Optimizing Crack Repair Policies using Value of Information Analysis considering Imperfect Inspection of Pipelines

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ABSTRACT:

This study presents an approach for optimizing policies on crack repair, which may take place after pipeline inspection, depending on the possible failure risk (i.e., the severity of crack) and the repair cost. The approach is built on the basis of Value of Information (VoI) analysis, and it seeks the optimal repair criterion by minimizing pre-posterior cost for re-inspection. For this purpose, a tool is developed for VoI analysis on a high-performance computing platform, which allows parallel computing to improve computational efficiency. The tool is specifically designed for inspection of a single critical crack in this study. The effectiveness of the presented approach in increasing VoI, i.e., taking better advantage of inspection, is demonstrated through its application to a hypothetical pipeline example. Different failure-to-repair cost ratios and prior uncertainties are also considered to reveal their effect on the optimal repair policies.

1. INTRODUCTION

Pipelines, as essential components of energy infrastructure, are prone to crack damage that can lead to costly leaks or ruptures (Belvederesi and Dann 2017). To prevent catastrophic loss due to crack damage, operators need to inspect pipelines to detect cracks and plan for appropriate repairs. However, determining the best inspection and repair methods/policies is not always straightforward, as it requires taking into account uncertainties from various sources, such as randomness in pipeline properties, inspection error in crack detection and size measurements. Value of information analysis (VoI) (Howard 1966), based on Bayesian statistical decision theory, provides the mathematical framework to calculate the benefits from inspection tools/strategies and repair methods/policies considering such uncertainties.

Specifically, VoI has been introduced to prioritize inspection tools and aid in the integrity management of pipelines in the literature. For instance, di Francisco et al. (2021) evaluated the impact of inspection features on VoI for offshore pipelines subjected to growing cracks, while Melo et al. (2020) used VoI analysis to identify the optimal locations for inspecting pipelines prone to internal corrosion. However, these studies mainly focused on inspection tools/strategies, without paying attention to different possible repair strategies/policies.

Current industrial repair policies for pipe cracks in North America are generally based on either empirical deterministic criterion such as design safety factors or risk-based repair policies. For instance, according to the pipeline design and evaluation (American Petroleum Institute (API) 2021; CSA 2019), operators repair cracks based on the crack depth and failure pressure ratio

(FPR), which is the ratio of pressure capacity to the operating pressure. Several studies (Blade 2020; Yan et al. 2020) have proposed reliability-based repair strategies where cracks with probability of failure larger than a certain threshold should be repaired. These thresholds are often derived based on tolerable safety risk criteria and environmental risk criteria (Nessim et al. 2004, 2014). In previous studies (e.g., Stephens and Nessim 1996), life-cycle cost, including failure cost and maintenance cost over the design life of pipeline, was minimized to find an overall optimal maintenance strategy/policy constrained with safety criteria. This approach may not necessarily lead to optimal usage of information obtained from pipeline inspection for a specific crack repair.

In industrial applications, re-inspection is often conducted to identify generation of environmentally induced cracking or growth of the previously detected cracks, and they can also be used to verify the results from previous inspections (Koduru et al. 2020; Melo et al. 2020). After re-inspection, the probability distribution function (PDF) of crack size, and the probability of failure can be updated. After this, an allowable probability of failure, referred to as repair threshold, is needed, based on which to determine whether a crack should be repaired or not. Typically the repair threshold is selected based on fixed safety criteria as recommended by industry codes, which may not necessarily lead to an optimal balance between failure risk and maintenance cost after re-inspection. This may lead to unnecessary repairs and resource misallocation between repair and inspection strategies.

In literature, VoI analysis was used to achieve optimal repair policies or heuristics (e.g., repair threshold for inspection planning) for other structures subjected to degradation (Kamariotis et al. 2020, 2022). When it comes to pipelines with cracks, no relevant work is found in literature. This study aims to propose optimal thresholds for repairing pipe cracks by minimizing the pre-posterior cost for re-inspection in the context of VoI. VoI is the difference between the prior expected loss for a system without information and the expected loss for the system considering all possible outputs of the inspection tool. The latter loss is known as the pre-posterior cost, which is the average of all posterior costs given different inspection outcomes. Optimal threshold is obtained by minimizing pre-posterior cost, while considering the constraint imposed by the tolerable threshold for public safety or environmental impact, to achieve a balance between repair cost and failure risk after re-inspection. Note that failure consequences including human fatalities, environmental effects and economic impacts can be converted to monetary values in VoI context (Haladuick and Dann 2018).

To accomplish the abovementioned task, a tool is developed based on VoI analysis in this study. Considering the high computational burden in pre-posterior analysis, in which Monte Carlo (MC) sampling is used, this tool is enhanced with parallel calculations in Python by taking advantage of cloud computing.

This paper is organized as follows. Section 2 presents the methodology, including the theoretical formulation of VoI analysis, the tool development, and the process of optimizing repair policies. Section 3 presents a numerical example, to demonstrate the methodology based on a hypothetical pipeline. Section 4 concludes this study with discussions about possible extensions of this study.

2. METHODOLOGY

The general decision-making framework using VoI analysis, including prior and pre-posterior analyses, are shown in Figure 1. Generally, operators have two primary choices in terms of inspection, i.e., “not inspect” or “inspect”. Correspondingly, prior analysis and pre-posterior analysis can be conducted, respectively, to calculate the prior cost and pre-posterior cost as defined later.

If operators choose not to inspect, they can either “do nothing” or “repair” a possible defect, denoted by actions A = a_0 and a_1, respectively. In this study, it is assumed the pipeline operator will not repair a possible crack detected during earlier inspections until re-inspection. Hence, the only action considered here is A = a_0, namely "do nothing", which will not change the system state. The pipeline system state, represented by a random vector (**X**) containing variables such as crack dimensions and other possible pipe parameters, can be described by the prior probability model elicited from earlier inspection data and/or engineering experience. Depending on the system state, the pipeline can possibly fail, causing fatalities, injuries, loss of product, reputation cost, service loss, and environmental cost. All these can be converted to monetary values. Thus, the associated failure cost C_f can be estimated. Considering the probability of failure, which can be estimated by performing reliability analysis, the failure risk, measured by prior cost C_{prior}, can then be estimated as explained in Section 2.1.

On the other hand, if operators choose to inspect, they can take an informed action, either "do nothing" or "repair" a possible crack for the pipeline, depending on repair policy and the inspection results. If the repair policy is based on the reliability of the system, reliability analysis needs to be done based on the updated information of the system state, e.g., crack size. This is referred to as updated reliability analysis. The reason behind this is because the re-inspection will provide further information about the system, via the crack size measurement **y**. Note that **y** contains measurement error inherited from inspection tools or devices. When the informed action is "repair", the additional cost involved would be repair cost *Cr*. With that, the pre-posterior cost C_{pp} can be calculated as detailed in Section 2.2, and the value of information (VoI) can be determined by Eq. (1).

$$VoI = C_{prior} - C_{pp} \qquad (1)$$

2.1. Prior Analysis

As mentioned earlier, if operators choose not to inspect, they will have to choose to "do nothing" for a single crack, i.e., accepting the risk of failure because they have not verified the size of the crack due to likely crack growth following a previous inspection. In this case, the prior cost can be calculated as shown in Eq. (2) (Straub 2014):

$$C_{prior}(a_0) = c[f_{\mathbf{X}}(\mathbf{x}), a_0] = C_f \cdot Pr[E_1] \qquad (2)$$

in which $Pr[E_1]$ is the probability of E_1 which denotes the failure event, in contrast to E_2 which denotes the safe event. $Pr[E_1]$ is simply the probability of failure P_f, as given by Eq. (3).

$$P_f = Pr(E_1) = \int_{\mathbf{X}} I_g(\mathbf{x} \in E_1) f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x} \qquad (3)$$

in which I_g is the indicator function (=1 when $\mathbf{x} \in E_1$ with limit state function g <0); $f_{\mathbf{X}}$ is the prior PDF of random vector **X**. For example, **X** = [D, L] when only the predominate uncertain variables in a cracked pipeline, such as crack depth (D**)** and length (L), are considered as in the application example in this study. Here, it is assumed that $f_{\mathbf{X}}$ can model the crack size uncertainty, including those associated with crack growth after previous inspection.

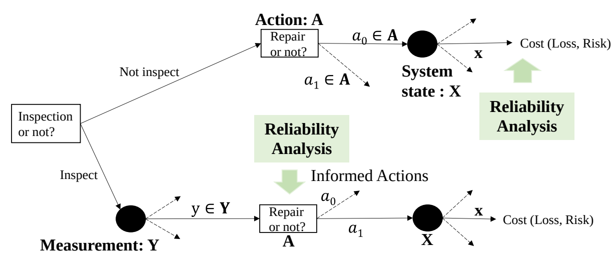

Figure 1: General decision-making framework

For the cracked pipeline problem, the failure mode of most concern is burst failure, which occurs when the burst pressure capacity is lower than the maximum operating pressure (MOP). To describe this failure mode mathematically, the limit state function $g(\mathbf{X})$ = CorLas(**X**) – *MOP* can be used such that g < 0 indicates failure. Here, CorLas(**X**) is the resistance burst pressure of a pipe, which is calculated by semi-empirical model CorLas (Jaske and Beavers 2001). Note that in previous studies (di Francesco et al. 2021; Haladuick and Dann 2018), only failure modes such as leaking were considered where simple limit state functions were used. However, burst failure is more important than leaking due to its higher economic loss. Thus, the burst failure limit state is considered in this study.

2.2. Pre-posterior Analysis and Repair Policies

In this section, a summary of the process for calculating C_{pp} is introduced. C_{pp} is the average value of $C_p(\mathbf{X=x,\ Y=y})$ over all possible realizations of random vectors **X** and **Y**, as shown in Eq. (4).

$$C_{pp} = E_{\mathbf{XY}}\left[C_p(\mathbf{X},\mathbf{Y})\right] \quad (4)$$

in which $C_p(\mathbf{X=x,\ Y=y})$ is the cost associated with a cracked pipe conditioned on a given true state **x** after inspection with a possible measurement outcome **y**. Note that C_p also depends on the possible repair actions, since they depend on the measurement. Different repair policies exist as discussed earlier, and two commonly used repair policies are introduced as follows. The first repair policy, π_1, is based on the relative ratio of repair cost (C_r) and failure cost (C_f), while the second repair policy, π_2, is based on the allowable probability of failure P_f^c, also known as the repair threshold. Specifically, repair actions will be taken when $Pr[E_1|\mathbf{y}] > C_r/C_f$ in the first repair policy, i.e., $C_f \times Pr[E_1|\mathbf{y}] > C_r$. In contrast, repair actions will be taken when $Pr[E_1|\mathbf{y}] > P_f^c$ in the second repair policy. Corresponding to each repair policy, $C_p(\mathbf{X=x,\ Y=y})$ can be calculated as shown in Eq. (5) and (6), respectively.

$$C_p(\mathbf{x},\mathbf{y}) = \begin{cases} C_f \times Pr[E_1 \mid \mathbf{x}] & \text{if } C_f \times Pr[E_1 \mid \mathbf{y}] < C_r \\ C_r & \text{if } C_f \times Pr[E_1 \mid \mathbf{y}] \ge C_r \end{cases} \quad (5)$$

$$C_p(\mathbf{x},\mathbf{y}) = \begin{cases} C_f \times Pr[E_1 \mid \mathbf{x}] & \text{if } Pr[E_1 \mid \mathbf{y}] < P_f^c \\ C_r & \text{if } Pr[E_1 \mid \mathbf{y}] \ge P_f^c \end{cases} \quad (6)$$

In this study, the optimal repair threshold P_f^{c*} would be the one that minimizes the pre-posterior cost, as calculated by Eq. (4), while considering the constraint imposed by $P_{f,\text{ safety}}$ for safety and environmental impact (Kamariotis et al. 2020; Straub 2004), see Eq. (7).

$$P_f^{c*} = \underset{P_f^c \le P_{f,\,Safety}}{argmin}\, C_{pp} \quad (7)$$

Here, $P_{f,\text{ safety}}$ is taken as 10^{-3} per feature per year, based on maximum tolerable safety criterion suggested in literature (Nessim et al. 2004, 2014).

As observed in Eq. (5) and (6), the updated probability of failure $Pr[E_1|\mathbf{y}]$ given a measurement outcome $\mathbf{y} = [y_D, y_L]$, needs to be calculated. $Pr[E_1|\mathbf{y}]$ will be obtained from Eq. (3) just by substituting updated PDF of system state, denoted by $f_{\mathbf{X|Y}}$. $f_{\mathbf{X|Y}}$ can be obtained through Bayesian updating (Straub 2014), as shown in Eq. (8).

$$f_{\mathbf{X|Y}}(\mathbf{x} \mid \mathbf{y}) = \frac{f_{\mathbf{X}}(\mathbf{x})\phi(\mathbf{y}-\mathbf{x};\mathbf{0},\Sigma_{ee})}{f_{\mathbf{Y}}(\mathbf{y})} \quad (8)$$

In. Eq. (8), the likelihood function, denoted by ϕ, is equal to $N(y_D - D;\ 0,\ \sigma_{eD})\cdot N(y_L - L;\ 0,\ \sigma_{eL})$ when the measurement $y_D = D + e_D$, and $y_L = L + e_L$, in which e_D and e_L is the zero mean Gaussian measurement error, with standard deviation of σ_{eD} and σ_{eL} for crack depth and length, respectively. Σ_{ee} is the diagonal covariance matrix of sizing error. $f_{\mathbf{Y}}$ is a normalization constant, which is equal to the integration of nominator in Eq. (8) over **X**. With that, sampling methods can be implemented to calculate $Pr[E_1|\mathbf{y}]$ and thus $C_{pp}=E_{\mathbf{XY}}[C_p(\mathbf{x},\mathbf{y})]$, as shown in the developed tool where MC sampling is used.

2.3. Tool Development

Figure 2 presents the flowchart of the tool, in which crude MC sampling is implemented based on available solutions in literature (Konakli et al. 2016; Straub 2014). First, prior samples $\mathbf{x}^k$ ($k = 1, 2, \ldots, n_x$) are generated according to the prior PDF of **X** from the reliability module to calculate prior P_f and C_{prior} for prior analysis. Second, in pre-posterior analysis, each prior sample $\mathbf{x}^k$ is combined with measurement error $\boldsymbol{e}_j$ ($j = 1, 2, \ldots, n_y$), which is j^{th} measurement outcome simulated according to the corresponding probability model, to obtain $\mathbf{y}^k_j = \mathbf{x}^k + \boldsymbol{e}_j$. This leads to a total of $n_x \cdot n_y$ possible measurement outcomes. For a given $\mathbf{y}^k_j$ reliability updating can be conducted to calculate $Pr[E_1|\mathbf{y} = \mathbf{y}^k_j]$ using the samples $\mathbf{x}^k$ ($k = 1, 2, \ldots,$

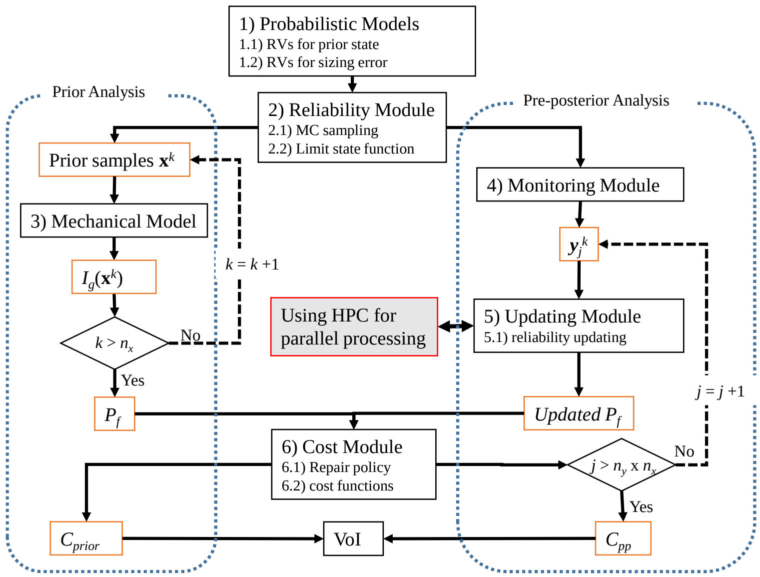

Figure 2: Architecture of developed tool for VoI calculation

n_x), according to Eq. (8). In addition, $C_p(\mathbf{x}^k, \mathbf{y}^k_j)$ is calculated in cost module according to (5) or (6). In the end, C_{pp} is calculated in the cost module using Eq. (4).

The computation required for pre-posterior analysis can be quite demanding, particularly for the repetitive calculation of likelihood, as shown in Eq. (8). This study develops Python modules that allow for parallel processing, using cloud computing service provided by Compute Canada. This study has utilized the powerful HPC capabilities to perform the computations shown in Figure 2. By dividing a large number of observations into smaller groups, reliability updating for each group can be processed in parallel as a separate job on Compute Canada. This enables effectively lowering computational barriers. The results from all groups can then be merged together, allowing for the efficient calculation of rare events with low probability that require a large number of samples. In the following section, a numerical example will be presented to illustrate the practical application of the developed tool.

3. APPLICATION

In this section, the proposed framework is applied on a hypothetical pipeline segment with grade X52, and properties summarized in Table 1. The size of a single crack has been estimated using a prior probability density function (PDF) derived from crack population statistics (Yan et al. 2020), and its distribution is presented in Table 2. The crack is susceptible to burst failure, which can result in a failure cost (C_f) ranging from $20 million to $100 billion based on previous statistics from pipeline failures. Note that extremely high failure cost (e.g., $100 billion) can be induced when considering indirect cost arising from socioeconomic consequences of pipeline failure in environmentally or culturally sensitive regions and potential secondary consequences near critical infrastructure facilities. To avoid failure, operators can repair the crack at a cost of $0.2 million, following re-inspection.

Table 1: Properties of pipeline

Parameter	*Value*	*Units*
Outside diameter	*508*	*mm*
Wall thickness	*6.35*	*mm*
Tensile strength	*455.05*	*MPa*
Toughness CVN	*85*	*J*
Operating pressure	*6.45*	*MPa*

The inspection tool used to measure the crack size has a sizing error, and the statistics for its measurement error are provided in Table 2. Note that the measurement error of the inspection tool is lower than the prior uncertainty in crack depth and length. Thus, measurement can help reduce uncertainty of crack size. Before implementing the inspection tool, the operator needs to conduct a Value of Information (VoI) analysis to calculate the cost of re-inspection. This analysis will be carried out in section 3.2 and 3.3, for repair policies π_1 and π_2, respectively.

Table 2: Prior PDF of crack size and statistics for measurement error of inspection tool

Parameter	*PDF Type*	*PDF Parameters*
D (mm)	*Gamma*	$(\mu = 1.725, \sigma = 0.89)$
L (mm)	*Gamma*	$(\mu = 97.041, \sigma = 51.395)$
e_D (mm)	*Normal*	$(\mu_{eD} = 0, \sigma_{eD} = 0.37)$
e_L (mm)	*Normal*	$(\mu_{eL} = 0, \sigma_{eL} = 15.6)$

3.1. VoI Analysis for repair policy π_1

VoI analysis comprises two main steps: prior and pre-posterior analysis. To conduct the prior analysis, Monte Carlo simulation (MCS) is employed with a total of n_x=10^6 sampled crack sizes generated from the prior PDF. The calculated prior probability of failure (P_f) using MCS is 1.865×10^{-3}, and the convergence of P_f is verified with this number of samples. For different failure costs (C_f) ranging from \$20 million to \$100 billion, the corresponding prior cost (C_{prior}) is between \$$3.73\times10^4$ to \$$1.865\times10^8$. C_{prior} is the same for both repair policies but C_{pp} is dependent on repair policy.

The pre-posterior cost (C_{pp}) for repair policy π_1 is calculated using the proposed framework in section 2.3, with n_y = 5. The results for C_{pp} are verified to converge, but are not presented here for brevity. For the repair policy π_1, considering the same range of C_f, the calculated C_{pp} is between \$$6.812\times10^3$ to \$$1.326\times10^5$ which leads to VoI between \$$3.0488\times10^4$ to \$$1.8637\times10^8$. Hence, the VoI varies depending on the failure cost C_f.

Apart from the failure cost, the sizing error of the inspection tool is also a crucial factor in determining the VoI. To compare the impact of failure cost and sizing error on the VoI for repair policy π_1, Figure 3 illustrates the sensitivity of VoI with respect to sizing error of crack depth while keeping the length sizing error close to zero for three different cost ratios. As the ratio of failure cost to repair cost (C_f/C_r) increases, VoI also increases, which is reasonable. Additionally, VoI is dependent on the prior failure risk, and an increase in failure cost leads to an increase in VoI. On the other hand, an increase in sizing error results in a decrease in VoI, indicating that the operator is willing to pay less for inspection tools that are less precise. Conversely, when the depth sizing error is close to zero, VoI approaches the value of complete perfect information.

Assuming that clairvoyance, or complete perfect inspection, is available, the decision-making process becomes simplified. This is because complete perfect inspection removes any uncertainty regarding the burst pressure capacity, and the decision reduces to two options: repair the crack and pay the repair cost (C_r) if the crack fails, or do nothing if the crack is deemed safe and pay zero cost. The use of an indicator function (I_g) allows us to calculate the posterior cost (C_p) as the product of the indicator and the repair cost. The average of the posterior cost over all possible values of **y**=**x** is equal to the product of the repair cost and the probability of failure (P_f), or C_{pp}=$C_r\times P_f$. the cost of repair is small in comparison to failure cost, resulting in C_{pp} being equal to $C_r\times P_f$=\$373, almost no pre-posterior cost when complete perfect inspection is available.

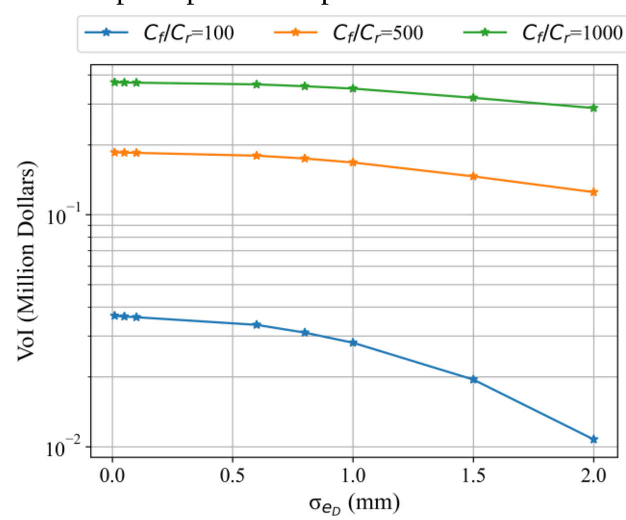

Figure 3: Sensitivity of *VoI* to depth sizing error and relative cost ratio C_f/C_r for repair policy π_1

3.2. VoI Analysis for repair policy π_2

This section explains the approach for calculating VoI and obtaining the optimal threshold for repair policy π_2. C_{prior} is the same as what is obtained for repair policy π_1. To calculate C_{pp}, the same approach used for repair policy π_1 with n_y=5 and

n_x=10^6 is implemented. An optimal threshold P_f^c can be selected for repair policy π_2 to maximize VoI for imperfect inspection. Figure 4 presents the variation of C_{pp} with respect to threshold P_f^c for repair policies π_1 and π_2, for two different orders of failure costs. To calculate C_{pp}, different values of P_f^c between 10^{-8} to 10^{-2} with logarithmic order were tested. Note that conventional repair policy π_1 is constant over all ranges of P_f^c because it is not dependent on P_f^c. To accelerate this analysis, the framework in Figure 2 was implemented with parallelized calculations and Compute-Canada was used, which significantly reduced computation times.

For C_f = \$100 billion, C_{pp} for repair policy π_2 would be between \$0.104 million to \$0.155 million which leads to VoI between \$186.34 million to \$186.4 million. As seen in Figure 4, optimal P_f^c equal to 6×10^{-8} leads to minimum C_{pp} equal to \$1.04×10^5. For C_f = \$100 billion, the trend of C_{pp} is increasing with respect to P_f^c. It means that for higher failure cost, C_{pp} increases by choosing higher threshold P_f^c due to increase possibility of failure in measurement scenarios. Hence, operator should choose a smaller threshold for higher failure cost and be more conservative.

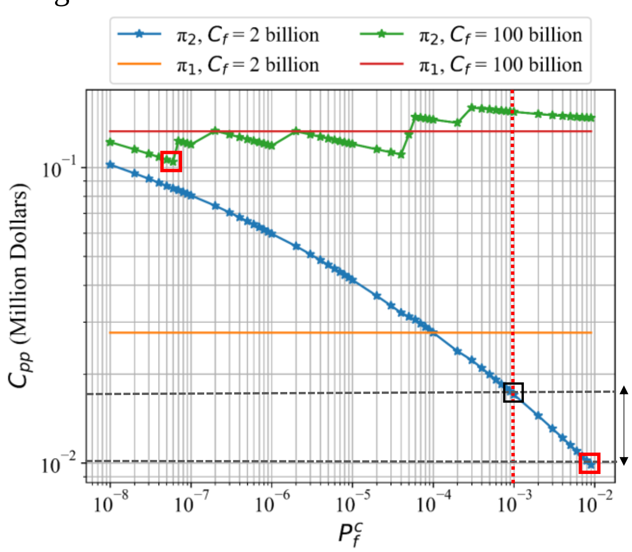

Figure 4: Variation of C_{pp} with respect to P_f^c for two different failure costs

For C_f = \$2 billion, considering the range of P_f^c between 10^{-3} to 10^{-8}, C_{pp} for π_2 would be between \$0.017 million to \$0.1 million which leads to VoI between \$3.71 million to \$3.63 million, as shown in Figure 4. For C_f=\$2 billion, P_f^c equal to 0.01 minimizes C_{pp} for repair policy π_2. However, safety constraint equals to 10^{-3} acts as an active constraint and optimal P_f^c is 10^{-3}. In order to meet safety constraint, an additional cost of \$7×10^3 compared to the minimum possible costs should be tolerated. For C_f = \$2 billion, the range of P_f^c between 10^{-3} to 10^{-4} maximizes VoI for repair policy π_2 leading to VoI equal or higher than VoI of repair policy π_1. In this case, higher P_f^c leads to optimal usage of maintenance resources and lower C_{pp}, as depicted in Figure 4. On the other hand, choosing smaller repair threshold leads to increasing C_{pp} due to increase in the portion of repairs in measurement scenarios of pre-posterior analysis.

Table 3: C_{pp} and VoI for each repair policy with C_f=\$2 billion, C_r=\$0.2 million

	Reliability-based, π_2 with optimal P_f^c = 10^{-3}		Conventional, π_1	
	Perfect	Imperfect	Perfect	Imperfect
C_{prior} (\$10^6)	3.73	3.73	3.73	3.73
C_{pp} (\$10^6)	3.73×10^{-4}	0.017047	3.73×10^{-4}	0.0276184
VoI (\$10^6)	3.73	3.71	3.73	3.70

The summary of results for a failure cost of \$2 billion are presented in Table 3. The chosen failure cost leads to a C_{prior} of approximately \$3 million and a VoI around the typical value of an ILI tool. Table 3 shows that the optimal repair threshold (P_f^c) for repair policy π_2 leads to a 40% lower C_{pp} compared to repair policy π_1, for imperfect inspection. However, the optimal VoI for repair policy π_2 is close to that of repair policy π_1 because the prior cost is the dominant factor in determining VoI. It should be noted that this is a special case, and when C_{pp} and C_{prior} are in same order, optimizing repair policies can lead to a higher difference in VoI. Additionally, the VoI in Table 3 is related to a single crack, but considering the population of cracks similar to the one analyzed here, the difference in VoI of inspection tool for different policies can be even larger.

Note that in this example, for simplicity, just uncertainties in crack size were considered. In a realistic case by considering uncertainties in material strength or geometry of pipeline, a more precise value for optimal P_f^c can be obtained depending on problem assumptions. Optimizing repair threshold for each problem with different prior information and inspection features can be computationally expensive. Nevertheless, this research proposes a systematic method using an HPC for parallel processing to accelerate VoI calculation process for operators. Note that the optimal repair policy in this study is proposed for a single critical crack based on prior information. In industry, this prior information is available from previous inspections or crack-growing models for all cracks in a pipeline. Hence, the proposed tool can be implemented to all other critical cracks in a system to find the optimal threshold for each crack.

4. CONCLUSIONS

In conclusion, this research has successfully demonstrated the effectiveness of using a Value of Information (VoI) analysis for optimizing repair policies for pipelines with surface cracks. By utilizing parallelized calculations and integrating a tool based on Python modules with Compute Canada, the time consumed for VoI analysis was significantly reduced. The research also highlighted the importance of considering cost variation and imperfect inspection of tools in the optimization process. The results confirm that the optimal repair policies are dependent on costs, prior information, and inspection imperfections. However, the proposed methodology and developed tool can help overcome the challenges of computational expense and prior information uncertainty, making it a valuable tool for pipeline operators. As a future direction, the research aims to extend the tool's capabilities to include the population of cracks in larger systems and the consideration of growth uncertainty in life-cycle analysis.

5. ACKNOWLEDGMENT

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