strategy ($\Delta T = 3$[EFPY])		Constrained strategy $\mathcal{S}_{REP}$
p_0 ($\times 10^{-2}$)	Parameters	Expected I&M cost	Expected I&M cost
5.0	$n_I = 0$, $p_{th} = 1$	0	634.6
1.5	$n_I = 152$, $p_{th} = 5.1 \cdot 10^{-7}$	351.4	721.4
1.0	$n_I = 195$, $p_{th} = 5.6 \cdot 10^{-7}$	379.1	840.7
0.5	$n_I = 167$, $p_{th} = 2.0 \cdot 10^{-6}$	399.9	890.7
0.1	$n_I = 147$, $p_{th} = 1.6 \cdot 10^{-4}$	628.5	1137.6

maintained system complies to the reliability level (see Figure 8), thus the optimal I&M costs is 0. For $p_0 < 1.6 \cdot 10^{-2}$, we find that the preventive maintenance planning parameter p_{th} increases with decreasing value of p_0.

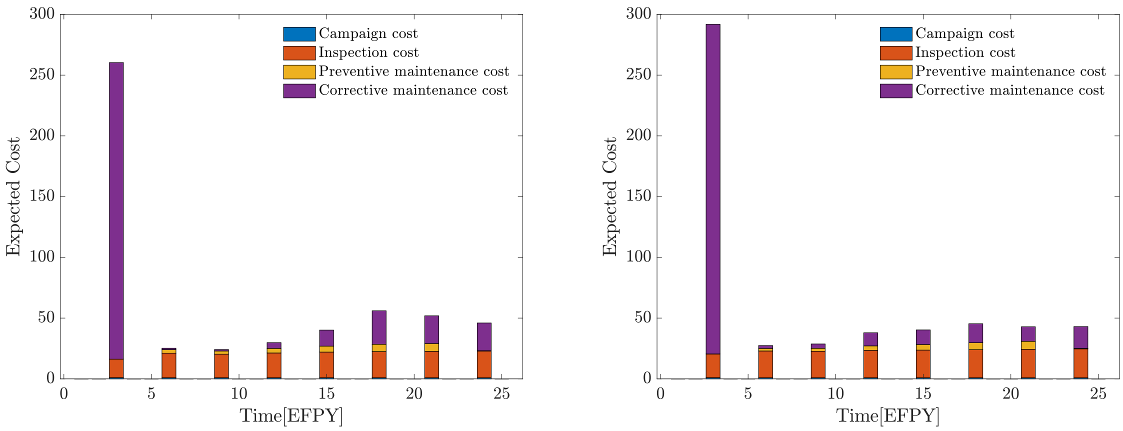
Figure 10 shows the average annual number of pipe replacements during the service life for the optimized heuristic strategy for $p_0 = 1.0 \cdot 10^{-2}$, as an example. The peak at time $t = 3$[EFPY] is due to corrective replacement (and eventual non-compliance of the plant) from early system failure. This effect is reflected in the annual failure rate of the non-maintained system. If the system does not fail in the early years, the number of expected replacement is in the order of magnitude with what is observed in the industry, i.e., that not more than 15 to 20 pipe are replaced, and that the replacements typically occur at the mid-life of the reactor. In addition, we see that the expected number of preventive replacement is in general higher than that of corrective replacement, which indicates that the optimized strategy is efficient in planning preventive maintenance. The corresponding cost breakdown is displayed in Figure 11.

We can compare these costs and actions with the constrained representative strategy $\mathcal{S}_{REP}$, shown in Figure 12. This shows that this strategy does not efficiently plan for preventive maintenance. This can also be due to the fact that the pipes inspected are not optimally selected to reduce the uncertainty in the deterioration rate. The strategy $\mathcal{S}_{REP}$ performs much worse than the opti-



(a) $p_0 = 1.5 \cdot 10^{-2}$ (b) $p_0 = 1.0 \cdot 10^{-2}$

Figure 10: Average number of pipes preventively or correctively replaced, following the optimal heuristic strategy found for a) $p_0 = 1.5 \cdot 10^{-2}$ and b) $p_0 = 1.0 \cdot 10^{-2}$. The initial peak of pipe maintenance is due to the early failure stage identified on Figure 8.

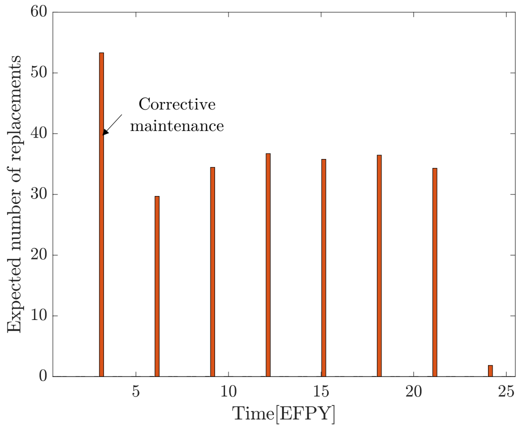


(a) $p_0 = 1.5 \cdot 10^{-2}$ (b) $p_0 = 1.0 \cdot 10^{-2}$

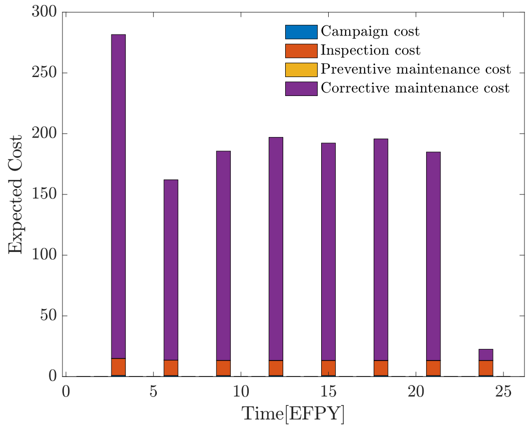
Figure 11: Undiscounted annual breakdown of the life-cycle I&M costs, for the optimal heuristic strategy found for a) $p_0 = 1.5 \cdot 10^{-2}$ and b) $p_0 = 1.0 \cdot 10^{-2}$.

mized heuristic strategies, but can be improved by adapting the selection rules as per the heuristic.

Heuristic A also allows one to vary the campaign interval ΔT. The resulting optimal heuristic



(a)



(b)

Figure 12: a) Average number of pipes preventively or correctively replaced for constrained strategy $\mathcal{S}_{REP}$ for $p_0 = 1.0 \cdot 10^{-2}$. b) Undiscounted annual breakdown of the life-cycle I&M costs, for the optimal heuristic strategy found for $p_0 = 1.0 \cdot 10^{-2}$.

parameters are given in Table 4. The added freedom of varying parameter ΔT yields lower optimal expected costs than those found in Table 3. We identify a clear trend on the optimal interval ΔT, which decreases with decreasing p_0. This is not surprising, as a more stringent reliability criterion will warrant more frequent inspections. The optimal value for p_{th} follows the trend identified above for fixed ΔT. For $p_0 = 1.5 \cdot 10^{-2}$, we note that the strategy recommends to inspect in fact almost all pipes once during the service life.

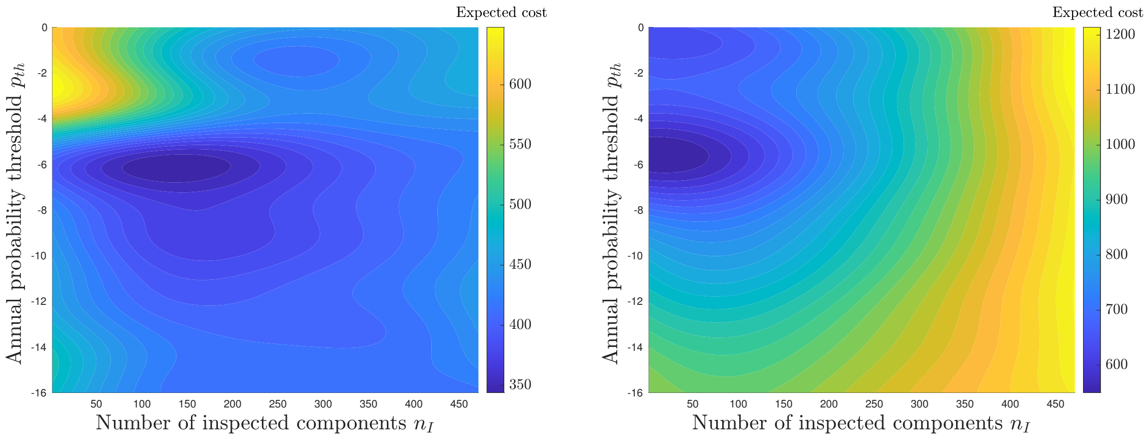
Table 4: Optimized heuristic parameters n_I, p_{th} and I&M campaign interval ΔT. For each value of p_0, the obtained optimal expected cost is lower than that calculated for fixed $\Delta T = 3$[EFPY] in Table 3.

	Optimal heuristic strategy (varying ΔT)	
p_0 ($\times 10^{-2}$)	Parameters	Expected I&M cost
1.5	$n_I = 349$, $p_{th} = 7.9 \cdot 10^{-12}$, $\Delta T = 18$	258.7
1.0	$n_I = 119$, $p_{th} = 2.5 \cdot 10^{-7}$, $\Delta T = 4$	377.5
0.5	$n_I = 117$, $p_{th} = 7.0 \cdot 10^{-6}$, $\Delta T = 2$	392.7
0.1	$n_I = 144$, $p_{th} = 2.9 \cdot 10^{-1}$, $\Delta T = 2$	540.6

7.5. *Sensitivity of expected cost to the heuristic parameters*

Here, we investigate the shape of the expected life-cycle I&M cost function for Heuristic A over the domain of parameters n_I and p_{th}, with fixed $\Delta T = 3$[EFPY], for $p_0 = 1.0 \cdot 10^{-2}$. To do so, we estimate the expected cost with Equation (8) and $n_{MC} = 1000$ sample histories for heuristic strategies defined by the pair (n_I,p_{th}) on a 408-point grid over the domain $p_{th} \in [10^{-16}, 1]$ and $n_I \in [0, 480]$. The estimation of the cost thus obtained at each points is not exact, hence, we fit a Gaussian process to the 408 estimated values to obtain a surrogate of the cost function. The resulting Gaussian field provides the predicted expected cost at for each parameter value set.

Figure 13a depicts the resulting Gaussian field and the predicted expected life-cycle I&M cost for any pair (n_I, p_{th}).



(a) (b)

Figure 13: Expected I&M life-cycle cost in function of p_{th} and n_I, parameters of Heuristic A, for $p_0 = 1.0 \cdot 10^{-2}$. The cost function is estimated by fitting a Gaussian process to values estimated with Equation (8) and $n_{MC} = 1000$, at 408 grid points with coordinates $p_{th} \in \{10^{-16}, 10^{-15}, ..., 10^{0}\}$ and $n_I \in \{20, 40, 60, ..., 480\}$. (a) for the cost model of Table 2; (b) with increased unit inspection cost $c_I = 0.5$.

The surrogate of the expected cost function thus obtained confirms the location of the optimum point found with the CE method. It should be noted that finding optimal heuristic parameter values using the Gaussian process using point estimates arranged in a grid here has a 20 times computation cost than the CE optimization method. A more efficient combination of the two methods is suggested in Bismut and Straub (2021).

We observe that in the vicinity of the found optimum, the expected cost is not highly sensitive to the number of pipes to be inspected at each campaign, n_I. This can reflect two things: first, the cost of pipe inspection is low compared to the cost of maintenance, therefore a variation of the order of 50 pipes inspected does not significantly affect the expected cost; second, the optimal number of inspected pipes is related to the amount of information that is provided by inspecting an additional pipe, which is in turn related to the efficiency of the inspection rule. This low sensitivity to the number of pipes inspected is also observed in Table 3.

It is also possible to see the effect of the cost parameters on the resulting expected cost function and optimal heuristic parameters. We increase 5-fold the unit cost of inspection, such that $c_I = 0.5$, and the expected life-cycle costs are evaluated again by applying Equation (8) with the modified cost parameters. A Gaussian process is fitted again to the 408 grid points. The resulting Gaussian field is depicted in Figure 13b. The effect of a higher inspection cost can be seen in the lower optimal parameter value of n_I, and an increased sensitivity to n_I and p_{th}.

7.6. Effect of the prior

We investigate the sensitivity of the expected cost and optimal heuristic parameters to the choice of the prior. More specifically, we modify the distribution of μ such that the c.o.v. is reduced to 20% from 100%. The annual failure rate for the non-maintained system is depicted in Figure 14. We note that the curve does not possess a bathtub curve shape as in Figure 8.

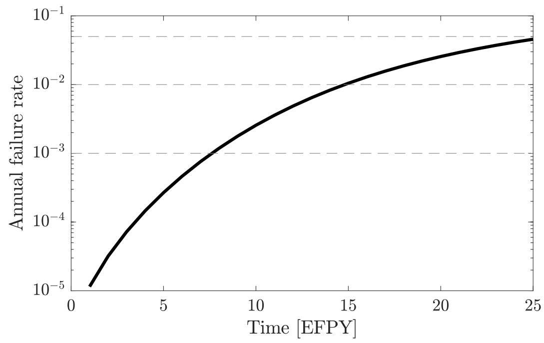


Figure 14: Annual failure rate for the non-maintained, non-inspected system, with a modified prior where the c.o.v of μ is 20%. The levels $\{0.1, 1.0, 5.0\} \cdot 10^{-2}$ are also indicated.

We evaluate strategy $\mathcal{S}_{REP}$ and optimize the heuristic parameters with fixed $\Delta T = 3$[EFPY].

Table 5: Results for modified prior.

	Optimal heuristic strategy		Constrained strategy $\mathcal{S}_{REP}$
p_0 ($\times 10^{-2}$)	Parameters	Expected I&M cost	Expected I&M cost
5.0	$n_I = 0$, $p_{th} = 1$	0	315.7
1.0	$n_I = 122$, $p_{th} = 1.1 \cdot 10^{-2}$	190	744.4
0.1	$n_I = 154$, $p_{th} = 1.4 \cdot 10^{-6}$	214.9	1773.4

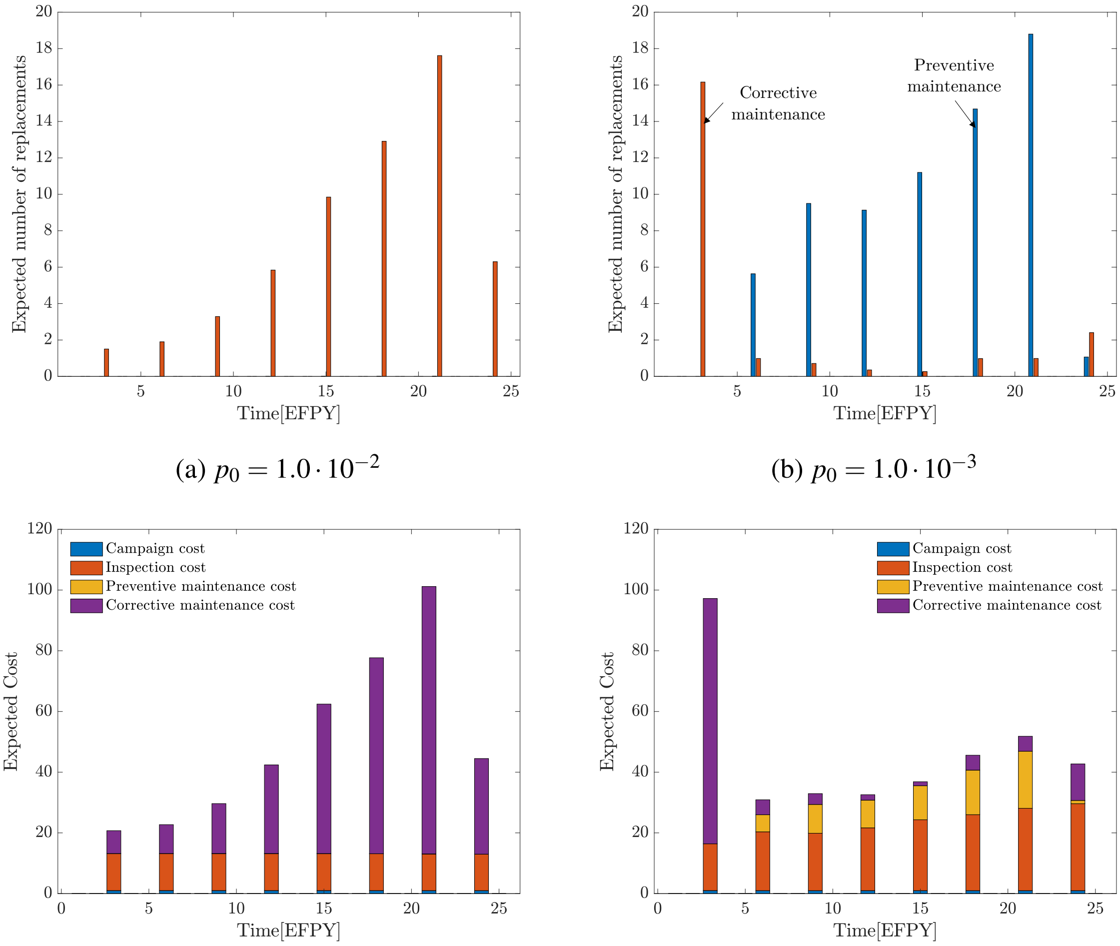
The expected number of pipe replacement and expected annual life-cycle I&M cost for the optimized strategy and the constrained strategy $\mathcal{S}_{REP}$ are detailed in Figure 15. For $p_0 = 1 \cdot 10^{-2}$, we note that the optimal heuristic strategy does not plan for preventive maintenance, and relies only on corrective maintenance to maintain the reliability level. This balance is likely to change with a different cost model. It also shows that the heuristic chosen might not be appropriate for this reliability level.

For lower $p_0 = 1.0 \cdot 10^{-3}$, the heuristic strategy is efficient in collecting information about the system and planning preventive maintenance. The constrained representative strategy $\mathcal{S}_{REP}$ performs noticeably worse. This can be attributed to the fact that it does not allow for more than 140 pipes to be inspected, regardless of the condition of the system, and therefore fails to reduce the uncertainty about the state of the system.

8. Concluding remarks

In this paper, we propose a reliability-based planning framework to improve standard I&M plans for nuclear feeder piping systems. This framework provides the means to assess the performance of any given I&M strategy subject to reliability constraint. It does not require the consequences of failure to be explicitly quantified, which makes it suitable for applications in NPP maintenance. Additionally, a heuristic description of the I&M strategies can be chosen and optimized. The heuristic formulation of the planning opens the possibility to explore different decision rules and to integrate regulatory constraints.

The framework considers a probabilistic predictive model for the deterioration process at the



(a) $p_0 = 1.0 \cdot 10^{-2}$ (b) $p_0 = 1.0 \cdot 10^{-3}$

(c) $p_0 = 1.0 \cdot 10^{-2}$ (d) $p_0 = 1.0 \cdot 10^{-3}$

Figure 15: Top: Average number of pipes preventively or correctively replaced, following the optimal heuristic strategy found for (a) $p_0 = 1.0 \cdot 10^{-2}$ and (b) $p_0 = 1.0 \cdot 10^{-3}$. The initial peak of pipe maintenance is due to the early failure stage identified on Figure 8. Bottom: Undiscounted annual breakdown of the life-cycle I&M costs, for the optimal heuristic strategy found for (c) $p_0 = 1.0 \cdot 10^{-2}$ and (d) $p_0 = 1.0 \cdot 10^{-3}$.

pipe level, with which the piping system reliability can be evaluated over time, including all the past inspection outcomes and maintenance actions.

The numerical application shows that integrating reliability computations in the decision process leads to better decisions and lower life-cycle I&M expected cost, compared to a strategy based on a non-Bayesian prediction model.

The uncertainty in the model affects the outcome of the assessment and heuristic optimization. The values of the prior model parameters can be calibrated based on expert knowledge and similar plant data. This uncertainty in the model parameters can be also addressed through adaptive planning (Bismut and Straub, 2021), whereby the heuristic I&M plan is modified as new information through inspections and monitoring becomes available. The effect of information gain on the improved strategy will be considered in future research.

Here, the model for FAC assumes a constant mean deterioration rate μ across all pipes. Plant data suggest that there are lead feeders in which the deterioration rate is higher than for other pipes Hazra et al. (2020a). This is likely due to geometry aspects, which are not considered here. A future improvement of this framework will include the efficient modelling of pipe groups with correlated wear rates, and will integrate uncertainty on the measurement data.

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Appendix A. FAC-predictive model

For this representative strategy $\mathcal{S}_{REP}$, the pipe replacement criterion is based on a simplified FAC-predictive model, in which the evolution of the wall thickness is described by a linear model with a constant wear rate for each pipe, as recommended by EPRI (2013).

The wear rate for pipe i is estimated as $\hat{R}_i$, based on the thickness measurements of this pipe. For simplicity, it is assumed that the replacement pipe retains the estimated wear rate of the pipe it replaces. For each inspected pipe i, this wear rate at time t is estimated by linear regression with quadratic loss using all measurements on pipe i until time t (Hazra et al., 2020a). With initial wall thickness $W_i(0)$, the wear rate estimate $\hat{R}_i(t)$ is

$$\hat{R}_i(t) = \frac{\sum_{j\in\mathcal{J}} (t_j - t_R) \cdot (W_i(0) - M_i(t_j))}{\sum_{j\in\mathcal{J}} (t_j - t_R)^2}. \tag{A.1}$$

t_j are the inspection times of pipe i up to and including time t, and t_R is the time of last repair of pipe i before time t_j.

$W_{i,pred}(t+\Delta t)$ is the predicted thickness at time $t+\Delta t$ of pipe i, and is calculated for all pipes inspected at time t:

$$W_{i,pred}(t+\Delta t) = W_i(\tau_i) - SF_i \cdot \hat{R}_i(t) \cdot (t+\Delta t - \tau_i), \tag{A.2}$$

$\tau_i < t$ being the time of last inspection or repair up to an including time t, and $W_i(\tau_i) = M_i(\tau_i)$ if the pipe is inspected but not repaired, $W_i(\tau_i) = W_0$ if it is repaired. As in Section 5.2, $M_i(t)$ is the measured wall thickness at time t.

A safety factor $SF_i = 1.1$ is applied to the prediction wear rates $\hat{R}_i(t)$ until the next I&M campaign at time $t+\Delta T$. For the pipes for which the measured wall thickness at time t $M_i(t)$ is lower than the predicted wall thickness from the previous I&M campaign, $W_{pred}(t)$, we postulate that the safety factor is increased to $SF_i = 1.5$. The choice of the safety factors affects the planning of preventive maintenance and inspection. Here we have not chosen the factors in a particular way that would optimize the strategy for the problem considered.

The remaining service life of the inspected pipes is calculated as

$$T_{i,SL} = \frac{M_i(t) - W_{accept}}{\hat{R}_i \cdot SF_i} \tag{A.3}$$

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