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

Elizabeth Bismut [a,*], Mahesh D. Pandey [b], Daniel Straub [a]

[a] Engineering Risk Analysis Group, Technische Universität München, Arcisstraße 21, 80290 München, Germany
[b] University of Waterloo, 200 University Ave West, Waterloo, ON, Canada N2L 3G1

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ABSTRACT

Inspection and maintenance (I&M) is essential to ensure the integrity of feeder pipes, which are parts of the primary heat transport system in a nuclear power plant. The pipes are subject to flow accelerated corrosion (FAC), which can compromise the integrity of the piping system and lead to high repair costs. 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, in which every pipe in the system meets the minimum thickness requirement at a specified annual probability. 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 with a case study, where the wall thinning due to FAC is modeled as a Gamma process with uncertain parameters. We compare the expected life-cycle cost of multiple strategies for I&M of a feeder system with 480 pipes. The proposed approach is compared with an I&M strategy currently used by the industry, which highlights the efficiency of the proposed optimization method.

1. Introduction

Operation and maintenance of a nuclear power plant (NPP) 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 goal of the operator. Regular maintenance of the reactor components is essential to prevent interruptions in energy production and associated loss in revenue.

In a Canada Deuterium Uranium (CANDU) reactor, the feeder piping system consists of inlet pipes that supply coolant to cool the nuclear fuel and of outlet pipes that bring the hot fluid to the steam generators (see Fig. 1). These hundreds of carbon steel pipes are susceptible to flow accelerated corrosion (FAC), which is largely responsible for wall thinning and leakage, particularly at the bends formed by the outlet feeder pipes [1–3]. Wall thinning and leakage can have serious consequences on the operability of the nuclear reactor. In the event of a leakage, total interruption of plant activity is typically required, at a very high cost. Inspection and maintenance (I&M) planning of feeder pipes is part of the FAC management program. Such planning is especially challenging 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 NPP in 1986 and to address the lack of a unified maintenance practice, guidelines and principles were drafted [1]. 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; (iv) 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 [4].

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.

To improve current I&M practice and to quantify the potential reduction in I&M costs, we propose a reliability-based planning framework for evaluating and optimizing I&M strategies of a multi-component

* Corresponding author.
E-mail addresses: elizabeth.bismut@tum.de (E. Bismut), mdpandey@uwaterloo.ca (M.D. Pandey), straub@tum.de (D. Straub).

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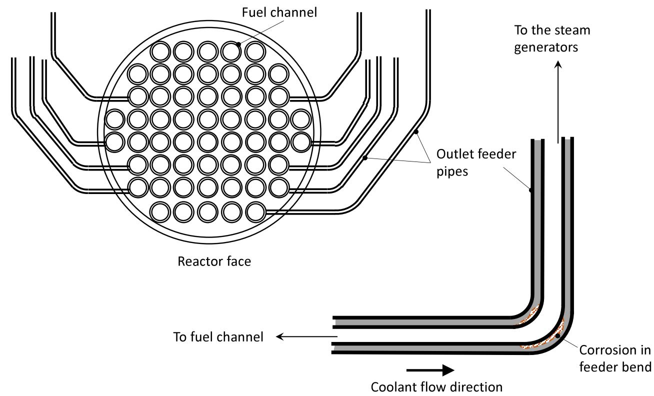


Fig. 1. Schematic of a CANDU reactor and its feeder piping system. Each fuel channel is connected to inlet and outlet feeders (not all depicted for clarity purposes). The outlet feeders transport the coolant from the fuel channel to the steam generators, where heat is exchanged. The coolant is then transported back to the fuel channels through the inlet feeders. Flow accelerated corrosion is responsible for pipe wall thinning, particularly at the first bend of the outlet feeders. After Lister et al. [2].

piping system subject to FAC, under a reliability constraint applied at the system level. The pipes correspond to the system components. The system reliability accounts for the inspection information at component level using Bayesian updating. This framework utilizes a deterioration model, which accounts for the components' interdependence and correlation. The expected cost optimization uses a heuristic description of I&M strategies, which enables the definition of I&M rules based on the reliability of individual components and of the system. The optimization is then performed on a few chosen heuristic parameters. The adopted heuristic optimization method was developed and formalized for risk-based I&M planning in [5,6] and notably allows for including eventual operator constraints. The framework proposed in this paper is designed to handle hidden system failures, which can only be detected through component inspection. Furthermore, it can cope with a large number of deteriorating components, as is typical of a nuclear piping system.

Individual aspects of this reliability-based planning framework have been proposed and implemented in past studies [7,8] but not in combination. Few studies have considered multi-level decision making for multi-unit systems [7,9]. Several studies have investigated the effect of a reliability requirement on the planning of I&M actions at the system level or at the individual component level (e.g., [10–14]), a few of which include the cost optimization [14–17]. In the studies that consider the interaction between the system and its components, the dependence between the component deterioration processes are not accounted for [18–21], and otherwise the methods are not adapted to a large number of system components [9,22–24]. In several studies that enable inspection decisions at the component level, preventive or corrective maintenance actions are limited to a major intervention at the system level [13,18,25], and failures (at the system or component level) are typically assumed to be self-announcing [19].

The paper is organized as follows: Section 2 presents the type of nuclear piping system as well as the cost and operational constraints for which the reliability-based framework is developed. Section 3 details the simulation-based evaluation of the expected cost of a given I&M strategy under reliability constraint, which is formulated as a threshold p_0 on the system failure rate (see Section 3.3). In Section 4, we present the associated reliability-based strategy optimization problem, whose solution via the heuristic approach is described in Section 4.2. The probabilistic model for FAC at the pipe level is described in Section 5. The computation and updating of the reliability of the system and the pipes are detailed in Section 6. In Section 7, the framework is demonstrated on a 480-feeder piping system subject to FAC. The I&M constrained expected costs of a strategy representative of current I&M practice are evaluated and compared to the optimized heuristic strategies for different values of p_0. The effect of the prior deterioration model parameters is also investigated.

2. Inspection and maintenance of a piping system

The presented methodology is applicable in general to I&M planning of nuclear piping system. Nevertheless, to facilitate the description of the reliability-based planning framework in Sections 3 and 4, we introduce here the configuration and planning constraints of the specific system investigated in Section 7.

2.1. Piping system

We consider a piping system of a CANDU power reactor. A CANDU piping system typically consists of different pipe geometries (angle of pipe bend, diameter of pipe, thickness of pipe) [26]. However, to restrict the analysis, the piping system considered here consists of N identical large-bore pipes of 2-inch diameter, with initial nominal thickness W_0 [27].

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 N 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 [27,28]. Failure to comply with this criterion at time t is indicated by the event $F(t) = \{\max_i D_i(t) > d_{max}\}$ and is here called *system failure*. The event $F_i(t) = \{D_i(t) > d_{max}\}$ is called *failure of pipe i*. It is $F(t) = \cup_i F_i(t)$.

The threshold d_{max} is based on a regulatory constraint, which typically includes a safety factor. In this case, a non-compliant pipe does not entail a failure (e.g., a leak) as such. Therefore, pipe failure as defined here is not self-announcing and can only be detected through wall-thickness inspection.

Time is measured in effective full-power year (EFPY). To simplify the notation, we refer to 1 EFPY as 1 year (yr). The design service life of the piping system is denoted by T.

2.2. I&M actions and cost model

To ensure compliance with the d_{max} criterion, 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 Fig. 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 labeled 'of interest' (for future inspection). Others are labeled '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

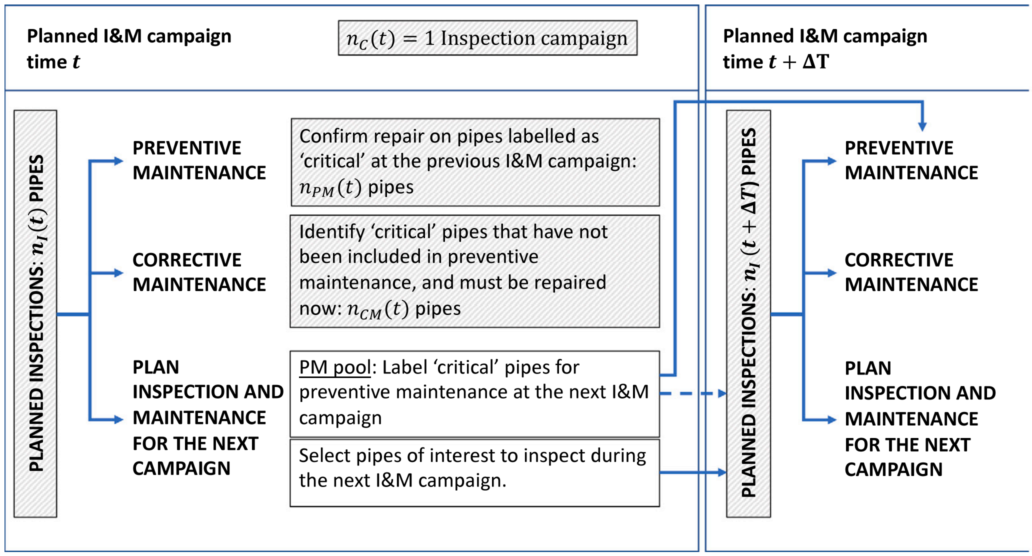


Fig. 2. Overview on I&M planning. Inspection and maintenance actions occurring at time t are indicated by lightly hatched boxes. Planning of I&M actions for the next I&M campaign are indicated by unhatched boxes. The PM pool consists of the pipes pre-selected for preventive maintenance for the next campaign, 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.

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 labeling 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 labeled 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 mobilization 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}.

3. Reliability-constrained I&M strategy

In this section, we present the framework to evaluate the performance of any operator-defined I&M strategy when constrained by a reliability criterion.

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 [6].

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 Eq. (8)) 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 [4]. 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 Eq. (8) 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, it has been observed that the current I&M practice implicitly leads to a certain level of reliability [10]. Most I&M strategies in the nuclear industry are, however, defined in a rule-based approach, without quantifying the system reliability (e.g., [4]), and they do not explicitly guarantee a reliability level.

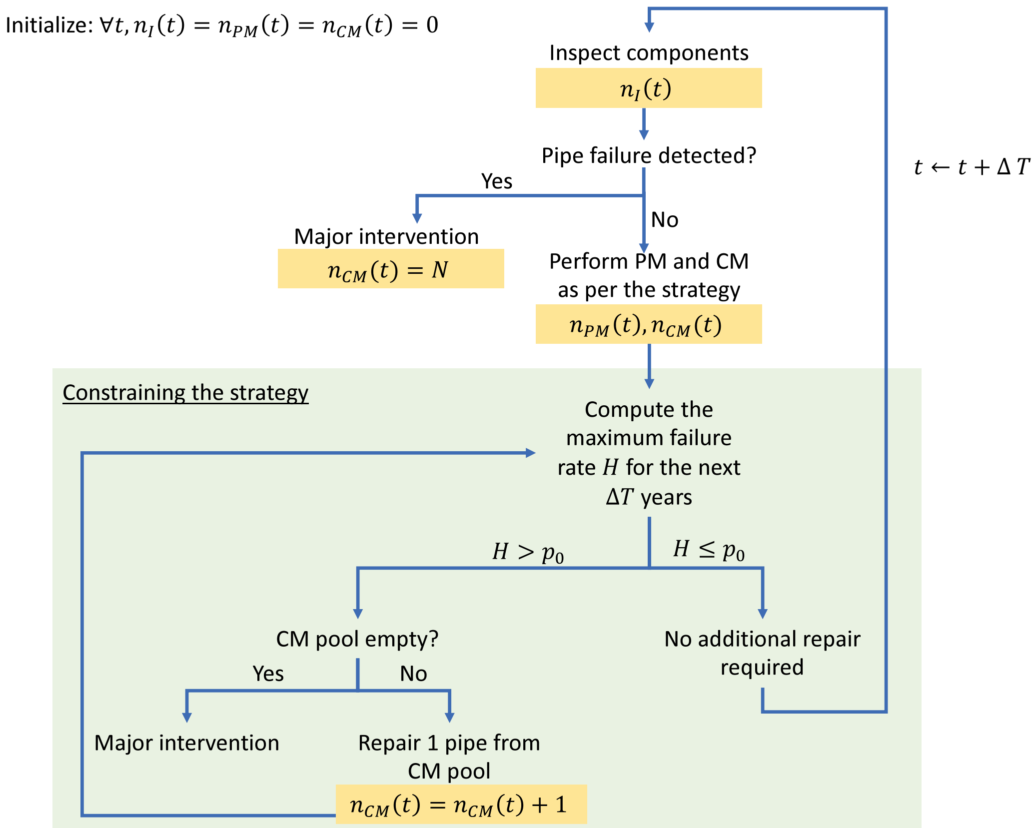


Fig. 3. Simulation of an I&M history following a given strategy $\mathcal{S}$ constrained to reliability criterion p_0 for the evaluation of a sample life-cycle cost (see Eqs. (4)–(9)). The definition of H is given in Section 3.3 and Eq. (3).

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 Fig. 3.

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 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}.

If system failure is detected, i.e., if an inspection reveals a non-compliant pipe, a major intervention is required and the simulated I&M history is interrupted. As explained above, we do not consider explicitly any costs or further I&M action resulting from system failure. A major intervention is also warranted in the unlikely eventuality that all pipes are replaced and the system is still not compliant, which might occur if the constant deterioration rate μ is too high (see Section 5).

3.3. Defining the reliability criterion

In this study, we express the reliability criterion as a threshold p_0 on the system failure rate at time t 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 failure rate evaluated at time t must be such that

$$H(t, \boldsymbol{M}_{0:t^-}) \leq p_0. \tag{2}$$

The failure rate is approximated by

$$H(t, \boldsymbol{M}_{0:t^-}) = \frac{\Pr\left[F_{cumu}(t+1)|\boldsymbol{M}_{0:t^-}\right] - \Pr\left[F_{cumu}(t)|\boldsymbol{M}_{0:t^-}\right]}{1 - \Pr\left[F_{cumu}(t)|\boldsymbol{M}_{0:t^-}\right]} yr^{-1}. \tag{3}$$

$F_{cumu}(t) = \bigcup_{\tau \leq t} F(\tau)$ is the accumulated system failure event at time t [29] and $\Pr\left[F_{cumu}(t)|\boldsymbol{M}_{0:t^-}\right]$ is the filtered cumulative probability of system failure at time t. $\Pr\left[F_{cumu}(t+1)|\boldsymbol{M}_{0:t^-}\right]$ is the predictive cumulative probability of system failure at time $t+1$.

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

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

$$C_{I,T}(\boldsymbol{M}) = \sum_{t=1}^{T} \left[c_I n_I(t) + c_C n_C(t)\right] \frac{1}{(1+r)^t} \tag{4}$$

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

$$C_{CM,T}(\boldsymbol{M}) = \sum_{t=1}^{T} c_{CM} n_{CM}(t) \frac{1}{(1+r)^t}, \tag{6}$$

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

$$C_T(\boldsymbol{M}) = C_{I,T}(\boldsymbol{M}) + C_{PM,T}(\boldsymbol{M}) + C_{CM,T}(\boldsymbol{M}). \tag{7}$$

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

$$C(\mathcal{S}) = C_{I,T}(\mathcal{S}) + C_{PM,T}(\mathcal{S}) + C_{CM,T}(\mathcal{S}), \tag{8}$$

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 [5] propose to approximate the distribution of $\boldsymbol{M}$ and evaluate the expected life-cycle I&M cost in Eq. (8) by sample averaging the I&M costs (Eq. (7)) associated with $1 \le k \le n_{MC}$ Monte Carlo (MC) sample observation histories $\boldsymbol{M}^{(k)}$ following strategy $\mathcal{S}$, as

$$C(\mathcal{S}) \simeq \sum_{k=1}^{n_{MC}} \left[C_{I,T}\left(\boldsymbol{M}^{(k)}(\mathcal{S})\right) + C_{PM,T}\left(\boldsymbol{M}^{(k)}(\mathcal{S})\right) + C_{CM,T}\left(\boldsymbol{M}^{(k)}(\mathcal{S})\right) \right]. \tag{9}$$

Furthermore, in the presented reliability-based framework each I&M sample history is generated in two phases: first by following the considered I&M strategy; then by checking if the reliability criterion is complied with and replacing additional pipes if necessary (see Fig. 3). This procedure requires many computations of the failure rate in Eq. (3) (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.

4. Reliability-based heuristic planning

In this section we introduce the reliability-based optimization framework to find an I&M strategy optimized for a fixed reliability level.

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:

$$\mathcal{S}^* = \arg\min_{\mathcal{S}} \left[C_{I,T}(\mathcal{S}) + C_{PM,T}(\mathcal{S}) + C_{CM,T}(\mathcal{S}) \right], \tag{10}$$
$$\text{such that } \forall \text{ I\&M history } \boldsymbol{M}, \forall t,\ H(t, \boldsymbol{M}_{0:t^-}, \mathcal{S}) \le p_0.$$

The planning problem expressed in Eq. (10) is 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 unconstrained, risk-based I&M planning problem [6,30–39]. Optimal reliability-based planning of the form of Eq. (10) has been investigated for multi-component systems, however, in this last case, with simplifying assumptions such as non-correlated components or small-sized systems (e.g., [9,20,21,23,24,40]). One particular challenge of this optimization is the verification of the reliability constraint, which requires to assess the evolution of the system reliability in combination with an I&M strategy. In the section below, we explain how we combine a heuristic formulation of the optimization with a history sampling method to address this challenge.

4.2. Heuristic formulation

The heuristic optimization approach formalized by Bismut and Straub [6] gives an approximate solution to Eq. (10). 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 $\boldsymbol{\omega} = \{\omega_1, \dots, \omega_n\}$ 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 Eq. (10) is restricted to a chosen heuristic and is thus reduced to an optimization of the parameter values ω_l.

$$\min_{\boldsymbol{\omega}}\ C_{I,T}(\boldsymbol{\omega}) + C_{PM,T}(\boldsymbol{\omega}) + C_{CM,T}(\boldsymbol{\omega}), \tag{11}$$
$$\text{s. t. } \forall \text{ I\&M history } \boldsymbol{M}, \forall t,\ H(t, \boldsymbol{M}_{0:t^-}, \boldsymbol{\omega}) \le p_0.$$

The selected heuristic has an effect on how optimal the strategy resulting from Eq. (11) is with respect to Eq. (10). 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 (e.g., [9,40,41]). In a previous study we observed that decision rules that account for past observations and associated uncertainty perform better than those which are formulated directly in terms of individual measurements [42]. 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 Fig. 4, where pipe replacements are carried

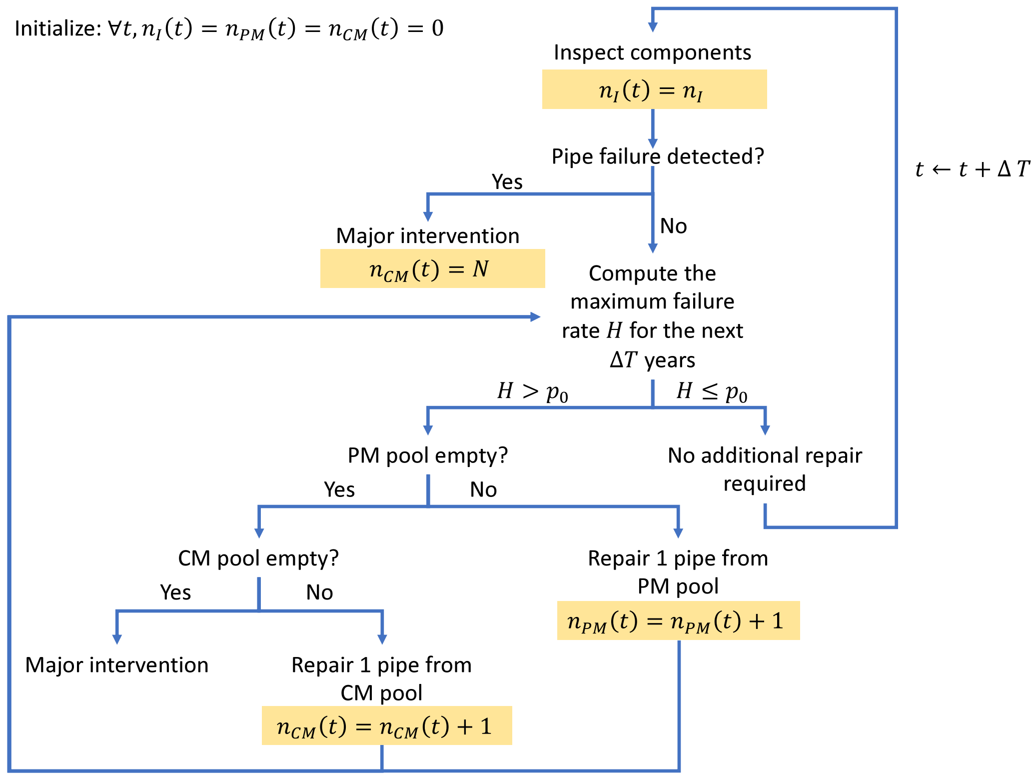


Fig. 4. Simulation of an I&M history for the evaluation and optimization of heuristic strategies under reliability constraint p_0.

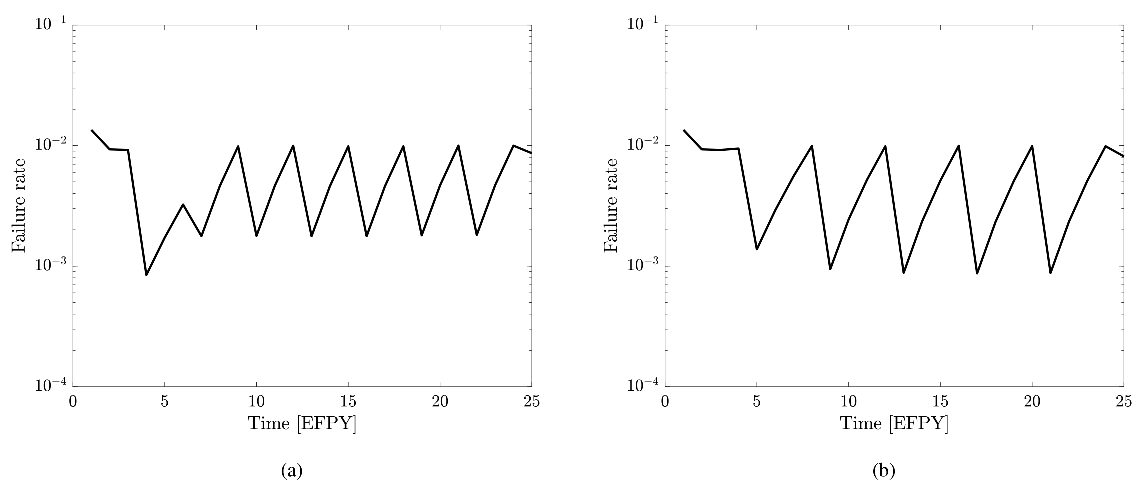


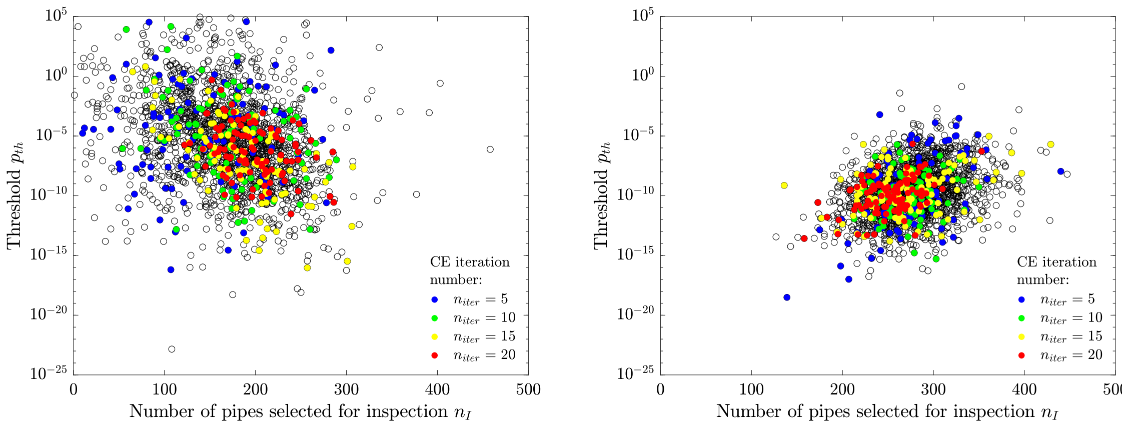
Fig. 5. Evolution of the failure rate $H(t, \boldsymbol{M}_{0:t^-})$ for a sample history, following two I&M strategies with different inspection intervals (a) $\Delta T = 3$ and (b) $\Delta T = 4$. In both cases, the strategy ensures that the system complies with the reliability constraint $p_0 = 1.0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

out specifically to satisfy the reliability criterion. An example of the system failure rate, where the I&M history is such that it follows the strategy and the constraint, is shown in Fig. 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 the actual cost of a major intervention to be defined.

4.3. Heuristic parameters optimization method

We implement the algorithm developed in [6] to optimize the heuristic parameters, based on the cross-entropy (CE) method [43]. An initial sampling density over parameters $\omega_1, \ldots, \omega_n$ is chosen, for instance a multivariate 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. The sample sets are ranked in increasing order of expected cost. The parameters of the CE sampling density for the next iteration are fitted to the top n_{CE} sample sets,



(a)

(b)

Fig. 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}. $\Delta T = 3$ yr is fixed. The expected cost of each strategy is evaluated with 10 sample histories. Colored dots indicate samples belonging to selected CE iterations. (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 elite samples. In the numerical investigation, we choose $n_S = 100$ and $n_{CE} = 20$. Samples values for discrete heuristic parameters, such as the number of inspected pipes n_I, are sampled from a continuous, truncated, Gaussian sampling density and rounded to the nearest integers. We also implement smoothed-updating [43] to avoid too fast convergence of the density. 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 Eq. (9) 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. The computational cost of generating an I&M history depends on the failure rate evaluation loop (see Fig. 4). The advantage of assigning a small value to n_{MC} is that little computational effort is spent on non-suitable, i.e., expensive, strategies. Here, we find that $n_{MC} = 10$ provides suitable accuracy and results for the CE optimization method. This optimization algorithm can be further optimized by running the computations in parallel. Previous works have demonstrated the efficiency of this computational setup [6].

Finally, the expected cost associated with the identified optimal heuristic parameters is estimated with Eq. (9) with 2000 MC sample histories.

The convergence of the CE method is illustrated in Fig. 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 (see Section 7.6 below).

5. Models of pipe deterioration and inspection and repair models

The reliability-based planning framework requires a probabilistic model describing the evolution of the state of the system and its components. Here, FAC in the pipes is modeled with a Gamma process with unknown parameters.

5.1. Modeling FAC with a mixed-scale Gamma process

Mechanistic models of FAC have been developed (e.g., [44]), 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 [26,45,46].

The service life between time 0 and T is discretized in time steps, corresponding to 1 year. The loss of thickness in one pipe i due to corrosion is modeled by a Gamma process with stationary increments ΔD_τ, with strictly positive shape and scale parameters $[\alpha, \beta]^\intercal$ [47]. 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

$$\Delta D = \sum_{\tau=1}^{\Delta t} \Delta D_\tau. \tag{12}$$

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

$$f_{\Delta D,\Delta t}(d) = \frac{1}{\Gamma(\alpha\Delta t)\,\beta^{\alpha\Delta t}} d^{\alpha\Delta t - 1} \exp\left(-\frac{d}{\beta}\right). \tag{13}$$

In the mixed-scale Gamma process, $\nu_i = \nu$ is a known constant and the mean of the yearly increment μ is modeled 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

$$f(\mu) = \frac{b^a}{\Gamma(a)} \left(\frac{1}{\mu}\right)^{a+1} \exp\left(-\frac{b}{\mu}\right). \tag{14}$$

The distribution of the increment 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

$$M_i(t) = W_i(t). \tag{15}$$

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. Furthermore, μ is assumed to be remain constant even if the piping system is fully replaced.

6. Piping system reliability

In this section, we derive the expressions for the probability of system failure for the FAC model presented in Section 5 as well as the characteristics of pipe damage distribution, conditional on past inspection outcomes. These quantities are required for the reliability constraint check and for implementing selected heuristic I&M strategies.

6.1. Cumulative probability of 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 failure rate of the system as per Eq. (3). As per the definitions given in Sections 2.1 and 3.3, the accumulated system failure event at time t is

$$F_{cumu}(t) = \bigcup_{\tau\le t} F(\tau) = \bigcup_{\tau\le t}\bigcup_{i} F_i(\tau). \tag{16}$$

The probability of this accumulated 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 we evaluate the filtered cumulative probability of system failure $\Pr\left(F_{cumu}(t)|\boldsymbol{M}_{0:t^-}\right)$. $\boldsymbol{\Theta}$ denotes the model parameters. Here $\boldsymbol{\Theta} = \mu$.

Using Eq. (16), one finds

$$\Pr\left(F_{cumu}(t)|\boldsymbol{M}_{0:t^-}\right) = 1 - \Pr\left(\bigcap_{\tau\le t}\bigcap_{i}\{D_{i,\tau} < d_{max}\}|\boldsymbol{M}_{0:t^-}\right). \tag{17}$$

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

$$\Pr\left(F_{cumu}(t)|\boldsymbol{M}_{0:t^-}\right) = 1 - \int_{\Omega_{\Theta}} \prod_{i} \Pr\left(\bigcap_{\tau\le t}\{D_{i,\tau} < d_{max}\}|\boldsymbol{M}_{i,0:t^-},\boldsymbol{\theta}\right) \times f_{\boldsymbol{\Theta}|\boldsymbol{M}_{0:t^-}}(\boldsymbol{\theta})\mathrm{d}\boldsymbol{\theta}, \tag{18}$$

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:

$$f_{\boldsymbol{\Theta}|\boldsymbol{M}_{0:t^-}}(\boldsymbol{\theta}) \propto \mathcal{L}(\boldsymbol{\theta}; \boldsymbol{M}_{0:t^-}) f_{\boldsymbol{\Theta}}(\boldsymbol{\theta}). \tag{19}$$

$\mathcal{L}(\boldsymbol{\theta}; \boldsymbol{M}_{0:t^-})$ is the likelihood of $\boldsymbol{M}_{0:t^-}$ conditional on $\boldsymbol{\Theta}$. The normalizing constant is $c = \int_{\Omega_{\Theta}} f_{\boldsymbol{\Theta}}(\boldsymbol{\theta})\mathcal{L}(\boldsymbol{\theta}; \boldsymbol{M}_{0:t^-})\mathrm{d}\boldsymbol{\theta}$. The measurements are independent conditionally on Θ. This is actually an approximation, due to the selection bias [48]. We will not correct this bias, as it does not significantly affect our results.

Thus

$$\mathcal{L}(\boldsymbol{\theta}; \boldsymbol{M}_{0:t^-}) = \prod_{i} \mathcal{L}(\boldsymbol{\theta}; \boldsymbol{M}_{i,0:t^-}). \tag{20}$$

$\mathcal{L}(\boldsymbol{\theta}; \boldsymbol{M}_{i,0:t^-})$ 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 cumulative probability of pipe survival

For a fixed time t, we denote by $\mathcal{I}_i = \{t_{I,1} < \cdots < t_{I,p}\}$ the inspection times and by $\mathcal{R}_i = \{t_{R,1} < \cdots < t_{R,q}\}$ 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 $D_{i,\tau}$ is monotonously increasing in the interval between two consecutive replacements. Therefore, the intersection of pipe survival events in Eq. (18) is equivalent to

$$\bigcap_{\tau\le t}\{D_{i,\tau} < d_{max}\} = \{D_{i,t} < d_{max}\} \bigcap \{\cap_{1\le j\le q}\{D_{i,t_{R,j}} < d_{max}\}\}, \tag{21}$$

where $D_{i,t_{R,j}}$ is the deterioration of pipe i just before it is replaced at time $t_{R,j}$. 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 cumulative probability of pipe survival as

$$\Pr\left(\bigcap_{\tau\le t}\{D_{i,\tau} < d_{max}\}|\boldsymbol{M}_{i,0:t^-},\boldsymbol{\theta}\right) = \Pr\left(D_{i,t} < d_{max}|\boldsymbol{M}_{i,t_{R,q}:t^-},\boldsymbol{\theta}\right) \times \prod_{1\le j\le q} \Pr\left(D_{i,t_{R,j}} < d_{max}|\boldsymbol{M}_{i,t_{R,j-1}:t_{R,j}},\boldsymbol{\theta}\right), \tag{22}$$

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

The distribution of state $D_{i,\tau}$ conditional on measurement and repair actions up to but not including time τ is fully determined either by the time of the last repair before τ or by the last pipe thickness measurement, whichever occurred last. Let τ_i be the larger of these times of last repair and last measurement.

– If repair occurred at time τ_i,

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

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

$$\begin{aligned}\Pr(D_{i,\tau} < d_{max}|\boldsymbol{M}_{i,0:\tau^-},\boldsymbol{\theta}) &= \Pr(D_{i,\tau} < d_{max}|\boldsymbol{M}_{i,\tau_i},\boldsymbol{\theta})\\ &= F_{\Delta D,\tau-\tau_i|\theta}(d_{max} - (W_{i,0} - M_{i,\tau_i})).\end{aligned} \tag{24}$$

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

$$\Pr(D_{i,\tau} < d_{max}|M_{i,\tau},\boldsymbol{\theta}) = \mathbb{1}_{W_{i,0}-M_{i,\tau}\le d_{max}}, \tag{25}$$

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

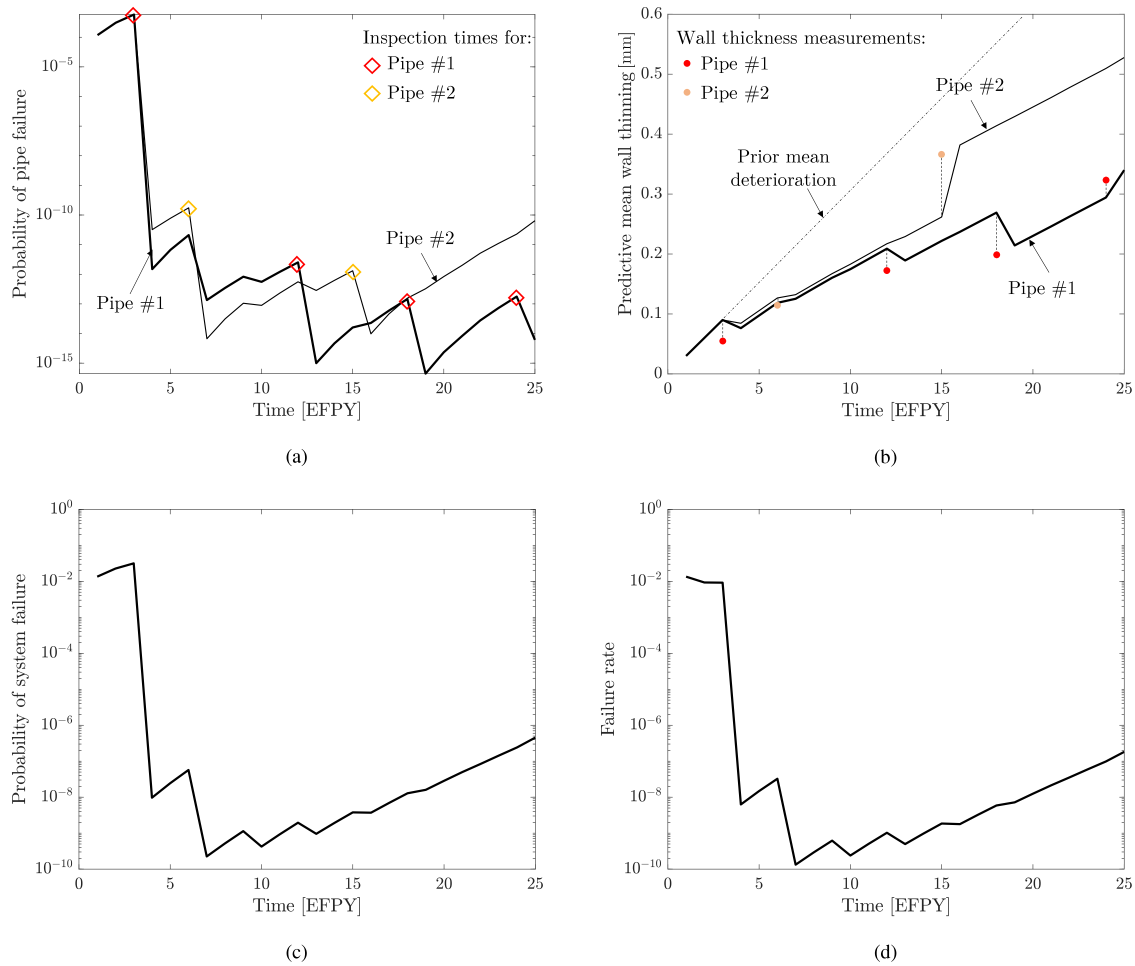


Fig. 7. (a) Filtered probability of pipe failure $\Pr(D_{i,t} > d_{max}|\boldsymbol{M}_{0:t^-})$, for pipes number 1 and 2. Pipe inspection times are indicated. (b) Evolution of the predictive mean wall thinning D_i for pipes number 1 and 2. Wall thickness measurements are indicated for these two pipes. In the assumed deterioration model, the predicted mean deterioration rate is the same for all pipes, hence the change of slope occurs also for non-inspected pipes. (c) Filtered cumulative probability of system failure $\Pr\left(F_{cumu}(t)|\boldsymbol{M}_{0:t^-}\right)$ obtained with Eq. (17). (d) Failure rate computed with Eq. (3).

never been repaired). The likelihood describing measurements on pipe i is

$$\mathcal{L}(\theta; \boldsymbol{M}_{i,0:t^-}) = \prod_{j\in\mathfrak{I}_i} f_{\Delta D,\Delta t_j|\theta}(W_{i,0} - M_{i,t_j}). \tag{26}$$

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 [49], the posterior (filtered) distribution of $\boldsymbol{\Theta} = \mu$ can be obtained by updating the parameters of the inverse gamma distribution with the (perfect) measurements $\boldsymbol{M}_{0:t^-}$, such that $\boldsymbol{\Theta}|\boldsymbol{M}_{0:t^-} \sim IGa(a_{post}, b_{post})$, with

$$a_{post} = a + \frac{\sum_{i=1}^{N}\sum_{j\in\mathfrak{I}_i}\Delta t_j}{\nu^2}, \tag{27}$$

$$b_{post} = b + \frac{\sum_{i=1}^{N}\sum_{j\in\mathfrak{I}_i}(W_{i,0} - M_{i,t_j})}{\nu^2}. \tag{28}$$

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 $2a_{post}$ [26,45,46]. 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

$$c.o.v.(D_{i,t}|\boldsymbol{M}_{0:t^-}) = \frac{1}{1 + \frac{d_M(a_{post}-1)}{b_{post}(t-\tau_i)}}\sqrt{\frac{\frac{(t-\tau_i)}{\nu^2} + a_{post} - 1}{\frac{(t-\tau_i)}{\nu^2}(a_{post} - 2)}}. \tag{29}$$

The probability of pipe failure is

$$\Pr(D_{i,t} > d_{max}|\boldsymbol{M}_{0:t^-}) = 1 - F_{\frac{2(t-\tau_i)}{\nu^2},2a_{post}}\left((d_{max} - d_M)/\xi\right). \tag{30}$$

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

6.5. Computation details

When the observation likelihood does not include measurement error, the integrand of Eq. (18) has a closed form and a numerical integration is appropriate to evaluate $\Pr\left(F_{cumu}(t)|\boldsymbol{M}_{0:t^-}\right)$.

On the contrary, if a measurement error is included in Eq. (15), the product of conditional probabilities of pipe survival in Eq. (18) is a product of integrals which do not have a closed form. Eq. (18) is an integral in high-dimensional space involving complex pdfs, for which adapted integration methods must be considered; for instance a

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

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

dynamic Bayesian network (DBN) model where each random variable is discretized is suitable for performing Bayesian inference in large systems [6,50].

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 described in Section 2.1, at the beginning of its service life, with $N = 480$, $W_0 = 5.5$ [mm], $d_{max} = 2.2$ [mm] and $T = 25$ yr.

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.

The prior distribution parameters of μ in Table 1 result in a prior expected value of 0.03 [mm/yr] and a c.o.v. of 100%. The choice of this prior model is based on the analysis of historical events: Lister et al. [2] states that wear rates at 0.02 [mm/yr] are “acceptable”. There is however a high variability in the wear rate. Indeed, wear rates between 0.07 [mm/yr] and 0.2 [mm/yr] have been recorded [2,27]. Usually, the reported wear rates in the literature are obtained from “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/yr] 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 system failure rate for the non-maintained system is shown in Fig. 8. The maximum failure rate of $1.6 \cdot 10^{-2}$ is reached at the end of the service life. It is clear that for any constraint p_0 larger than this value, the optimal strategy according to Eq. (10) is to do nothing.

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

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

To test the reliability-constrained strategy approach of Section 3, we construct a strategy $\mathbb{S}_{REP}$ representative of the current I&M practice.

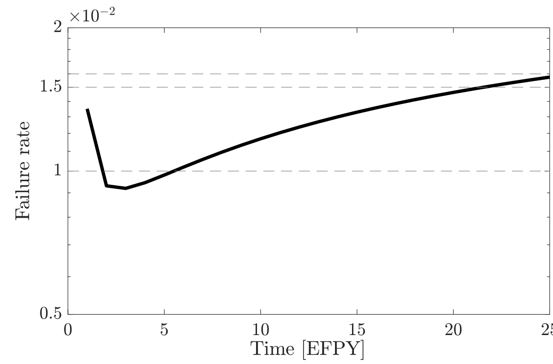


Fig. 8. Failure rate for the non-maintained, non-inspected system. The levels $\{0.5, 1.0, 1.5, 1.6\} \cdot 10^{-2}$ are also indicated.

7.2.1. Description of the strategy and associated FAC prediction model

EPR [4] and Walker [51] 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 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 [4,51]. 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.

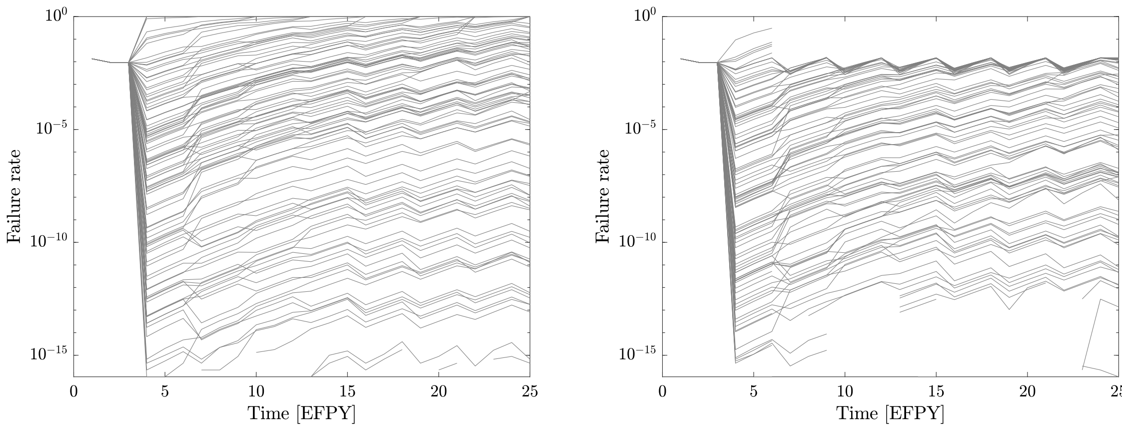
The strategy is summarized below.

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

- The interval between I&M campaigns is $\Delta T = 3$ yr.
- Pipe inspections: Inspect pipes that have been labeled ‘of interest’ and those labeled 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 labeled 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).

Planning for the next campaign

- 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 labeled as ‘critical’ for the next I&M campaign.
- Plan inspections for next campaign: a total of $n_I = 140$ 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 (Eq. (A.3)).



(a) (b)

Fig. 9. (a) Failure rate $H(t, \boldsymbol{M}_{0:t^-})$, following unconstrained strategy $\mathcal{S}_{REP}$ for 100 sample I&M histories. (b) Failure rate for 100 sample I&M histories following the strategy $\mathcal{S}_{REP}$ constrained to $p_0 = 1.5 \cdot 10^{-2}$. The histories are interrupted when the constraint on the failure rate cannot be met (i.e., a major intervention is required).

Table 3
Optimized heuristic parameters n_I and p_{th} of Heuristic A (see Section 7.3) for fixed $\Delta T = 3$ yr 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.

p_0 ($\times 10^{-2}$)	Optimal heuristic strategy ($\Delta T = 3$ yr)		Constrained strategy $\mathcal{S}_{REP}$
	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

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 $\Delta T = 3$ yr in Table 3.

p_0 ($\times 10^{-2}$)	Optimal heuristic strategy (varying ΔT)	
	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

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

7.2.2. Unconstrained vs constrained strategy

Fig. 9(a) depicts samples of the evolution of the 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 some of the inspections or pipe replacements prescribed by the strategy are not necessary to comply with the reliability criterion. Fig. 9(b) shows samples of the evolution of the failure rate following the constrained strategy. Only the histories which would have exceeded the criterion are affected by the reliability constraint.

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 Fig. 4.

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

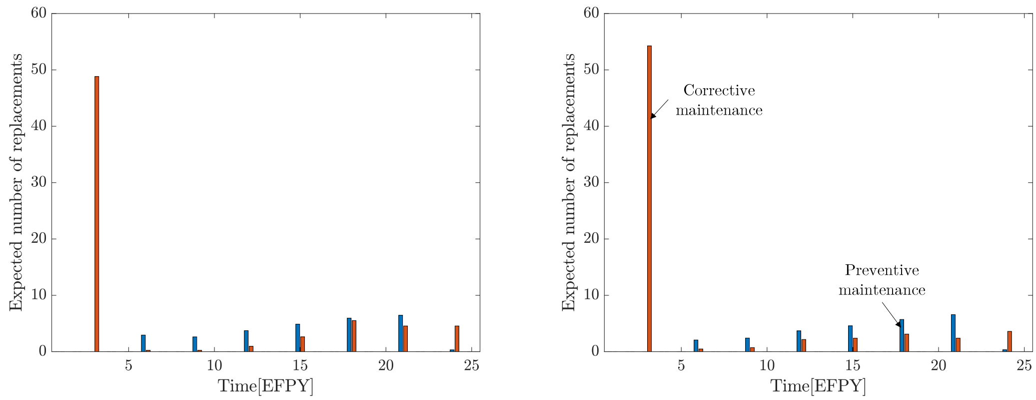
- ΔT is the constant inspection interval. The only I&M opportunities are at the planned inspection times.
- Pipe inspection at first campaign: n_I pipes are randomly selected and inspected.
- Pipe inspection at next campaigns: n_I is the number of pipes selected for inspection (labeled 'of interest') at each campaign, according to the prioritization rule (see point below). To these pipes are added those that have been labeled 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 $t + \Delta T$ (labeled as 'critical') based on their probability of failure $\Pr(D_i(t + \Delta T) > d_{max} | \boldsymbol{M}^-_{\boldsymbol{0}:t})$ 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 Eq. (29).

7.4. Computational cost

Each optimization was performed in parallel on a 2.2 GHz, 10 cores, 128 GB of RAM computer and took in the order of 3.5 h.



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

Fig. 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 Fig. 8.

7.5. 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 Eq. (11) and of the constrained strategy $\mathcal{S}_{REP}$. For $p_0 > 1.6 \cdot 10^{-2}$, the non-maintained system complies to the reliability level (see Fig. 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.

Fig. 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 $t = 3$ yr is due to corrective replacement (and eventual non-compliance of the plant) associated with a rate μ sampled from the tail of the distribution (see Section 7.1 above), which can lead to early system failure. This effect is also reflected in the higher failure rate of the non-maintained system in the first years of service, as depicted in Fig. 8. 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 replacements is in general higher than that of corrective replacements, which indicates that the optimized strategy is efficient in planning preventive maintenance. The corresponding cost breakdown is displayed in Fig. 11.

We can compare these costs and actions with the constrained representative strategy $\mathcal{S}_{REP}$, shown in Fig. 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 optimized 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 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.

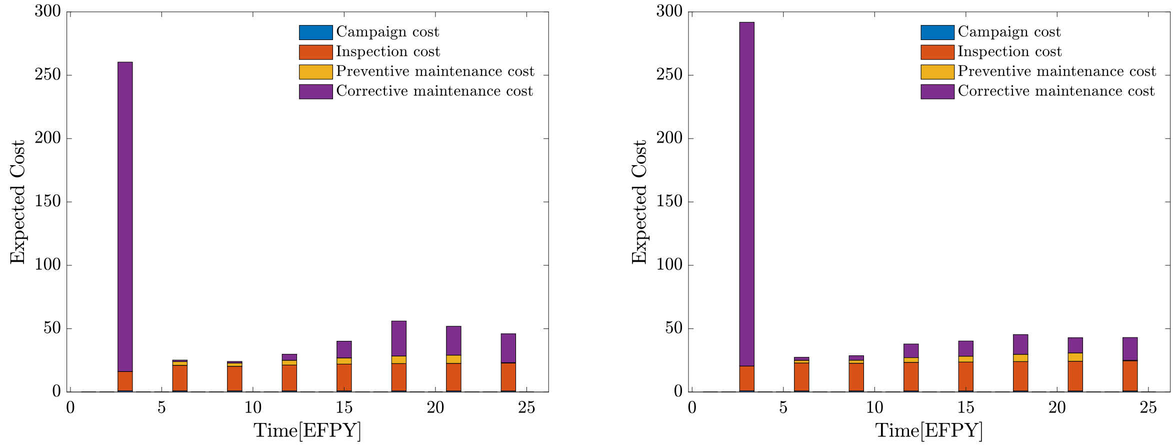
7.6. Sensitivity of expected cost to the heuristic parameters

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 $\Delta T = 3$ yr, for $p_0 = 1.0 \cdot 10^{-2}$. To do so, we estimate the expected cost with Eq. (9) 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 with a standard error of $4-7\%$, 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. Fig. 13(a) depicts the resulting Gaussian field and the predicted expected life-cycle I&M cost for any pair (n_I, p_{th}).

The surrogate of the expected cost function thus obtained confirms the location of the optimum point found with the CE method (Table 3). It should be noted that finding the optimal heuristic parameter values by fitting a Gaussian process to point estimates arranged in a grid here has 20 times the computation cost of the CE optimization method. A more efficient combination of the two methods is suggested in [6].

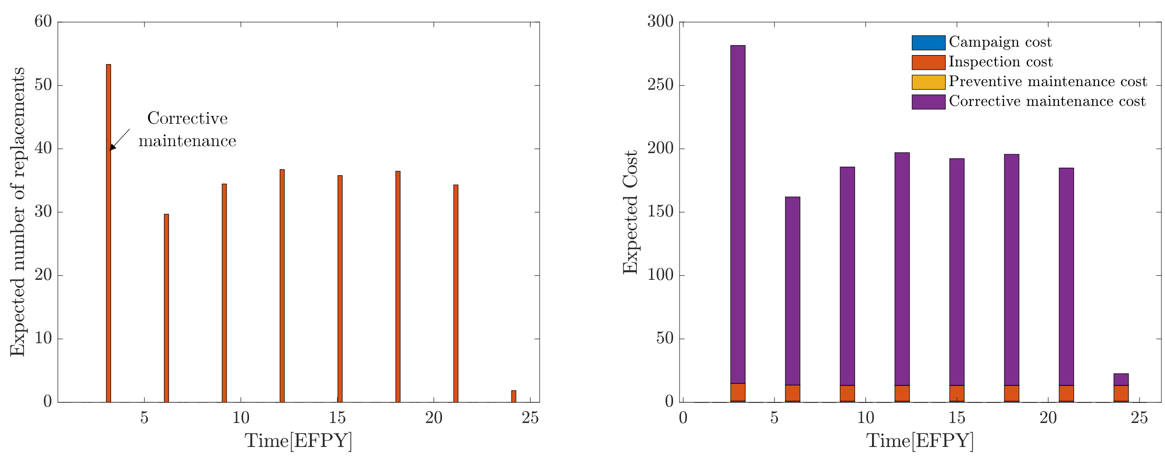
We observe that in the vicinity of the found optimum, the expected cost is not highly sensitive to the number of pipes to be inspected at each campaign, n_I. This can reflect two things: first, the cost of pipe inspection is low compared to the cost of maintenance, therefore a variation of the order 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 Eq. (9) with the modified cost parameters. A Gaussian process is fitted again to the 408 grid points. The resulting Gaussian field is depicted in Fig. 13(b). 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}.



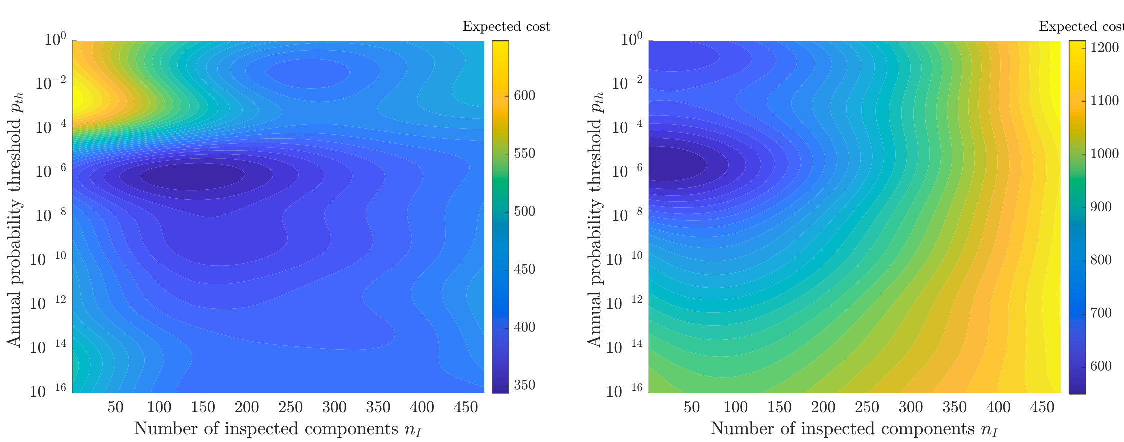
(a) $p_0 = 1.5 \cdot 10^{-2}$ (b) $p_0 = 1.0 \cdot 10^{-2}$

Fig. 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) $p_0 = 1.0 \cdot 10^{-2}$.



(a) (b)

Fig. 12. (a) Average number of pipes preventively or correctively replaced for constrained strategy $\mathbb{S}_{REP}$ 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 $p_0 = 1.0 \cdot 10^{-2}$.



(a) (b)

Fig. 13. Expected I&M life-cycle cost as a 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 Eq. (9) and $n_{MC} = 1000$, at 408 grid points with coordinates $p_{th} \in \{10^{-16}, 10^{-15}, \dots, 10^{0}\}$ and $n_I \in \{20, 40, 60, \dots, 480\}$. (a) for the cost model of Table 2; (b) with increased unit inspection cost $c_I = 0.5$.

Table 5
Results for modified prior.

p_0 ($\times 10^{-2}$)	Optimal heuristic strategy		Constrained strategy $\mathcal{S}_{REP}$
	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

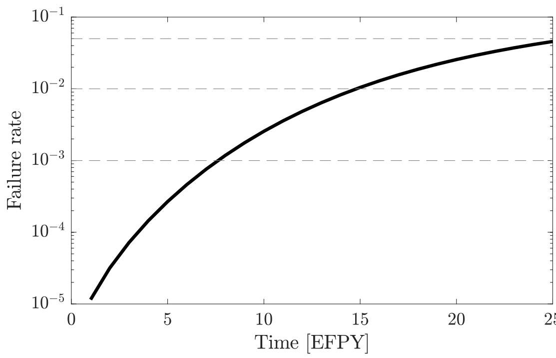


Fig. 14. Failure rate for the non-maintained, non-inspected system, with a modified prior where the c.o.v of μ is 20%. The levels $\{0.1, 1.0, 5.0\} \cdot 10^{-2}$ are also indicated.

7.7. 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 failure rate for the non-maintained system is depicted in Fig. 14. We note that the curve does not possess a bathtub curve shape as in Fig. 8.

We evaluate strategy $\mathcal{S}_{REP}$ and optimize the heuristic parameters with fixed $\Delta T = 3$ yr (see Table 5). 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 Fig. 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 under a specified 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, which opens the possibility to explore different decision rules and to integrate regulatory constraints. The framework includes a probabilistic predictive model for the deterioration process at the 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 deterministic prediction model.

This study shows that the choice of a cost model influences the outcome of strategy assessment and optimization. Other aspects must be considered by the analyst for the implementation of this reliability-based planning and optimizing framework in practice, such as the fact that 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 [6], 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.

The deterioration model can be altered to reflect various probabilistic dependence structures. Here, the model for FAC assumes a constant mean deterioration rate μ across all pipes and enables the evaluation of the system reliability at a low computational cost. Plant data suggest that there are lead feeders in which the deterioration rate is higher than for other pipes [27]. This is likely due to geometry aspects, which are not considered here. A future improvement of this framework will include the efficient modeling of pipe groups with correlated wear rates, and will integrate uncertainty on the measurement data. Increasing the complexity of the deterioration and observation models comes at a cost, since the generation of a sample I&M history requires the system reliability to be evaluated at every time step. To ensure the efficient and fast computation of the system reliability, a discretized hierarchical DBN model, as proposed by Luque and Straub [50], can be utilized to model correlated deterioration rates μ.

Finally, while the presented framework has been developed for a specific type of system and a specific application, it can be extended to systems with different configurations, dependence structures and deterioration processes.

CRediT authorship contribution statement

Elizabeth Bismut: Conceptualization, Methodology, Formal analysis, Software, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Mahesh D. Pandey:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Daniel Straub:** Conceptualization, Methodology, Supervision, Writing – review & editing, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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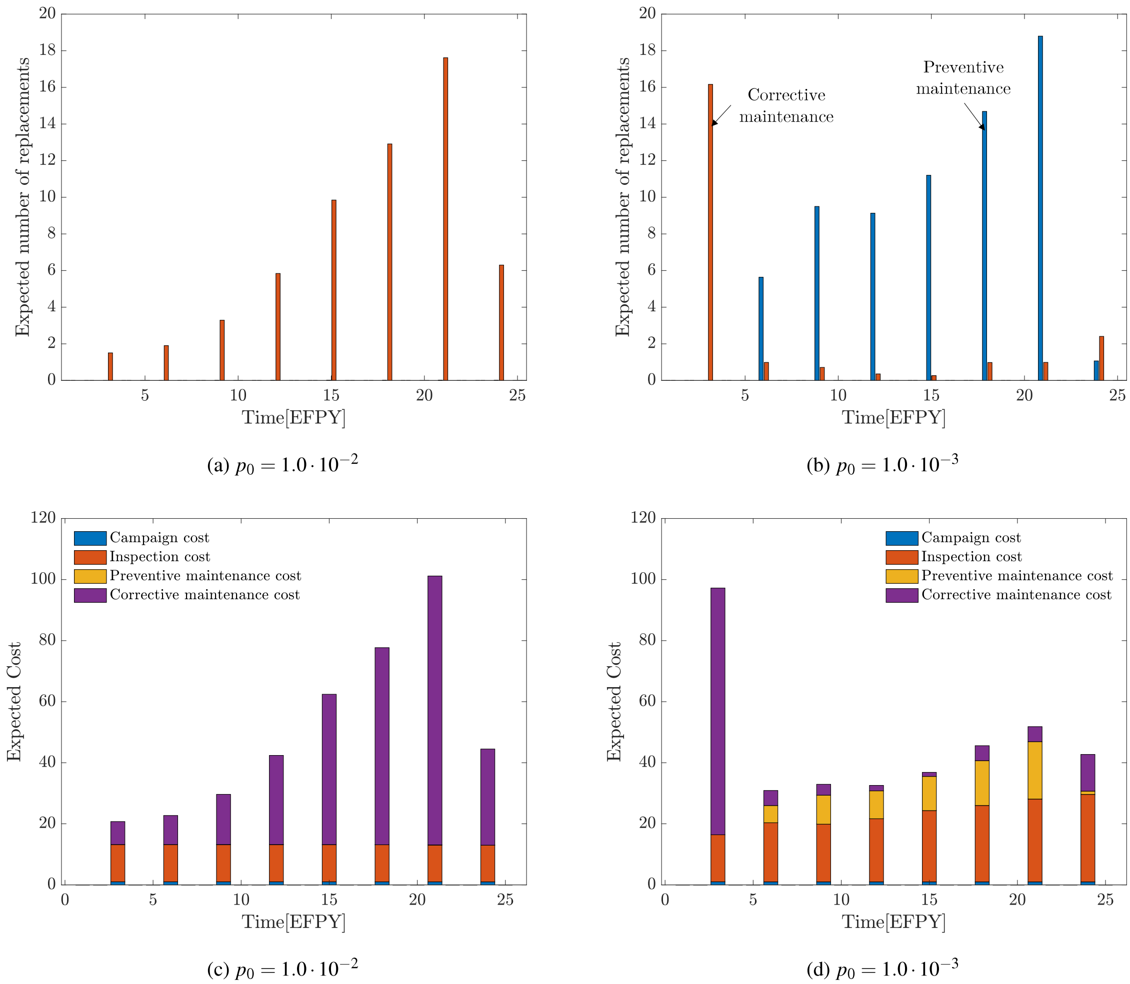

(a) $p_0 = 1.0 \cdot 10^{-2}$ (b) $p_0 = 1.0 \cdot 10^{-3}$

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

Fig. 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 Fig. 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) $p_0 = 1.0 \cdot 10^{-3}$.

Appendix. FAC-predictive model

For the representative strategy $\mathcal{S}_{REP}$ described in Section 7.2.1, 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 EPR [4].

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 [27]. 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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