Risk-based optimization of pipe inspections in large underground networks with imprecise information

Article *in* Reliability Engineering [?] System Safety · March 2016

DOI: 10.1016/j.ress.2016.03.011

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Abstract

In this paper, we present a novel risk-based methodology for optimizing the inspections of large underground infrastructure networks in the presence of incomplete information about the network features and parameters. The methodology employs Multi Attribute Value Theory to assess the risk of each pipe in the network, whereafter the optimal inspection campaign is built with Portfolio Decision Analysis (PDA). Specifically, Robust Portfolio Modeling (RPM) is employed to identify Pareto-optimal portfolios of pipe inspections. The proposed methodology is illustrated by reporting a real case study on the large-scale maintenance optimization of the sewerage network in Espoo, Finland.

1 Introduction

Large infrastructure networks, such as gas or water pipelines, are subjected to preventive renovation and condition inspection programmes which account for a significant portion of the network operating costs ([47], [48]). The optimization of inspections is therefore fundamental for the efficient management and competitiveness of these complex networks. Information about the current condition of the network items is needed for developing the optimal renovation programme; however, in practice, the actual conditions of network items such as pipes can be determined only approximately through inspections that can be very costly, especially in the case of large underground networks.

This calls for the optimization of renovation planning, which can be seen as a two-step process:

i) identification of an optimal set of inspections of the network items whose subsequent renovation actions (if necessary) can be expected to reduce network-related risks most while reducing the cost of expected negative consequences as much as possible;

ii) assessment by inspection of the degradation state of the network items in the selected portfolio and optimal planning of maintenance actions for the whole network.

In this paper, we develop a novel risk-based methodology for addressing the first issue, whereas the second issue is left for future research. The methodology has been motivated by and developed in the context of a real case study.

Although there are several definitions for risk (e.g., see [3], [4] for reviews and comparisons), in maintenance engineering it has always been viewed as a combination of two attributes: *likelihood* (i.e., a description, even rough, of the uncertainty in the occurrence of the failure event) and *severity* (i.e., a quantification of the impact of the failure on properties, environment, safety, production, etc.) [21].

The idea of optimizing maintenance actions on the basis of a risk evaluation in view of likelihood and severity dates back to the 1980s, when the American Petroleum Institute (API) started the Risk-Based Inspection (RBI, [8], [20], [29]) project whose aim was to define a procedure for prioritizing and managing the efforts of an inspection programme. In this procedure, resources are allocated to provide a higher level of coverage to high-risk items while maintaining an adequate effort on lower-risk equipment [17]. This methodology has become popular also in the nuclear industry (e.g., [43]) in which Probabilistic Risk Assessment (PRA) is used for maintenance prioritization: the more a given maintenance action on a basic event can reduce the overall plant risk, the higher the priority of this action.

Later, especially after the year 2000, Risk-Based Maintenance (RBM, [7]) has gained popularity with the inclusion of risk-based inspection within the Reliability Centered Maintenance (RCM) paradigm and the Condition-Based Maintenance (CBM) strategies ([1], [24], [35], [42]). Subsequently, it has been applied in different industrial contexts (e.g., [1]), including critical infrastructures. For example, RBM models have been developed by Dey ([13], [14]) for oil and gas pipelines by using the Analytic Hierarchy Process (AHP) to guide the allocation of maintenance resources on the most risky pipeline stretches. However, the AHP method suffers from limitations such as the rank reversal phenomenon (i.e., the relative ranking of two alternatives may change when a new alternative is introduced), shortcomings of the 1-9 ratio scale, and pitfalls in quantification of qualitatively stated pairwise comparisons [36]. Moreover, the methodology proposed in [13], [14] does not tackle the problem of how to optimize the inspection campaign, which, as a topic, has been addressed by researchers who have built RBI plans for wastewater networks (e.g., [6], [18]).

Hahn et al. [18] propose an approach to RBI based on Bayesian Belief Networks (BBN) for prioritizing the sewerage inspections (i.e., the domain of the case study discussed in this work). The model accounts for the uncertainty in the expert beliefs. However, the resulting decision recommendation considers neither the uncertainty in the state of the pipe nor any budget constraint. Moreover, it does not account for possible project interdependencies (e.g., cost synergies of checking pipes in the same region) and constraints concerning portfolio balance (e.g. to ensure that portfolios contain sufficiently many pipes with different characteristics).

A Multi-Objective Genetic Algorithms (MOGA, [11], [15]) has been developed in [6] to identify the set of Pareto-optimal inspection programmes. Network items are ranked based on how many times they are selected by the multi-objective algorithm to create an archive of “optimal” inspection policies. Although the selection of the items with the highest selection frequency approximately maximizes the expected number of correct item choices [31], this methodology for prioritizing network item inspections lacks a sound theoretical justification. Furthermore, the solution can be heavily dependent on the algorithm settings (e.g., number of generations, mutation rates, etc.). As a result, the Decision Maker (DM) cannot be sure that the proposed final solution belongs to the set of optimal solutions. Finally, this methodology is not able to deal with uncertain and imprecise information.

Against these backdrops, we propose a rigorous methodology for the optimal targeting of inspection activities in a generic underground network, with the aim of maximizing the aggregate value of these inspections as achieved through their contribution to risk reduction, subject to budget constraints and the presence of possible interdependencies among inspections and uncertainties about the model parameters. Our methodology combines aspects of Robust Portfolio Modelling (RPM, [27], [28], [31]) with the dynamic modelling approach [40] which uses multi-attribute value functions to model preferences on the quality distributions of assets and provides guidance for the optimal allocation of maintenance resources at the Finnish Road Administration. In particular, our methodology accommodates qualitative expert judgements about the risk of network items.

Our risk-based methodology for prioritizing network item inspections consists of two steps:

1. Rank all items of the network based on their risk level.
2. Select optimal portfolios of inspections among the items that have been ranked highest.

The separation of the two parts is motivated by practical reasons: the direct application of the procedure at the second step to all the items would require an excessive computational effort. Nonetheless, in the case of large networks, the number of risky items selected at step 1 is typically in the order of thousands and searching such a large search space is not computationally feasible. Thus, we have implemented the non-exhaustive search of the algorithm proposed by Mild et al. ([31]) to determine a large subset of optimal portfolios.

The proposed approach is able to guide risk-based inspection planning based on rough field data and qualitative statements from experts who have knowledge about the pipe degradation process as well as the risk scenarios caused by pipe failures. Alternatively, model-based risk estimates can be derived through analytical approaches and associated models. However, such models involve parameters whose values are usually not precisely known and may have to be fine-tuned on case-by-case basis; moreover, the more advanced analytical approaches also require model simulation [44]. In this sense, one advantage of our approach is that it offers a viable compromise between the need to incorporate sound risk estimates based on field data about the physical phenomena and the need to build a parsimonious model for the risk assessment of a very large number of maintenance items.

We also note that this methodology for identifying optimal portfolios of risk-based inspection programmes is generic in that it can be applied to different types of underground networks (gas, water, wastewater, etc.). We illustrate this methodology by reporting a real case study in which it was applied to a large sewerage network in Espoo, Finland.

The rest of the paper is structured as follows. Section 2 presents the methodology, focusing on risk identification, risk value trees definition and risk assessment in its first subsection, and describing the methodological steps to assess the inspection benefits and, on this basis, select the cost efficient inspection portfolios, in the second subsection. Section 3 presents the case study and describes the process and outcomes of eliciting statements by experts to build the value trees. Finally, Section 4 concludes the paper and outlines extensions for future research.

2 Overview of the methodology

Our approach builds on Multi-Attribute Value Theory (MAVT, [16], [23]), which is a systematic methodology for evaluating decision alternatives with regard to multiple objectives. In MAVT, these objectives are operationalized by defining corresponding attributes which have performance scales for measuring the performance of alternatives. In our paper, the alternatives are network items which are evaluated with regard to the two main objectives of impacting most the likelihood of failures and contributing most to the severity of failure consequences, in order to establish inspection priorities. Each subset of these network items is called a “portfolio”.

Figure 1 summarizes the two-step risk-based methodology proposed for prioritizing item inspections in the presence of incomplete knowledge. The steps are detailed in the next subsections.

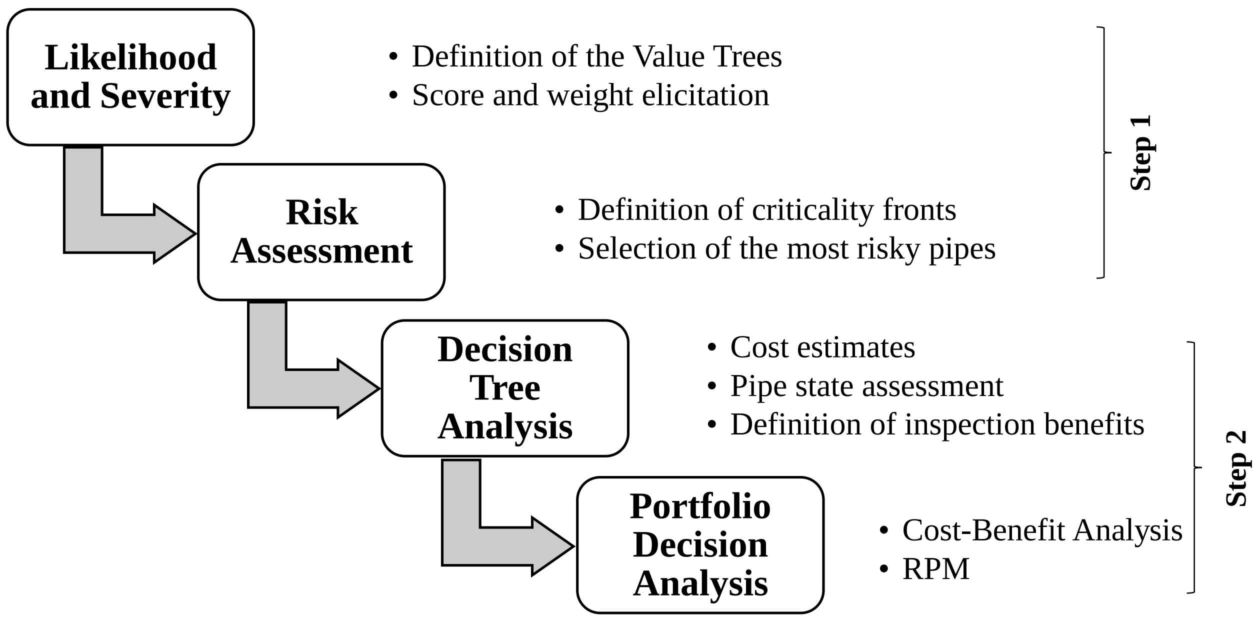

Figure 1: methodology snapshot

2.1 Rating of network items based on risk

In the proposed MAVT-based framework, the risk-based rating of network items has two main objectives:

1. Identify items which are most likely to fail.

2. Identify items whose failure has the most severe consequences.

For each objective, a team of experts analyzes which attributes contribute to failure likelihood and severity. These attributes are structured as a hierarchy when the overall objective (i.e. failure likelihood and failure severity) is decomposed into subobjectives until the lowest level of the hierarchy, which contains attributes with regard to which the alternatives can be meaningfully evaluated [23]. In particular, the hierarchy provides the DM with an overall view of the relationships between the different subobjectives and facilitates the assessment of the relative importance of objectives on each level. The decomposition proceeds until the experts agree that attributes do not need to be further disaggregated. The attributes at the lowest level of the hierarchy are called leaf attributes. For example, in the value tree for the objective of impacting most the likelihood of failure, the leaf attribute "Material" of a pipe has several material quality classes so that a pipe matches one of the following: "PVC", "cast iron", "concrete", "polyethylene", "renovated with trenchless socks".

For simplicity, suppose that the value tree of failure likelihood is composed of two levels. Specifically, assume that the first level l_1 represents the failure likelihood $V_L(x^j)$ of alternative x^j and the second level l_2 includes the set of leaf attributes A_L of failure likelihood (the same approach is used to build the value tree of failure severity). Each alternative x^j is characterized by specific quality classes x_i^j for each attribute i. For example, a pipe is characterized by a specific material among "PVC", "cast iron", "concrete", "polyethylene" and "renovated by trenchless socks". Each of these quality classes is assigned a score $v_i(x_i^j)$, which is evaluated through a modified SWING procedure [46] so that the expert assesses the relative importance of different quality classes x_i^j in determining the failure likelihood. Specifically, the weakest material ("renovated by trenchless socks") is assigned score $v_i(x_i^j) = 100$, whereas the most reliable one ("concrete") is assigned score $v_i(x_i^j) = 0$: every other quality class is scored according to these two reference points, whereby scores $v_i(x_i^j)$ can alternatively be evaluated through interval valued scores so that $v_i(x_i^j) = [\underline{v}_i(x_i^j); \overline{v}_i(x_i^j)]$. For example, score $[60 - 80]$ is assigned to quality class "cast iron" given that its reliability is much closer to "concrete" than "renovated by trenchless socks". Once the quality classes of every attribute have been scored, each alternative x^j is fully defined by the set of interval-valued scores $v_i(x_i^j)$ of the quality classes that characterize that alternative. Thus, the values of failure likelihood $V_L(x^j) = [\underline{v}_L(x^j); \overline{v}_L(x^j)]$ are calculated as the intervals

$$\underline{v}_L(x^j) = \min[\sum_{i \in A_L} w_i \, \underline{v}_i(x_i^j)] \quad (1)$$

$$\overline{v}_L(x^j) = \max[\sum_{i \in A_L} w_i \, \overline{v}_i(x_i^j)] \quad (2)$$

where w_i represents the weight of attribute i.

In this context, weights w_i are specified by the experts who may give imprecise preference statements about attributes such as "attribute $i \in A_L$ is more important than attribute $i' \in A_L$ which in turn is more important than attribute $i'' \in A_L$". These preference statements imply weight constraints that limit the set of feasible weights. In the previous example, the imprecise statements lead to the weight constraints $w_i \geq w_{i'} \geq w_{i''}$ so that the feasible weight set consists of the extreme points

$(1\ 0\ 0)$; $\left(\frac{1}{2}\ \frac{1}{2}\ 0\right)$; $(\frac{1}{3}\ \frac{1}{3}\ \frac{1}{3})$ and their convex combinations. Under mild assumptions, which are here fulfilled, the maximum and minimum values of Eqs. (1) and (2) are attained at the extreme points of the feasible weight set [41].

In value trees with multiple levels, the calculation of Eqs. (1) and (2) is propagated throughout the hierarchical structure until the topmost objective (i.e. failure likelihood or failure severity) is reached. The definition of failure likelihood and failure severity of each alternative x^j is based on the extension [38] of the PAIRS method [37], which admits imprecise preference statements about attributes. Specifically, PAIRS solves linear problems of Eqs. (1) and (2) at level l_h to identify the interval-valued scores at the next higher level l_{h-1}, and the computations are then repeated until the topmost objective of the value tree is reached. Note that Eqs. (1) and (2) are based on the assumption that the leaf attributes are mutually preferentially independent [18] which can usually be guaranteed by structuring the problem so that the contribution of a higher score on some leaf attribute to the overall performance does not depend on what the performance levels on other leaf attributes are.

Note that every item is characterized by a quality class for each leaf attribute. For instance, a pipe is characterized by a specific material, a specific diameter, etc. Thus, the score elicitation is applied to the quality classes of every leaf attribute so that the overall values of failure likelihood and failure severity of every pipe can be estimated once the pipe quality classes of every leaf attribute have been assessed. As a result, the calculation of failure likelihood and failure severity values does not take much computation time even if the number of items is large.

In the risk assessment part of the methodology, the aim is to identify the most critical network items with respect to failure likelihood and failure severity. These items form the Pareto optimal set, because they are not dominated by any other item, i.e., another item with a greater failure likelihood will have a lower failure severity or vice versa.

However, this concept of dominance needs to be extended for our analysis, because the overall values of both likelihood and severity are intervals (V_L and V_C, respectively). That is, for interval scores, item x^j is said to dominate item x^k ($k \neq j$) if and only if the intervals $V_L(x^j)$ and $V_C(x^j)$ both lie above $V_L(x^k)$ and $V_C(x^k)$, respectively:

$$x^j \succ x^k \leftrightarrow \begin{Bmatrix} \underline{v}_L(x^j) \geq \bar{v}_L(x^k) \\ \underline{v}_C(x^j) > \bar{v}_C(x^k) \end{Bmatrix} \vee \begin{Bmatrix} \underline{v}_L(x^j) > \bar{v}_L(x^k) \\ \underline{v}_C(x^j) \geq \bar{v}_C(x^k) \end{Bmatrix} \tag{3}$$

This dominance definition allows us to identify the different Pareto-optimal frontiers F_i ([12], [23]), where $i \in \{1,2,3, \dots\}$ represents the index of the non-dominated frontiers ([10], [12]) and $|\cdot|$ indicates the dimension of the set.

On this basis, the items of the network can be compared to each other to identify those that have the highest failure likelihood and highest failure severity. In this respect, given the uncertainty in both the likelihood and severity values, the pairwise dominance concept of [38] is applied to select non-dominated items (i.e., the Pareto optimal set) in the two-dimensional space failure likelihood–failure severity. The second step of the analysis (i.e. portfolio optimization) is carried out on this reduced set F_1, containing the items which have been assessed to have the highest risk.

2.2 Portfolio optimization

The purpose of portfolio optimization is that of performing a cost-benefit analysis of the most critical network items with the aim of identifying the subset of those items whose inspection is expected to give the highest benefit in terms of reducing the cost of disruption.

The main goal is to make those inspection and renovation decisions that maximize the benefit-cost ratio of performing inspections in order to reduce expected disruption costs. We also account for the uncertainty in the direct and indirect costs associated to the pair of decisions, as well as the uncertainty in the actual degradation state of the pipe. In our setting, inspection plans are revised annually based on the available budget and the historical record of past inspection outcomes and maintenance actions. The prioritization of inspections is updated annually by relying on expert judgements, which, if needed, can also be elicited to revise the definition of the attributes and to adjust the weights.

Towards this end, we first build a decision tree model ([16], [23]) to help experts decide whether an item needs inspection and whether or not it pays off to carry out maintenance actions on it. A decision tree shows the relationships between the decisions, the chance events that may occur, and the values that are generated through sequences of decisions and events. Probabilities are assigned to the chance events so that expected values are determined for each possible outcome.

For every network item in the previously selected set of risky items, the experts have two successive decisions to make:

1. Decide whether the item should be inspected. This decision tree is indicated by two branches corresponding to the two possible decisions: ‘Yes’ and ‘No’.
2. If the item has been inspected, the next decision is whether or not to carry out renovation actions which may reduce the network disruption probability and consequently the expected

severity of consequences. Otherwise, the indirect costs of not inspecting the item are considered (i.e., the expected disruption consequences). This second part of the decision tree is case-specific.

Consider the decision tree in Figure 2, which is employed in the case study in Section 3. The DM first has to decide whether pipe x^j, $j \in F_1$ should be inspected to determine its degradation state (part 1 in Figure 2). In this paper we employ a discrete, multi-state description of the degradation level of the network maintenance items, which is often the case in many industrial applications [26]. If no inspection is carried out, then the DM needs to associate with this decision the cost of indirect consequences. We assume that renovations are always preceded by item inspection, because it is not meaningful to carry out renovation activities without inspecting first. The expected value of disruption is calculated over the possible pipe degradation states (Figure 2, bottom part). The more degraded the item state, the higher the probability of disruption.

If the item is inspected, the next decision is what renovation actions (part 2 in Figure 2), if any, should be taken to improve the state of the items and, thus, to reduce the probability of disruption. In particular, items that have been renewed are all assumed as good as new, with disruption probability equal to that of the State 1.

To solve the decision tree, it is necessary to elicit case-specific probability and cost information which are attached to its branches.

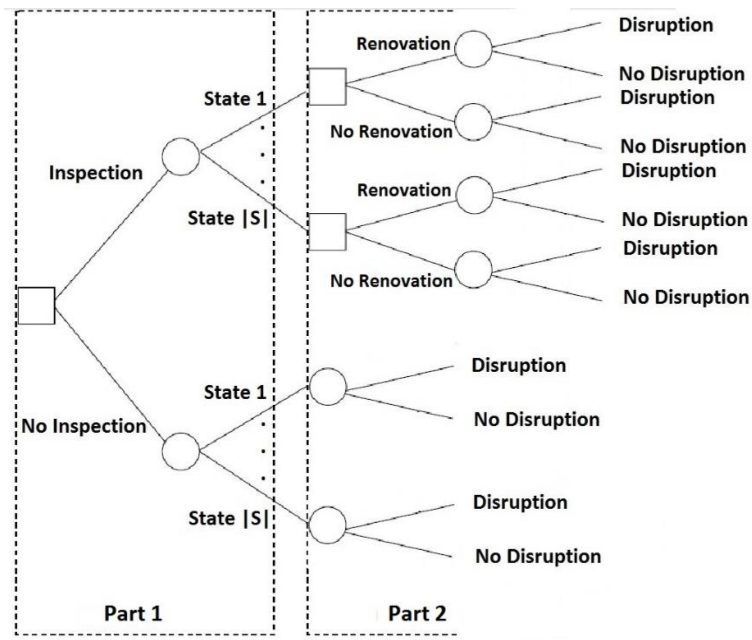

Figure 2: Decision tree

Firstly, we need to estimate the probability of item x^j belonging to degradation state $s \in S = \{1, \dots, \Sigma\}$. Here, different methodologies of probability elicitation can be employed, based on the available data and the specific case.

In our case, we considered the actual inspection outcomes on the J items and calculated the corresponding likelihood intervals $V_L(x^j) = [\underline{v}_L(x^j), \bar{v}_L(x^j)]$ derived from expert statements. Then, for every likelihood score $v_L = \{v_L \in \mathbb{N} | 0 \leq v_L \leq 100\}$, we selected all items x^j for which $v_L \in V_L(x^j)$. The resulting intervals were used to estimate the probability $p(s^j = s)$ of item x^j being in state $s \in S$. Namely, consider the interval $V_L(x^j)$ of likelihood values $v_L(x^j)$, then the probability $p(s^j = s)$ is

$$p(s^j = s) = \sum_{v_L \in v_L(x^j)} \left[p(s^j = s | v_L(x^j) = v_L) \cdot p(v_L(x^j) = v_L) \right], \tag{4}$$

where

$$p(s^j = s | v_L(x^j) = v_L) = \frac{|\{j \in \cup_\varphi F_\varphi | v_L \in V_L(x^j) \wedge s^j = s\}|}{|\{j \in \cup_\varphi F_\varphi | v_L \in V_L(x^j)\}|} \tag{5}$$

$$p(v_L(x^j) = v_L) = \frac{1}{\bar{v}_L(x^j) - \underline{v}_L(x^j)}, \tag{6}$$

if we assume a uniform distribution over the likelihood interval scores $v_L \in V_L(x^j)$. For simplicity, we only considered integer likelihood values. This makes it possible to solve Eq. (4) as a sum rather than as an integral.

The disruption probabilities are contingent on the item states. To account for the corresponding uncertainty about disruption probability, experts were asked to estimate lower bounds $\underline{p}_s^d$ and upper bounds $\overline{p}_s^d$ of the disruption probability of each degradation state $s \in S$. As mentioned before, if the item is renovated, then the corresponding disruption probability is the one for the best State 1, i.e. $[\underline{p}_1^d, \ \overline{p}_1^d]$.

In addition, it is necessary to estimate (i) the disruption consequences, which are estimated as one number representing both direct and indirect costs $c_j^d = [\underline{c}_j^d; \bar{c}_j^d]$; (ii) the renovation costs $c_j^s = [\underline{c}_j^s; \bar{c}_j^s]$, $s \in S$ and (iii) the inspection costs $c_j^t = [\underline{c}_j^t; \bar{c}_j^t]$.

These parameters can be elicited as intervals defined by lower and upper bounds that are stated by the experts. Note that the choice of describing by intervals the uncertainty in the expert-estimated probability and consequence values is justified by the sake of generality of the proposed methodology.

In fact, other approaches to represent uncertainty (e.g. by median and variance) would require more specific knowledge from experts, which is not always available. Note also that the interval-valued representation of uncertainty is compliant with non-probabilistic approaches to handle uncertainty, such as p-box and Dempster Shafer Theory of Evidence (e.g. [2], [21]).

After the elicitation process, the analysis is based on the decision tree in Figure 2 in which the goal is to select the optimal decision between committing or not committing renovation actions, which is applicable only when the item is inspected (top right part of the tree in Figure 2). Specifically, we define the set $R = \{r^+, r^-\}$ such that $r = r^+$ stands for committing renovation actions while $r = r^-$ stands for not committing any renovation action.

The expected cost ϑ^{r_s} for action $r = r^+$ on item x^j in degradation state $s \in S$ is given by the sum of the actual cost for item renovation and the expected disruption cost in case of item renovation. Then, the interval of possible values of ϑ^{r_s} is given by

$$\underline{\vartheta}_j(r_s^+) = \left[\min \left\{c_j^d \cdot p_s^d\right\}\right] + \underline{c}_j^s = \underline{c}_j^d \cdot \underline{p}_1^d + \underline{c}_j^s \qquad \forall s \in S, j \in F_1 \tag{7}$$

$$\bar{\vartheta}_j(r_s^+) = \left[\max \left\{c_j^d \cdot p_s^d\right\}\right] + \bar{c}_j^s = \bar{c}_j^d \cdot \overline{p}_1^d + \bar{c}_j^s \qquad \forall s \in S, j \in F_1. \tag{8}$$

On the other hand, the expected cost ϑ^{r_s} for action $r = r^-$ on item x^j in degradation state $s \in S$ is given by the expected disruption cost, where the disruption probability is contingent to the item states

$$\underline{\vartheta}_j(r_s^-) = \left[\min \left\{c_j^d \cdot p_s^d\right\}\right] = \underline{c}_j^d \cdot \underline{p}_s^d \qquad \forall s \in S, j \in F_1 \tag{9}$$

$$\bar{\vartheta}_j(r_s^-) = \left[\max \left\{c_j^d \cdot p_s^d\right\}\right] = \bar{c}_j^d \cdot \overline{p}_s^d \qquad \forall s \in S, j \in F_1. \tag{10}$$

In the presence of incomplete information, the optimal alternative $r_s^*(x^j) \in R$, given that the item is in degradation state $s \in S$, is the one which minimizes the expected cost:

$$r_s^*(x^j) = \begin{cases} r^+ & \leftrightarrow \quad \bar{\vartheta}_j(r_s^+) < \underline{\vartheta}_j(r_s^-) \\ r^- & \qquad\qquad otherwise \end{cases} \qquad \forall s \in S, j \in F_1. \tag{11}$$

Note that renovation is an optimal decision only if the total costs of renovation are lower than the cost of not renovating. Thus, if the intervals overlap (i.e., there is no dominance structure), $r_s^*(x^j) = r^-$ is the preferred action in state $s \in S$.

For every possible state $s \in S$, we know the optimal decision $r_s^*(x^j) \in R$ for item x^j. To determine whether item x^j needs to be inspected, we consider the benefit from the inspection, which results from reduced cost of eventual disruption. That is, if the optimal choice in state $s \in S$ is not to renovate the item, then there is nothing to be gained from the inspection. On the other hand, if the optimal choice in state $s \in S$ is to renovate, then there is the benefit of reducing the expected disruption costs due to renovation.

From this, the benefit $B_j^s = [\underline{B}_j^s; \bar{B}_j^s]$ for item x^j in state $s \in S$ turns out to be an interval of values such that:

$$\underline{B}_j^s = \begin{cases} 0 & , \quad if\ r_s^*(x^j) = r^- \\ \underline{\vartheta}_j(r_s^+) - \bar{\vartheta}_j(r_s^-) & , \quad if\ r_s^*(x^j) = r^+ \end{cases} \tag{12}$$

$$\bar{B}_{j^1}^s = \begin{cases} 0 & , \quad if\ r_s^*(x^j) = r^- \\ \bar{\vartheta}_j(r_s^+) - \underline{\vartheta}_j(r_s^-) & , \quad if\ r_s^*(x^j) = r^+ \end{cases} \tag{13}$$

When the benefit for every state $s \in S$ has been assessed, the aggregate inspection benefit $B_j = [\underline{B}_j; \bar{B}_j]$ for item x^j is modeled as the weighed sum of the state benefits, whose bounds are

$$\underline{B}_j = \sum_{s \in S} p_j^s \cdot \underline{B}_j^s \qquad \forall\, j \in F_1 \tag{14}$$

$$\bar{B}_j = \sum_{s \in S} p_j^s \cdot \bar{B}_j^s \qquad \forall\, j \in F_1, \tag{15}$$

where $p_j^s = p(s^j = s)$ is the probability of item x^j being in state $s \in S$.

The decision tree provides useful insights for the next step of the renovation management process in which the decision is whether or not to perform renovation actions based on the inspection result. Specifically, from the decision tree of each item x^j, we determine the lowest item state $s_j^* \in S$ in which renovation is the preferred action

$$s_j^* = \min_{s \in S} \{s | r_s^*(x^j) = r^+\} \qquad \forall\, j \in F_1. \tag{16}$$

This helps the DM decide when to renovate, assuming that there is no uncertainty in the inspection outcomes. However, this decision also depends on the optimization of the renovation actions based on the inspection outcomes.

Finally, Portfolio Decision Analysis is used to identify the cost efficient portfolios of item inspections. An inspection portfolio is cost-efficient if no other feasible portfolio gives a higher overall benefit B at a lower inspection cost c. Such portfolios can be determined from an optimization problem which has two objectives $T = \{c, B\}$, where the former is to be minimized and the latter maximized.

Given that costs and benefits are measures by intervals, we employ RPM ([27], [28], [31]) to identify efficient inspection portfolios. In RPM it is possible to incorporate network synergies and/or logic constraints among the inspection activities as well.

The optimization problem we are tackling is very complex, because the search space of the possible inspection portfolios contains $2^{|F_1|}$ solutions, with $|F_1| \gg 1$ (e.g., 2000). Consequently, the exact dynamic programming algorithms proposed in [27], [28] are not applicable. We therefore use the extended RPM developed in [31].

In this approximate methodology, which is summarized in the Appendix, we employ uniform distribution to draw weights $w \in S_w$ and random scores from $v \in S_v$, defined by

$$S_w = \{w \in \mathbb{R}^{|T|} | w^\tau \geq 0 \ \ \forall \tau \in T, \sum_{\tau \in T} w^\tau = 1\} \tag{17}$$

$$S_v = \left\{v = [v^1; v^2] \in \mathbb{R}^{J^1 \times |T|} \middle| v_j^1 \in \left[-\bar{c}_j^t; -\underline{c}_j^t\right], v_j^2 \in \left[\underline{B}_j; \bar{B}_j\right] \ \ \forall j \in F_1\right\} \tag{18}$$

Note that the minus sign for v_j^1 is introduced to change the minimization problem into a maximization one.

In the RPM framework, an inspection portfolio $p \subseteq F_1$ is a subset of possible item inspections; thus, the set of all possible portfolios is the power set $P \coloneqq 2^{F_1}$. The overall value of a portfolio is the sum of the overall values of its item inspections. For a given score matrix v and attribute weights w, the overall value of portfolio p is

$$V(p, w, v) \coloneqq z(p) \cdot v \cdot w, \tag{19}$$

where $z(\cdot)$ is a bijection $z: P \rightarrow \{0,1\}^{|F_1|}$such that $z_j(p) = 1$ if $x^j \in p$ and $z_j(p) = 0$ if $x^j \notin p$.

Under incomplete information about attribute weights and scores $\Upsilon = S_w \times S_v$, portfolio p dominates portfolio p' if p has an overall value greater than or equal to the one of p' for all feasible attributes weights and scores and strictly greater for some, i.e.,

$$V(p, w, v) \geq V(p', w, v) \ \text{ for all } (w, v) \in \Upsilon \tag{20}$$

$$V(p, w, v) > V(p', w, v) \ \text{ for some } (w, v) \in \Upsilon \tag{21}$$

Thus, a non-dominated portfolio is identified by maximizing the overall value $V(p, v, w)$ of the inspection portfolio $p \in P_F$ from the Integer Linear Programing Problem (ILP)

$$\max_{p \in P_F} \left\{V(p, v, w) = z(p) \cdot v \cdot w | z(p) \in \{0,1\}^{|F_1|}\right\} \tag{22}$$

The set of feasible portfolios P_F is defined by a set of q linear inequalities, whose coefficients are recorded in matrix $A \in \mathbb{R}^{q\times|F_1|}$ and vector $U \in \mathbb{R}^q$ such that $P_F \coloneqq \{p \in P | A \cdot z(p) \leq U\}$.

This procedure of sampling values of w and v, is repeated until a sufficient number of non-dominated portfolios have been identified. Hence, the output consists of portfolios, which are known to be potentially optimal, although the algorithm may not find all non-dominated portfolios very quickly.

To analyze the solutions provided by the algorithm, we consider the Core Index (CI) metric. Namely, the CI of item x^j represents the percentage of efficient portfolios which include inspection on that specific item x^j. When the CI of an item inspection is 1, then the item is included in all the identified efficient portfolios.

3 Case Study

Helsinki Region Environmental Services Authority (HSY) provides water and wastewater services to one million customers. It was founded in 2010 through the merger of four separate water companies. Currently, this water utility is harmonizing its practices for network renovation, condition inspection and renovation planning.

The analyses in this paper are based on the large sewerage network in Espoo (a neighboring city of Helsinki) where there are more than 33000 pipes with a total length of about 900 km. In this case study, we analyze a subset of $J = 6103$ pipes for which earlier inspection outcomes are available. This makes it possible to compare the results of our methodology with real inspection outcomes and to derive insights to calibrate the methodology. The analysis accounts for individual pipes, because the inspection and renovation decisions are typically made on this scale. However, the methodology could be applied on smaller scale network items as well, such as pipe length of one meter.

To support the effective management of the network, HSY has a database which contains the following information about every pipe:

- Pipe features: The ID code, installation year, location (in terms of spatial coordinates for both endpoints), diameter, type (gravitational or pressure sewer), renovation year (in case the pipe has been renovated) and material. The most common pipe material is concrete but some pipes are made of cast iron, polyethylene, PVC or they have been renovated by trenchless socks.
- Inspection results: The possible inspection year and outcome. For each inspected pipe, the inspection result is stored in the database together with the location and type of each defect that has been detected during inspection (e.g., slump, hole, tree roots, pile-up).

- Maintenance history: The number of blockages and flushing events.
- External context of the pipe: Other significant information related to the surrounding environment in which the pipe is located (i.e., buildings, traffic load, groundwater areas, and soil type).

In this case study, the methodology was tested using statements from one expert only. Further research will focus on incorporating the expertise of a group of experts, such as utility employees [45].

3.1 Failure Likelihood and Severity

A well-founded risk analysis forms the basis of the risk-based maintenance methodology [32], which, in this case, helps understand the risks associated with pipes by encoding expert statements about the likelihood and consequences of failures.

Figure 3 shows the hierarchical objective structure of failure likelihood, identified by expert interviews. The attributes on the second level are:

• Pipe features: Pipe-specific characteristics, such as pipe material, age since last renovation and diameter are important determinants of failure likelihood.

• Past events: This attribute is relevant because it comes from the consideration that the larger the number of past blockages and flushing, the higher the probability of failures in the near future.

• Local circumstances: The elements of the surrounding environment can significantly contribute to the failure likelihood. In our case study, soil type and traffic load were considered the most important factors by expert judgement.

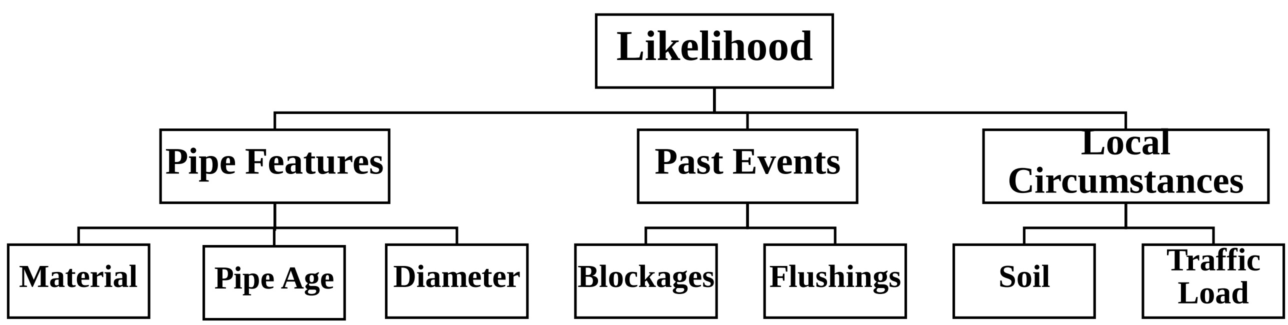

Figure 3: Likelihood attribute hierarchical structure

The weights were elicited with the PAIRS method [37]: for every objective at the second level, l_2, of the hierarchical tree, the attributes were ranked according to expert assessment on how important determinants of failure likelihood they were. The attribute 'Local circumstances' was reported to be the least important for failure likelihood, with no preference between 'Pipe Features' and 'Past Events'. These statements correspond to the following inequalities on attribute weights

$$w_{pipe\ features} \geq w_{local\ circumstances} \tag{23}$$

$$w_{past\ events} \geq w_{local\ circumstances}, \tag{24}$$

which, together with the constraint that the weights have to sum to 1, define the feasible region which contains the weight vector $(w_{pipe\ features}, w_{past\ events}, w_{local\ circumstances})$.

When evaluating the importance of the attributes on the third level, l_3, with regard to those at the second level, l_2, the expert stated that:

- 'Diameter' is the most important sub-indicator among those of the pipe features–the smaller the diameter, the higher the failure likelihood.
- The number of past 'Blockages' is more important than the number of past 'Flushings'.
- 'Soil' is as important as 'Traffic Load'.

On the other hand, the consequence tree is a hierarchical representation of the conditions which define how severe impacts pipe failures have on properties, environment, and safety and how possible network malfunctions affect water consumers. In principle, the same methodology for assigning a likelihood value to the pipes could be adopted to evaluate the severity values. However, in this study, we derived these estimates from recent results on the evaluation of consequences mainly based on pipe location and surroundings as well as the estimated annual pipe specific sewage flow [25].

A severity value was assigned to each pipe based on the conditions in Table 1. A pipe was assigned to Class 1 only if it met at least one of the conditions 1-8; otherwise, if the pipe met one of the conditions 9-19, it was assigned to Class 2. The other pipes were assigned to the third class.

Table 1: Conditions used for evaluating the pipe-specific criticality classification for sewerage pipes ([25])

	Class 1	**Disruption Cost Estimate**
1	Undoubled pressure pipes from critical pump stations	40000 €
2	Main tunnels	50000 €
3	Sewer mains and pressure sewers that are within significant groundwater areas	40000 €
4	Sewers close to primary or secondary raw water resources	30000 €
5	Pipes under railways	24000 €

6	Pipes under significant roads	35000 €
7	Sewer mains of crucial functional importance for the whole network	50000 €
8	Very high pipe-specific flow	50000 €
	Class 2	
9	Sewer mains not included in Class 1	30000 €
10	Sewers in protected areas / nature conservation areas	10000 €
11	Pipes crossing main water tunnels	24000 €
12	Pipes going under a water body (river, lake, sea)	35000 €
13	Pipes under buildings	40000 €
14	Pipes close to protected ditches	14000 €
15	Pipes close to swimming beaches	10000 €
16	Pipes other than sewer mains which are within significant groundwater areas	30000 €
17	Sewer mains within groundwater areas of less significance	24000 €
18	Sewers close to critical underground structures (e.g. subway)	20000 €
19	High pipe-specific flow	30000 €
	Class 3	
20	Every remaining pipe	10000 €

The SWING methodology [46] was applied to elicit scores by rating the pipes on each leaf attribute. For each attribute, the best measurement value (i.e., the one impacting the failure likelihood or severity the most) and the worst one (i.e., the one impacting the failure likelihood or severity the least) were assigned rates 100 and 0, respectively. Reminding the example of subsection 2.1, for the leaf attribute 'Material' in the failure likelihood tree, the most reliable material is "concrete", while the least reliable material is "renovated by trenchless socks": these two have ratings 100 and 0, respectively.

Next, elicitation questions were posed by first mapping out expert opinions on ordinal preferences for quality differences. Specifically, the expert was asked which 'swing' from a specific attribute value to the best one would result in the largest improvement, the second largest improvement, etc. Again using the 'Material' attribute as an example, the answers to these questions led to the following ranking in ascending order: "concrete", "polyethylene", "cast iron", "PVC" and "renovated by trenchless socks".

Finally, the intermediate quality classes were evaluated with the extreme values and, for validation, with respect to each other, too. For example, one of the questions for the 'Material' attribute was: "Is the quality difference between cast iron and concrete pipes more or less significant than that between PVC and cast iron pipes?". The criticality of cast iron pipes is closer to concrete pipes than pipes renovated by trenchless socks, therefore, its interval score is closer to 0 (criticality score of concrete pipes) than 100 (criticality score of pipes renovated by trenchless socks).

In this way, interval scores were assigned to each class: after being recorded into an Excel file, they were adjusted and validated. By this procedure, an interval cardinal score in the range of $0 - 100$ was assigned to each leaf attribute class of the failure likelihood tree based on expert opinion.

Failure severity was evaluated for each pipe in view of the conditions in Table 1, which lists them according to their level of severity. For example, a pipe disruption close to a railway is more severe than a pipe failure near a beach. For this reason, the interval score of the former pipe is larger than that of the latter.

These critical conditions, then, were assigned uncertain ratings by applying the SWING procedure. Specifically, zero score was assigned to pipes of class 3, whereas a score of 100 was assigned to the most critical condition in class 1 (no. 8: "Very high pipe-specific sewage flow"). The remaining 18 intermediate conditions of severity conditions were evaluated by comparing the two extreme conditions and the other elicited ratings, which resulted in score intervals. This way, interval scores in the range of $0 - 100$ were identified for all intermediate conditions by expert opinion.

Alternative overall value $V_L(x^j)$ was determined following the procedure detailed in subsection 2.1, so that the uncertainty with the score intervals of the leaf attributes was propagated through the likelihood value tree. The overall value $V_L(x^j)$ of failure likelihood was obtained per each pipe $x^j, j \in J$.

On the other hand, the severity overall value $V_C(x^j)$ was determined by the interval scores of the critical conditions that pipe x^j met. As in [25], it was assumed that the pipe belonged to more than one condition and, then, the most critical one met by that pipe was considered.

3.2 Risk Assessment

Risks were assessed by accounting for pipe overall values in the two-dimensional space failure likelihood–failure severity. That is, we first selected the $|F_1| = 2079$ non-dominated solutions among the J=6103, which belonged to the first Pareto front F_1 (circle marker and solid line in Figure 4) in the remaining set. This procedure was applied until the set of remaining non-dominated solutions was empty. In the case study of Espoo sewerage system, three Pareto frontiers were identified; the third, F_3, is marked by squares in Figure 4. The three frontiers indicate three different levels of criticality, which are defined according to the dominance relations between the pipes, as detailed in Eq. (3). In particular, the first Pareto frontier represents the set of most critical pipes, on which we focus the following analysis.

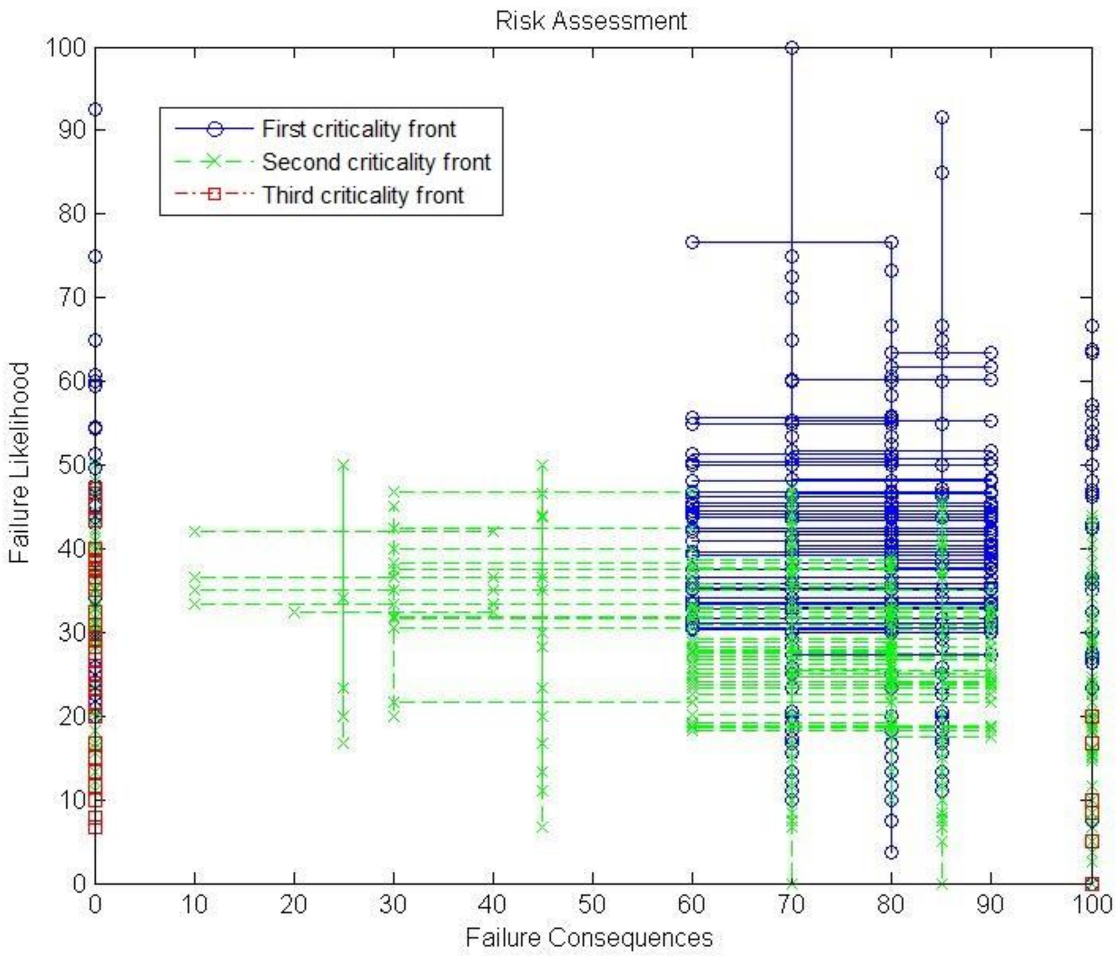

Figure 4: Overall values of failure likelihood and severity of the 6103 pipes considered in the Espoo sewerage system.

3.3 Decision Tree

In order to identify optimal inspection strategies, we accounted not only for the actual inspection costs but also for the expected costs of future renovation actions or consequences of possible failures, given that the expected total pipe inspection cost depends on two decisions: whether or not to inspect, and whether or not to renovate.

To estimate the inspection costs in this situation, we used decision tree modelling ([16], [23]).

The condition data input in this case study consisted of the CCTV inspection results which included information on several types of defects found in inspected pipes. For simplicity, the defect scores were aggregated into 6 states for each pipe, denoted by $s \in S = \{1; 2; 3; 4; 5; 6\}$. The inspection results in Figure 5 indicate the states of the inspected pipes as determined in the past inspections; the dash-dot lines in Figure 5 represent the thresholds that map the underlying states of the HSY model into the 6 states considered in the case study.

In Figure 5, we map the failure likelihood values (abscissa) onto the most significant percentiles (i.e., 5th, 50th and 95th) of the pipe states upon inspection. Specifically, for each value of likelihood v_L, we consider the subset of pipes $x^j, j \in J$ whose estimated likelihood value interval $V_L(x^j)$ includes v_L. The distribution of the degradation states at inspection of the pipes in such subset is summarized by its 5th, 50th and 95th percentiles, which are shown in Figure 5 by squares, circles and diamonds, respectively.

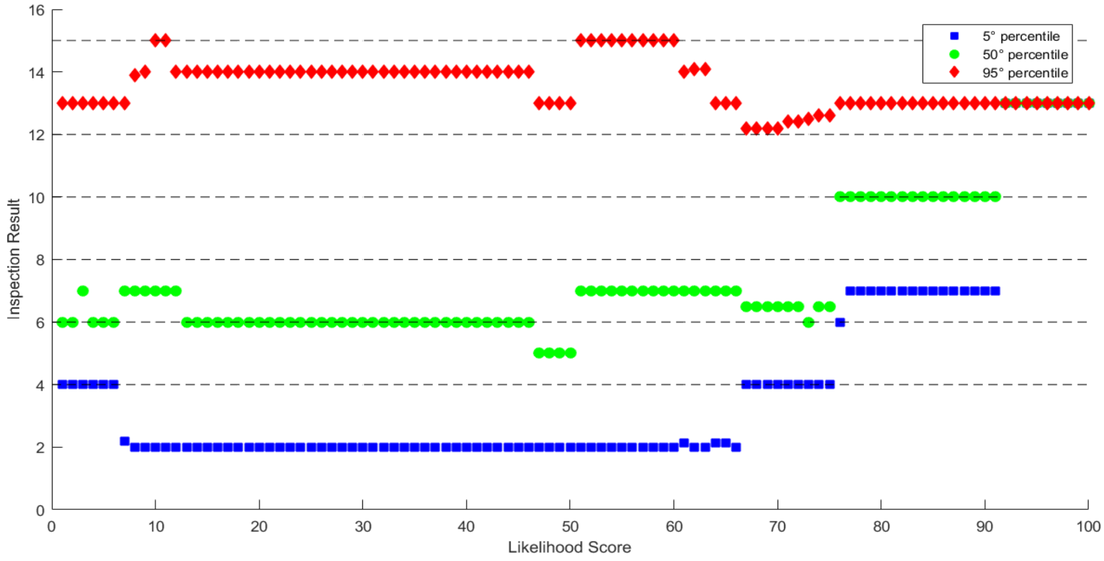

Figure 5: Mapping between likelihood scores and past inspection results

The resulting statistics, which are summarized by their most significant percentiles in Figure 5 (i.e., 5th, 50th and 95th), were used to estimate the probability $p(s^j = s)$ of the most critical pipes, as discussed in subsection 2.2. Note that the most valuable information arises from high likelihood scores, given that our analysis focuses on the most risky pipes.

Figure 6 summarizes the information available in the HSY dataset. Specifically, Figure 6 shows the probability of a generic pipe being in state $s \in S$ given a specific value of failure likelihood (abscissa).

The calculation of these probabilities (see subsection 2.2) is based on the results of the past pipe inspections as recorded in the HSY dataset.

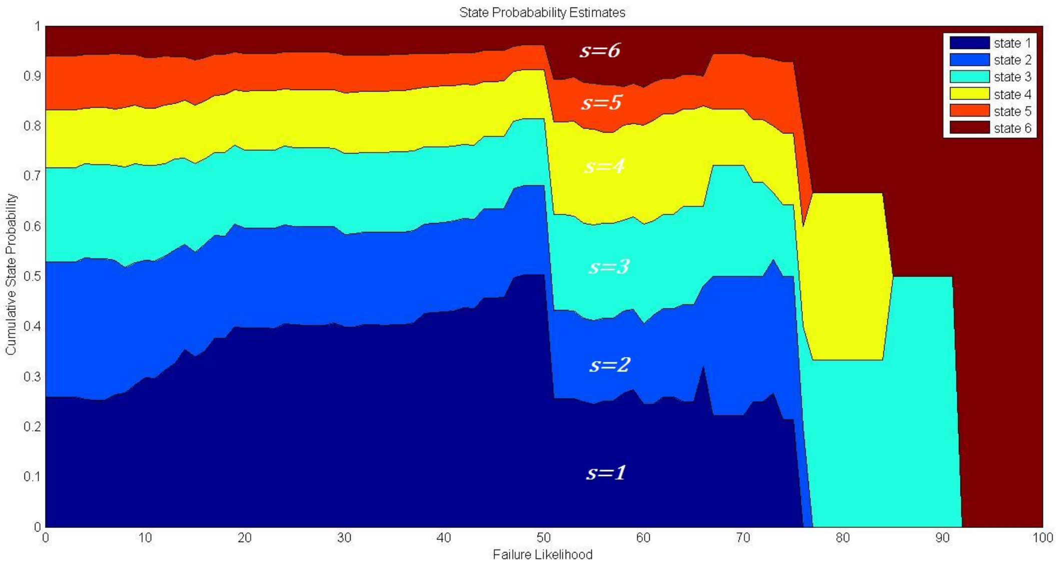

Figure 6: Correspondence between failure likelihood and degradation state probability

The probability of low degradation states decreases as the likelihood estimated by expert opinion increases, and the probability for the highest degradation states becomes larger with increasing level of estimated failure likelihood. The correspondence for State 4 and State 5 is not strong, partly because there are few pipes in these degradation states. As more condition inspections will be carried out, the growing dataset is expected to reveal a clearer connection between estimated failure likelihood and state probability.

Based on the above analysis and the information elicited from expert views (knowledge and information resulting from experience and past events), the link was established between the degradation state of the pipes and the probability of disruption.

Table 2: Disruption probabilities for every degradation state: lower and upper bounds

Degradation State	$\underline{p}_s^d$	$\overline{p}_s^d$
$s = 1$	0	0.3
$s = 2$	0.3	0.5
$s = 3$	0.4	0.6
$s = 4$	0.5	0.7
$s = 5$	0.6	0.8

$s = 6$	0.7	0.9

Estimates of disruption costs were provided by the expert for each identified critical condition in Table 1, whereby both direct and indirect costs were taken into account. From these estimates, we calculated for each pipe x^j the expected disruption cost $c_j^d = [\underline{c}_j^d; \bar{c}_j^d]$ as the sum of the costs of the critical conditions it meets.

Estimates of both inspection costs c^t and renovation costs c^s were based on the length of each pipe (Table 3). Renovation costs can be contingent to the pipe states, but for the sake of simplicity we assumed the pipe replacement is always preferable to trenchless rehabilitation or patch repair. Note that rehabilitation and repairing techniques can be included in the decision process by increasing the complexity of the model.

Table 3: Direct inspection and renovation costs, expressed in euro per meter

Cost Estimates	Lower Bound [€/m]	Upper Bound [€/m]
$[\underline{c}^t; \bar{c}^t]$	5	5
$[\underline{c}^s; \bar{c}^s], s = 1 \dots, 6$	343	370

Finally, the inspection benefits $B_j = [\underline{B}_j; \bar{B}_j]$ for each pipe x^j were determined by following the procedure explained in subsection 2.2.

Thus, from the decision tree of each pipe x^j we determined the lowest pipe state $s_j^* \in S$ in which renovation becomes the dominant solution. Figure 7 shows the distributions of $s_\varphi^* = \{s_j^* \in S | x^j \in F_\varphi\}$, φ=1, 2, 3, where F_φ represents the set of pipes belonging to the φ-th risk-based Pareto frontier and the additional pipe state 0 refers to the pipes for which renovation is never a dominant alternative, not even in case the pipe is in the worst condition state ($s = 6$).

From Figure 7, one can note that large ranks of risk-based Pareto frontiers correspond to large portions of pipes for which the renovation is not worthwhile. In the case of the least critical pipes (third Pareto frontier in Figure 4), the percentage of these pipes is more than 90%.

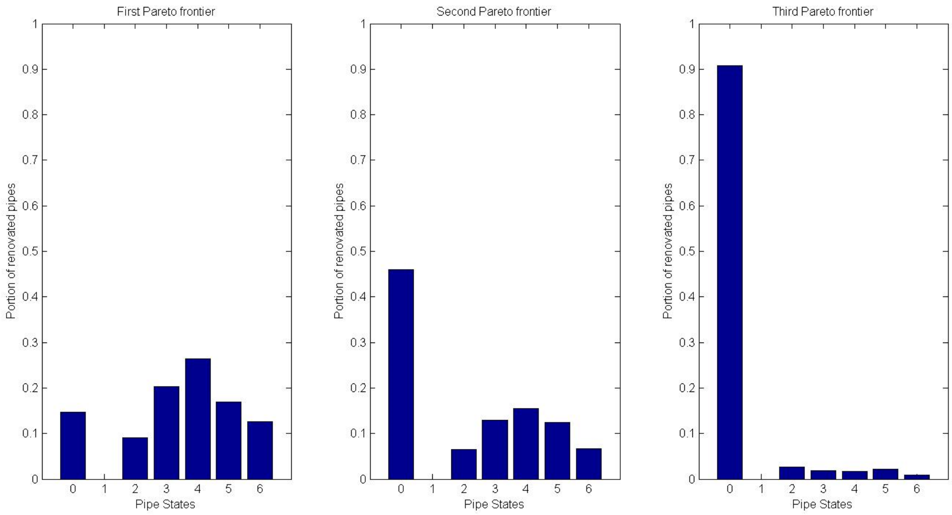

Figure 7: Renovation Policy

As can be expected, the portion of pipes in state 1 is always 0. This is due to the fact that there is no benefit from renovating a pipe in state 1, as this action does not improve pipe condition.

3.4 Results

The implementation of the approximate RPM accounted for the inspection benefits $B_j = [\underline{B}_j; \bar{B}_j]$ and costs $c_j^t = [\underline{c}_j^t; \bar{c}_j^t]$, for each pipe x^j. To identify the set of feasible inspection portfolios, the expert estimated the maximum yearly budget for inspections to be 300 000€ and indicated that there is a need to inspect at least 40km of pipelines per year.

With respect to the approximate RPM algorithm, its termination condition was set as the convergence of the projects' Core Indexes. More specifically, the algorithm was set to stop when the difference of each project CI among the last 1000 iterations was lower than 1%. With this setting, the RPM algorithm provided more than 2000 efficient solutions in approximately 30 minutes (6529 iterations). Figure 8 presents the CIs of the 2079 critical pipes (i.e., selected by risk assessment (subsection 2.1)).

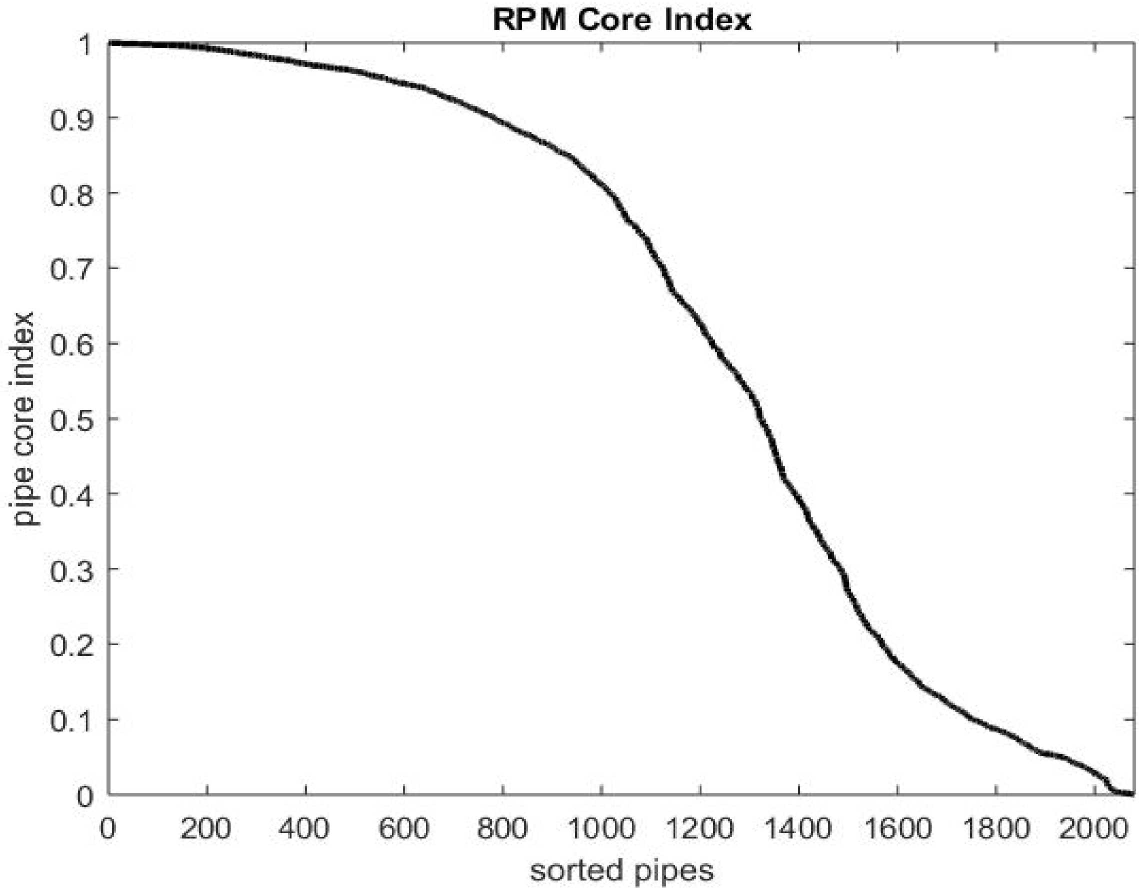

Figure 8: RPM sorted Core Indexes of the most critical pipes

Recognizing that it can be difficult to choose from the set of non-dominated portfolios, the choice of the portfolio could be determined according to appropriate decision rules such as the *maximin* rule, which recommends the portfolio that yields the highest minimum overall benefit, or the *minimax-regret* rule, which recommends the action for which the worst case overall benefit difference is the smallest compared to the other portfolios. These rules coincide with the absolute robustness and robust deviation measures, respectively, in robust discrete optimization [28]. The results of decision rules depend on the set of non-dominated portfolios. This emphasizes the importance of finding as many non-dominated portfolios as possible.

Finally, as stressed in [27] and [28], one way to limit the number of optimal portfolios is to reduce the uncertainty in the expert preference statement and estimation and to choose appropriate constraints (positioning, strategic, budget, etc.) to limit the search space. In this respect, the continuous updating of inspection and maintenance data on the HSY network will reduce uncertainties in the model parameters and therefore lead to more conclusive results.

4 Conclusions

We have developed a risk-based inspection methodology for large infrastructure networks and described its application to the underground sewerage network in Espoo, Finland. The risk assessment based on failure likelihood and failure severity helps identify the most critical pipes among which the optimal portfolios of inspections can be found.

Another clear advantage of the methodology is that it allows for iterative improvement. Expert judgements may be biased or erroneous, especially regarding factors which have an impact on pipe states. This can lead to suboptimal pipes being included in the final portfolio for inspections. However, as inspections are carried out annually, the validity of decision attributes can be evaluated recurrently and modified if necessary.

Moreover, our methodology is capable of handling incomplete information by the use of SWING weighting, decision tree modelling and RPM. In particular, it accommodates incomplete information about state probabilities. In this respect, other ways to estimate the state probabilities are possible, such as logit regression or clustering. These will be investigated in future work.

In this case study on the underground sewerage network in Espoo, the large number of critical pipes in the network gives rise to a huge search space of inspection portfolios. Therefore, it is useful to perform the pipe risk assessment before the portfolio analysis. On the other hand, even if the set of pipes is reduced, there are still computational challenges in finding all solutions. Therefore, future research will focus on investigating the capability of the NSDE heuristic algorithm [10] in exploring large search spaces and in comparing its performance to that of RPM. Finally, future work will also focus on the definition of optimal renovation actions after pipe inspections, eventually avoiding the assumption of independence among pipe failures.

The proposed methodology can potentially be adapted for optimizing the inspections of other types of networks, such as gas distribution networks. In the future, we plan to investigate how the methodology can be extended to other systems by modifying the parameters affecting failure likelihood, failure severity as well as the costs of inspections and renovation actions.

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6 Appendix

Approximate computation of Non-Dominated Portfolios in RPM ([31])

Let $V^u = [V_1^u, V_2^u]$ denote a utopian vector that sets strict upper bounds for the overall value of feasible portfolios in the extreme points $w_{ext}^{T=c^t} = [1,0]$ and $w_{ext}^{T=B} = [0,1]$ of S_w, such that:

$$V_\tau^u > \max_{p \in P_F} V(p, w_{ext}^\tau, \bar{v}) \quad \forall \tau \in T$$

where $\bar{v} = [-\bar{c}, \bar{B}]$.

The weighted max-norm distance of a portfolio p to the utopian vector is:

$$d(p,\mu,v) = \max_{\tau \in T}\left[\mu_\tau\left(V_\tau^u - V(p, w_{ext}^\tau, v)\right)\right] = \max_{\tau \in T}\left[\mu_\tau V_\tau^u - \mu_\tau z(p) v w_{ext}^\tau\right]$$

where $\mu \in M = \{\mu \in \mathbb{R}^2 | \mu_\tau \geq 0, \sum_{\tau \in T} \mu_\tau = 1\}$ and $v \in S_v$. With given $\mu \in M$ and $s \in S_v$ the set of feasible portfolios that minimize the distance to the utopian vector and are not dominated by another portfolio within the equal distance, is:

$$P_Q(\mu, v) = \{p' \in \arg\min_{p \in P_F} d(p,\mu,v) \,|\, \nexists p'' \in \arg\min_{p \in P_F} d(p,\mu,v) \;\; s.t.\, p'' \succ_S p'\}$$

where $S = S_v \times S_w$.

The set of portfolios $\arg\min_{p \in P_F} d(p,\mu,v)$ is obtained by solving the MILP problem

$$\min_{p \in P_F} d(p,\mu,v) = \min_{\substack{z(p) \in \{0,1\}^{J^1} \\ \Delta \in \mathbb{R}}} \{\Delta | \Delta \geq \mu_\tau V_\tau^u - \mu_\tau z(p) v w_{ext}^\tau \;\; \forall \tau \in T, \qquad Az(p) \leq U\}$$

Portfolios in $P_Q(\mu, v)$ are non-dominated for any $\mu \in M$ and $v \in S_v$, and any non-dominated portfolio belongs to $P_Q(\mu, v)$ for some $\mu \in M$ and $v \in S_v$ (proof presented in [31]).

The algorithm that identifies a set of non-dominated portfolios $\hat{P}_N \subseteq P_F$ can be formulated as follows:

1. **Initialization.** Construct the utopian vector V^u as explained previously. Set $\hat{P}_N \leftarrow \emptyset$.
2. **Computation.** Repeat until enough non-dominated portfolios have been found:
    a. Generate random $\mu \in M$ and $v \in S_v$.
    b. Determine $\arg\min_{p \in P_F} d(p, \mu, v)$.
    c. Define $P_Q(\mu, v)$.
    d. Set $\hat{P}_N \leftarrow \hat{P}_N \cup P_Q(\mu, v)$.

There are several methodologies for specifying the termination condition for the Computation loop consisting of steps 2a-2d. One methodology is tracking the number of new non-dominated portfolios found per iteration and, then, terminate the loop if, for instance, no new non-dominated portfolios have been found in the last 100 iterations. Another methodology is to compute the projects' Core Index values at each iteration based on the set of portfolios $\hat{P}_N$ and then terminate the loop when these values stabilize.

Generating values for scores and the max-norm weights in Step 2a can be implemented by considering systematic grid of values or by randomly choosing these values from suitable distributions. In this work, we have mainly relied on uniformly distributed weights within the simplex M and scores that have equal probability to be set to their lower or upper bounds per project.

Uniformly distributed max-norm weights are given by $\mu_\tau = {}^{\rho_\tau}\!/_{\sum_\tau \rho_\tau}$, where ρ_τ:s are drawn from an exponential distribution with expectation equal to one (Rubinstein, 1982).