Visual inspection and bridge management

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Abstract

This paper estimates visual inspection quantitatively prior to its implementation in a Bridge Management System (BMS) using a Value of Information (VoI) approach employing a Bayesian pre-posterior analysis. Information from a significant number of real bridges from Ireland and Portugal are considered in this regard following existing commercial practices. The variation of different parameters on the estimated VoI is investigated including the assumed probabilistic models of the prior bridge state, the likelihood of inspector assigned condition ratings and the economic setting surrounding the cost matrix for maintenance decision alternatives. The values of no information, perfect information and imperfect information are presented and the change in the optimal strategy based on such information is assessed. The effect of human imperfections in assessment and difference in condition rating scale are also estimated. The studies and findings of this paper are expected to allow a better insight for practising engineers and researchers working in bridge management.

Keywords: Bridge maintenance, visual inspection, condition rating, value engineering, cost estimates, decision-making, Bayesian Networks.

Acronyms: Bridge Management System (BMS), Value of Information (VoI), Value of Perfect Information (VOPI), Value of Imperfect Information (VOII), Bayesian Network (BN), Influence Diagram (ID), Maximum Expected Utility (MEU), Limited Memory Influence Diagram (LIMID), Decision Maker (DM).

1.0 Introduction

This paper aims to addresses the gap in knowledge that exists in an organised estimate of visual inspection, measured through Value of Information (VoI), within a bridge management system (BMS) framework. A significant number of operational bridges have been used for these estimates to be useful and multiple countries have been considered. The impact of human effects, variation in inspection accuracy and precision, impact on current bridge state on visual inspection and the variations of estimates from using different BMS have been considered. Collectively, the results assess the visual inspection for individual BMS and allow infrastructure managers of other BMS to assess their bridge stock and take decisions on inspection based on their method, accuracy and precision – thereby ensuring the portability of the method and findings to a range of disparate situations.

Successful infrastructure management is fundamental to economic growth and international competitiveness (ASCE, 2013). Bridges age over time and often exceed their design life. Comprehensive BMSs facilitate owners in inspecting, maintaining and rehabilitating deteriorating bridge stock within the limitations of financial resources (Mirzaei et al., 2014). A BMS refers to a set of decisions, in relation to design, construction, maintenance; and structural intervention, made by infrastructure management over time, to maximise performance (Sánchez-Silva et al., 2016). Uncertainties of either epistemic or aleatory nature complicate such decision problems and may lead to suboptimal actions or even actions with catastrophic consequences (Der Kiureghian & Ditlevsen, 2007). Information is fundamental to reduce uncertainties; information about the state of bridges and its components, and about the consequences of various decision alternatives (Konakli et al., 2015). Information gathering practices (Znidaric et al., 2011) are central to the success of a BMS, and can be broadly categorised under three main levels - visual inspection; principal inspection; and special inspection.

Visual inspection is typically the first step in a BMS, whereby each bridge is visually evaluated and assigned a pre-defined condition rating, providing a condition assessment of the selected stock of bridges (Chase et al., 2016). These condition ratings can be and are often used to predict the future condition state of elements (Zanini et al., 2016), to determine if maintenance or structural intervention is to be carried out, commonly using the Markovian deterioration model (Wellalage et al., 2014; Li et al., 2014; Beck & Au, 2002). Otherwise, condition ratings are simply used to identify areas for future evaluation; either through structural assessment (Saydam et al., 2013) or further inspection via principal inspection (NRA, 2008), special inspection (Browne et al., 2010; Duffy, 2004) or emerging technologies (Vaghef et al., 2011; Washer & Fuchs, 2015; Zink & Lovelace, 2015). In this regard, for earthquake loadings, a risk-based metric can be adopted (Morbin et al., 2015). While principal inspections refer to visual assessments, special inspections (Pakrashi et al., 2012) can involve significant mechanical and chemical testing of the structure as per requirements and the cost of special inspection can be significantly higher than principal inspections and variable based on the requirement of tests and the size of the bridge.

There is a lack of understanding of the estimated benefit of visual inspection information since explicit information regarding the mechanical properties of the material or structural components are unavailable. Empirical attempts have been made with limited success to use visual inspection results to update reliability analysis of bridges using conservative assumptions (Estes et al., 2004; Wang, 2010). Visual inspection data can be incomplete and is uncertain in comparison to testing and monitoring involving emerging technologies. A specific defect or parameter is usually updated by monitoring at optimum time intervals and can be used to directly update the reliability of a structure (Luque & Straub, 2015). Assigning a quantitative value to the reduction of uncertainty via condition rating information is essential in bridge management to ensure that there is a correct basis for allocating resources (Weninger-Vycudil et al., 2015) to visual inspection strategies (Deshmukh & Bernhardt, 2000). Srinivasan & Kumar (2013) provided a methodology to compare the merits of different condition monitoring approaches, one being visual inspection, for underground tunnels. However, in bridge management, focus has centred around the accuracy of visual inspection data, rather than benefit estimates (Graybeal et al., 2002; Moore et al., 2001). Probabilistic models exist for condition rating (Attoh-Okine & Bowers, 2006; Gattulli & Chiaramonte, 2005; Pozzi et al., 2010; Rafiq et al., 2015) but the VoI concept is significantly unexplored.

VoI (Lindley (1956); Raiffa & Schlaifer (1961); DeGroot (1984)), typically calculated as the difference between the prior and pre-posterior analysis and represented in terms of maximum expected utility (Von Neumann & Morgenstern, 1953), is a powerful tool for assessing the merits of an inspection technique prior to implementation, and for choosing the optimal inspection strategy among possible alternatives (Pozzi & Der Kiureghian, 2012). Since being introduced to civil and structural engineering (Ang & Tang, 1975; Benjamin & Cornell, 1970; Tang, 1973), Bayesian updating of probabilistic models with inspection results have provided the basis to optimise inspections in aircraft and offshore structures subject to fatigue deterioration (Madsen et al., 1989; Sørensen & Thoft-Christensen, 1986). A similar method based on Markovian deterioration models was employed in infrastructure management (Madanat, 1993). Recent research has focussed on the value of deterministic information, albeit imperfect or uncertain, and the ability of this information to directly update the prior belief of the degradation state or reliability of a structural component or system (Konakli et al., 2015). Structural reliability methods (SRM) can be used to effectively model the VoI (Straub, 2014) by measuring the evolution of structural performance as a support to maintenance interventions (Goulet et al., 2015; Pozzi & Der Kiureghian, 2011; Straub & Faber, 2005). VoI analysis has had widespread applications (Goulet & Smith, 2013; Malings & Pozzi, 2015; Pozzi et al., 2010) for SHM prsactices, including sensor placement (Krause, 2008), investigating long term benefits of SHM (Pozzi & Der Kiureghian, 2011) and the comparison of alternative SHM methods (Pozzi & Der Kiureghian, 2012). The impact of SHM on decision making, in economic terms, has been quantified (Zonta et al., 2014). In the field of natural hazards, VoI has been utilised to prioritise post-earthquake bridge inspections (Bensi et al., 2015; Bensi, 2010) and De Leon et al. (2015) used it to develop economic strategies to reduce the expected number of fatalities and losses for bridge sites exposed to hurricane risk.

A graphical framework is proposed to quantify the VoI of visual inspection by use of Bayesian Network (BN) and Influence Diagram (ID) (Jensen & Nielsen, 2007; Koller & Friedman, 2009). A cohort bridges is often comprised of deterministic and random factors that interact with each other; dependencies occur naturally and are important to account for (Biondini & Frangopol, 2016). Although a probabilistic model is a logical format, where the state of an infrastructure system is represented via a joint distribution, even in the simplest case, the explicit solution of this joint distribution is unmanageable due to computational demands and statistical data requirements. BNs can represent high dimensional distributions by exploiting conditional independence, (Koller & Friedman, 2009) and can be quantified through physical variables linked to the degradation process in an intuitive way through expert judgment combined with field measurements. Firstly, the condition-based maintenance strategy must be modelled, considering the decision alternatives and associated utilities. This model must describe the condition-based deterioration and allow for updating based on a sample of visual inspection results (Memarzadeh & Pozzi, 2016), so that a revised expected life-cycle management cost (after inspection results are observed) can be deduced. Bayesian inference allows updating of the probabilities when observations, such as bridge condition ratings, become available (Bensi et al., 2013; Kosgodagan et al., 2015). Dynamic Bayesian Networks (DBNs), BNs with a time-indexed sequence of nodes, can be used to analyse problems with time-varying domains, including inspection and monitoring (Bensi et al., 2013; Straub, 2009). The type of deterioration examined in this paper, relating to concrete and masonry arch bridges, is more varied and is commonly assessed through condition indicators, which have complex interdependencies. Attoh-Okine & Bowers (2006) and Rafiq et al. (2015) have presented condition based deterioration models of such bridge structures, using both BN and DBN models.

The mathematical framework is presented in the next section, followed in Section 3 by an application for individual decision maker managing a single bridge in Section 4. This is extended to the value that visual inspection provides to infrastructure asset managers operating a BMS using Irish and Portuguese datasets for a regional road area (Section 5). Numerical investigations demonstrate how the decision problem is influenced by the assumed probabilistic models. The paper concludes with a summary of the main findings and a discussion on the challenges and potentials of VoI analysis for condition rating data.

2.0 Value of Information Analysis

This section presents a brief outline of VoI analysis for completeness. The inspection strategy is the one that maximises the VoI minus the cost of the strategy. A decision problem under uncertainty where (i) the action alternative chosen depends on the state of an uncertain variable, (ii) the true state is unknown, but (iii) it is possible at a cost to obtain information about the state of the uncertain variable, the optimal action (a_{opt}) maximising the expected utility (Von Neumann & Morgenstern, 1953)s given by:

$$a_{opt} = \arg\max_{a \in A} E_X[u(a, X)] \tag{1}$$

where $a \in A$ is an action chosen from space *A*, $x \in X$ is an uncertain variable in space *X*, $y \in Y$ an observed sample composed of *n* observations $\{y_1, ..., y_n\}$, $u(a, x)$ is the utility function of *a* and *x* and the expected utility (*U*) is given by the expectation (*Ex*):

$$U = E_X[u(a_{opt}, X)] \tag{2}$$

Information gathered prior to making a decision in the form of an inspection strategy, *s* leads to the revised decision problem of finding the combination of inspection strategies *s* and action alternatives *a*, that maximise utility. If the optimal decision is chosen based on existing knowledge of the system prior to the acquisition of any additional information; represented as a prior probability distribution $p(x)$ and if another optimal decision is determined by updating probabilities based on information received from an inspection, the posterior distribution is defined as the probability of an unknown parameter conditional on the information obtained, given as $p(x \mid y) = p(y \mid x)p(x)$. The two functions are related via Bayes rule, given as:

$$p(x \mid y) = \frac{p(y \mid x)\,p(x)}{p(y)} \tag{3}$$

In pre-posterior analysis, the optimal decision is determined by updating probabilities based on expected information prior to implementation of an inspection strategy and the potential of additional information to improve decision making is assessed before the inspection strategy is implemented. The pre-posterior distribution $p(y)$ is defined as the distribution for future expected information based on the information that has already been seen. It does not depend on the unknown parameter as in the posterior case, as the unknown parameter has been integrated out.

2.1 Prior Analysis

In the prior analysis, optimal decision is determined based on existing knowledge of the system i.e. with no information from inspection, given by:

$$a_{opt} = \arg\max_{a \in A} E_X[u(a, X)] = \arg\max_{a \in A} \int_X u(a, x) f_X(x) dx \tag{4}$$

where $f_X(x)$ is the prior probability density function (PDF) of *X* and $u(a, x)$ is the utility associated with a given set of actions *a* and realizations *x*. The corresponding prior expected utility is given by:

$$U_{prior} = E_X[u(a_{opt}, X)] = \int_X u(a_{opt}, x) f_X(x) dx \tag{5}$$

2.2 The Value of Perfect Information

Data is considered as perfect, if it is directly informative of the parameter of interest. A decision problem with perfect information is the unrealistic situation, in which there is no uncertainty on *X*. For a given *x*, the DM can always choose the optimal action as:

$$a^*_{opt}(x) = \arg\max_{a \in A} u(a, X) \tag{6}$$

The conditional value of perfect information (CVPI≥0) is the value of an inspection after the information has been received and given as:

$$CVPI(x) = u(a^*_{opt}(x), x) - u(a_{opt}, x) \tag{7}$$

while the true value of *X* is not known a priori, it is possible to calculate the expected value of perfect information (EVPI) defined as the expected increase in utility that the DM obtains from gaining access to a sample of perfect observations, before making a decision and defined as:

$$EVPI = E_X[CVPI(X)] = \int_X [u(a^*_{opt}(x), x) - u(a_{opt}, x)] f_X(x) dx \tag{8}$$

$$EVPI = \int_X \max_{a \in A} u(a, x) f_X(x) dx - U_{prior} \tag{9}$$

representing the upper bound of the value of inspection strategy chosen. If the cost of an inspection strategy is greater than is EVPI, it is inefficient.

2.3 The Value of Imperfect Information

If data is measured with noise, it is imperfect and visual inspection provide imperfect information on the true state *X*. In posterior analysis, imperfect information is received and stored in the vector *y* and the probabilistic description of *X* is updated based on this information. The optimal action is given by:

$$a_{opt|y} = \arg\max_{a \in A} E_{x|y}[u(a, X)] = \arg\max_{a \in A} \int_X u(a, x) f_{X|y}(x \mid y) dx \tag{10}$$

where $f_{X|y}(x \mid y)$ is the joint PDF of *X* conditioned on *y* (posterior PDF) obtained from Bayes' rule. The posterior expected utility is given as:

$$U_{posterior}(y) = E_X\{u[a_{opt|y}, X]\} \tag{11}$$

The difference between the posterior and prior expected utility, a measure of the VoI and termed Conditional Value of Imperfect Information, is expressed as:

$$CVII(y) = U_{posterior}(y) - U_{prior} \tag{12}$$

$CVII(y)$ is zero if the posterior optimal decision $a_{opt|y}$ is the same as the prior optimal decision a_{opt} and positive otherwise. For a BMS, $CVII(y)$ has limited benefits. Once an observation y is made i.e. through an inspection strategy, it is futile to compare $U_{posterior}(y)$ to the results of the original prior utility U_{prior}, which only answers questions after the fact, such as 'What was the least expensive maintenance strategy employed last year?' The interest of this paper is in the VoI contained in *y*, before the imperfect information is received i.e. before a costly inspection strategy is implemented.

The expected value of imperfect information (EVII) is the expected value of the CVII with respect to all possible measurements outcomes. The information is modelled via a random vector *Y*, where the pre-posterior distribution $f_Y(y)$ defines all measurement outcomes:

$$EVII = E_Y[CVI(Y)] = E_Y[U_{posterior}(y)] - U_{prior} \tag{13}$$

Substituting in values for U_{prior} and $U_{posterior}(y)$ gives:

$$EVII = E_Y\{\max_{a \in A} E_{X|Y}[u(a,X)]\} - \max_{a \in A} E_X[u(a,X)] \tag{14}$$

$$EVII = \int_Y \left[\max_{a \in A} \int_X u(a,x) f_{X|y}(x \mid y) dx \right] f_Y(y) dy - U_{prior} \tag{15}$$

EVPI provides an upper bound for EVII and a rationally an inspection strategy, with a cost C_s is chosen if:

$$EVII - C_s \geq 0 \tag{16}$$

The optimal inspection strategy $\{s \in S\}$ will be the one that has the minimum cost:

$$s_{opt} = \arg\max_{s \in S}[EVII(s) - C_s(s)] \tag{17}$$

3.0 Value of visual inspection information to an individual decision maker managing a single bridge

3.1 VOI calculation

For calculation of VoI, the *Bridge_state*$_i$ indicates the condition state of a (i^{th}) bridge which takes three possible values: good (G), degraded (D) or poor (P). The *Action*$_i$ variable consists of three maintenance actions: do nothing (DN), repair (R) and major rehabilitation (MR). The utility variable *Cost*$_i$ measures the total cost in monetary terms and is related to *Bridge_state*$_i$ and *Action*$_i$. A condition rating is assigned based on the finding of a trained bridge inspector but human factors remain in variations of such rating. This imperfect observation is represented by CR_i, which can take three possible values: CR1, CR2 or CR3, corresponding to 'good', 'degraded' or 'poor' state, respectively. The 'degraded' state is assumed to have a 15% probability of failure, the 'poor' state is assumed to lead to certain failure. The main cost values are as follows: cost of repair C_R = €25,000, cost of major rehabilitation C_{MR} = €50,000, and cost of bridge failure C_F = €250,000. The values are chosen after considering a number of representative commercial cases available to the authors. The variables: *Bridge_state*, *Action*, *Cost* and Condition Rating (*CR)* are represented as *X*, *A*, *C* and *Y*, respectively.

3.1.1 Prior analysis

The prior probability is given as the vector $[P(G) \quad P(D) \quad P(P)] = [0.5 \quad 0.35 \quad 0.15]$. The minimum expected cost in the prior case is given as:

$$C^{prior} = \min_{a \in A} \left\{ \sum_X c(x,a)\, p(x) \right\} \tag{18}$$

$$C^{prior} = \min_{a \in A} \left\{ \begin{matrix} [0.5 \times (0) + 0.35 \times (37.5) + 0.15 \times (250)], \; [0.5 \times (25) + 0.35 \times (25) + 0.15 \times (250)], \\ [0.5 \times (50) + 0.35 \times (50) + 0.15 \times (50)] \end{matrix} \right\} \tag{19}$$

$$C^{prior} = \min_{a \in A} \{50.625,\ 58.75,\ 50\} \tag{20}$$

$$C^{prior} = 50 \tag{21}$$

which is an average cost value. The optimal action is to 'major rehabilitation' in the prior case, as it is the action with the minimum expected cost.

3.1.2 Calculating the value of perfect information

$$C_{perfect}(x) = \sum_X \min_{a \in A} \{c(a,x)\}\, p(x) \tag{22}$$

$$C_{perfect}(x) = [0.5 \min\{0,25,50\}] + [0.35 \min\{37.5,25,50\}] + [0.15 \min\{250,250,50\}] \tag{23}$$

$$C_{perfect}(x) = 16.25 \tag{24}$$

The optimal strategies are as follows: i) 'do nothing' when the bridge is in the 'good' state; ii) 'repair' when the bridge is in the 'degraded' state and iii) 'major rehabilitation' when the bridge is in the 'poor' state with:

$$VOPI = C_{prior} - C_{perfect}(x) = 33.75 \tag{25}$$

which represents a €33,750 expected cost saving with perfect information. The actual value in terms of monetary units is subject to assumptions related to the original values on savings and how utility is converted to such monetary units.

3.1.3 Calculating the value of imperfect information

The value of imperfect information taking into account the test likelihood matrix in Table 2 is given as:

$$C_{imperfect}(y) = \sum_Y \min_{a \in A} \{E(c(a, x \mid y)\}\, p(y) \tag{26}$$

$$C_{imperfect}(y) = 0.485\min\{13.15, 31.975, 50\} + 0.31\min\{41.74, 35.89, 50\} + 0.205\min\{152.75, 156.718, 50\} \tag{27}$$

$$C_{imperfect}(y) = 27.754 \tag{28}$$

The optimal strategies are as considered for perfect information:

$$VOII = C_{prior} - C_{imperfect}(y) = 22.246 \tag{29}$$

which represents a €22,246 expected cost saving with imperfect information.

3.2 Graphical solution of the VoI

The graphical computation of the VOPI and the VOII is solved via the LIMID algorithm using the Bayes Net Toolbox in MATLAB (Murphy, 2001). The VOII is the MEU of the prior case subtracted from the MEU of the pre-posterior case and the results are shown in Table 1. For no information, the optimal strategy is to 'do nothing'. In the case of perfect and imperfect information, the optimal strategy is to 'do nothing' when the bridge is in the 'good', 'repair' when the bridge is in the 'degraded' state and to carry out 'major rehabilitation' when the bridge is in the 'poor' state. If a visual inspection strategy is implemented that yields imperfect information regarding the bridge state, the DM should expect to receive a cost saving of approximately €22,250. The VOPI of €33,750 represents the upper bound in the decision problem. A rational agent will decide to undertake a visual inspection strategy *s*, only if the cost of the strategy C_s is less than €22,250 i.e. $VOII - C_s \geq 0$.

Case	**Optimal Strategy**	**E[C] (€)**	**VoI (€)**
No Information (prior)	Major rehabilitation	-50,000	-
Perfect Information	Do nothing if in the good state; repair if in the degraded state; and major rehabilitation if in the poor state.	-16,250	33,750
Imperfect Information	Do nothing if in the good state; repair if in the degraded state; and major rehabilitation if in the poor state.	-27,750	22,250

Table 1. LIMID outputs for each case.

The outcome of Equations (5), (9) and (15) depend on the specific values assigned to the prior probability of the bridge state; the likelihood of inspector assigned condition ratings; and the cost values of the action alternatives. Figures 1 and 2 outline two numerical examples to examine how the accuracy of condition rating data and the prior probability of the bridge state affect the value provided by visual inspection. In Figure 1, the accuracy of visual inspection is varied with the other parameters in the model remaining constant. As the accuracy increases, the expected cost of gathering condition rating data decreases. A visual inspection with 0% accuracy and 100% accuracy is identical to a visual inspection with no information and perfect information respectively. At an accuracy level of 12%, the value of imperfect information equals the visual inspection cost (Figure 1b).

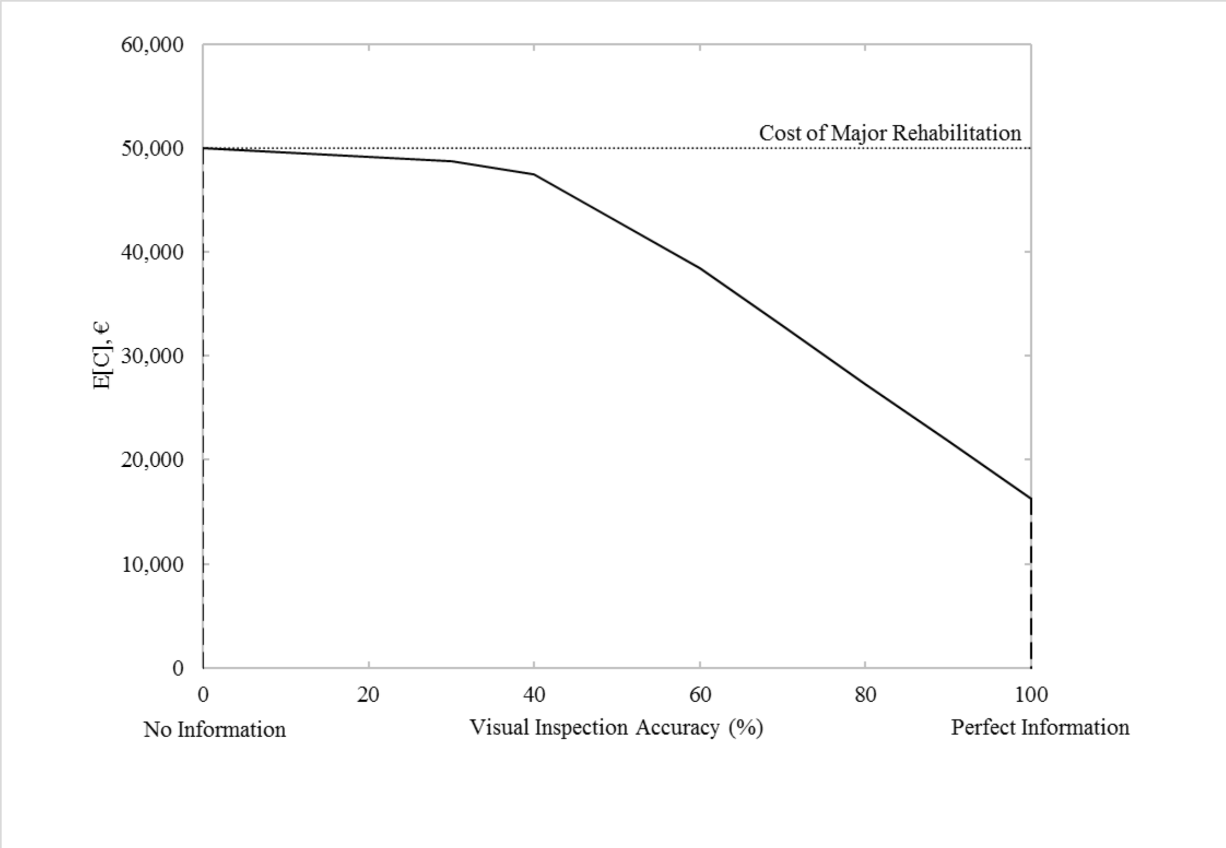

Figure 1a. Expected cost of imperfect information conditional on the accuracy of visual inspection.

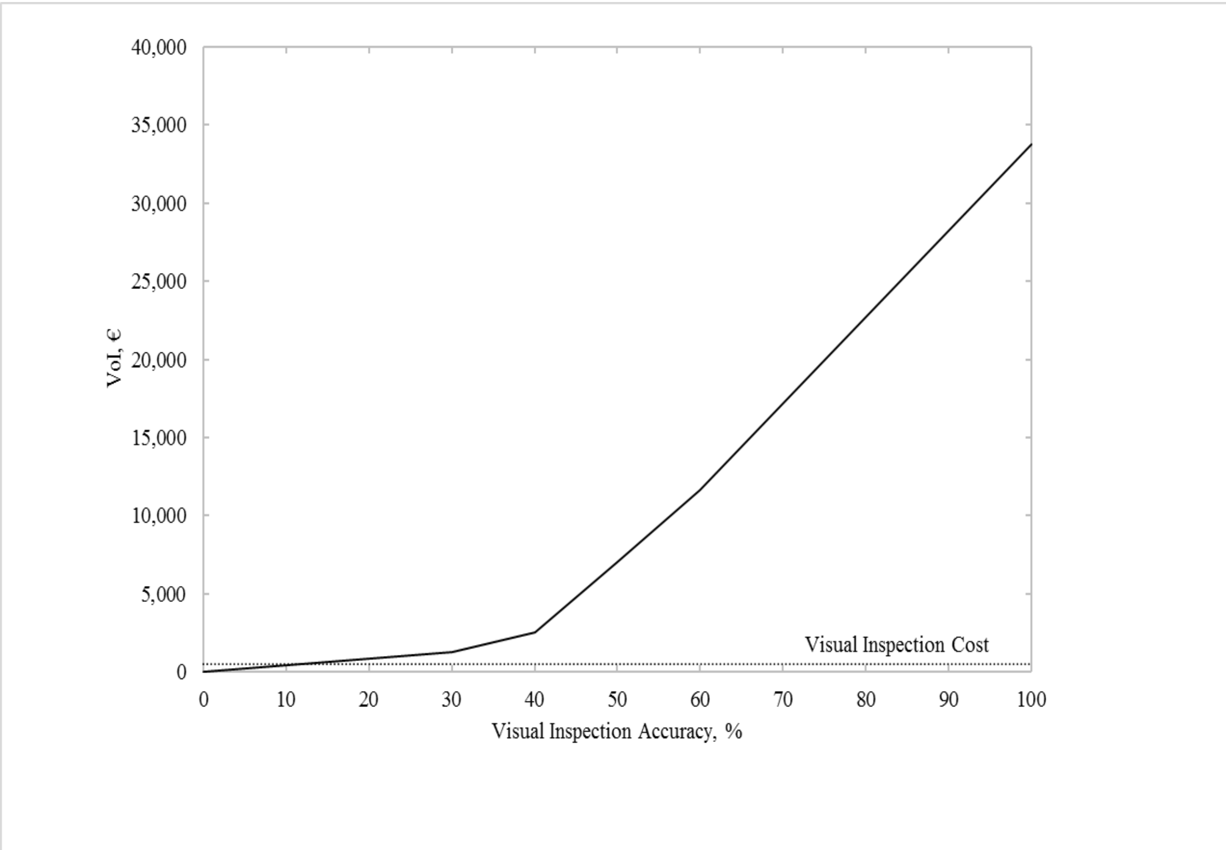

Figure 1b. Expected value of imperfect information (VoII) conditional on the accuracy of visual inspection.

In Figure 2, the prior probability of the 'poor' bridge state, which is the same as the prior probability of failure P_F is varied from 0 to 1.0, with the other two bridge states, 'good' and 'degraded', fixed respectively. Three different scenarios (70% accuracy, 80% accuracy, and 90% accuracy) of visual inspection are suggested.

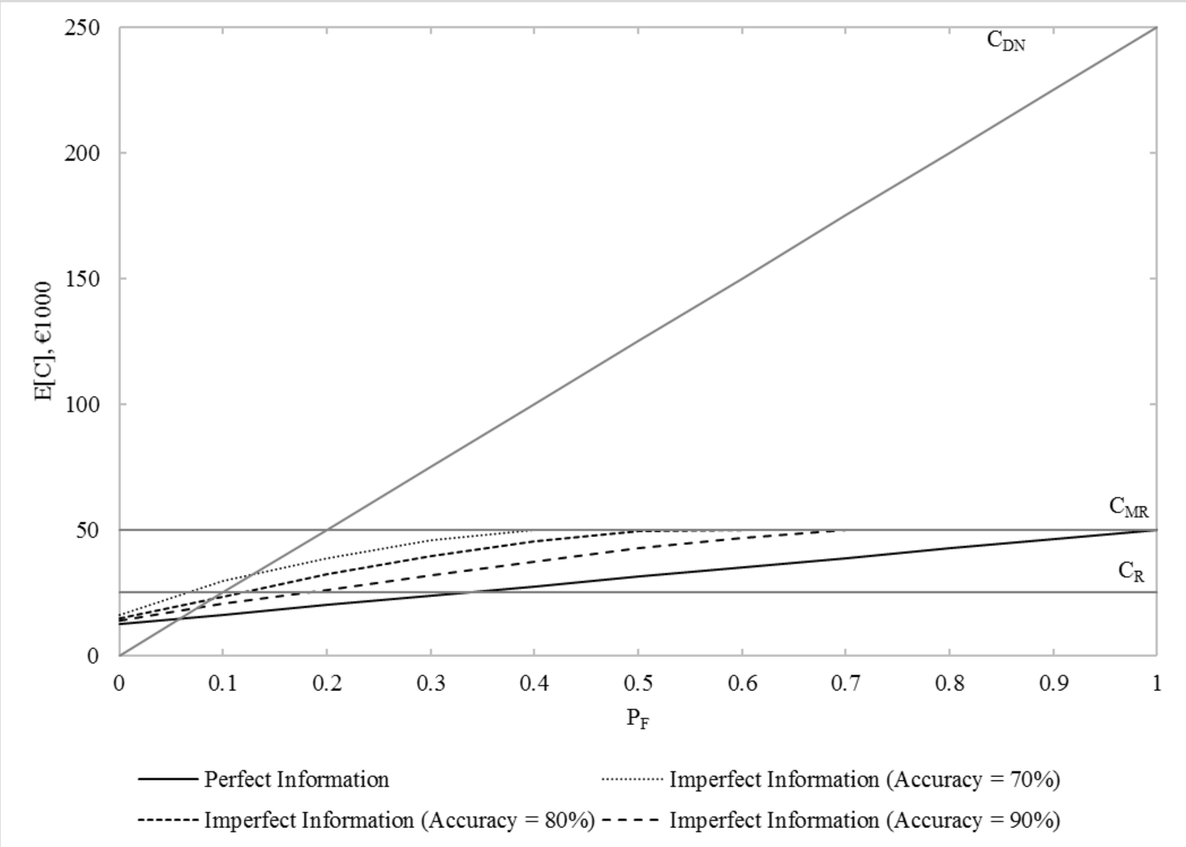

Figure 2a. Expected cost conditional on the probability of failure, P_F.

As the prior probability of failure increases, the cost of inspection also increases. The expected cost of inspection is equivalent to the cost of major rehabilitation C_{MR} for P_F = 0.4, 0.6, and 0.7 for accuracies of 70%, 80% and 90%, respectively. This observation is reinforced in Figure 2b, where the expected VoI reduces to 0 for the above probabilities and inspection accuracy scenarios. In Figure 2b, the expected VoI peaks at P_F = 0.2, which is due to the fact that in the case of 'no information', the optimal maintenance action is: 'do nothing' when $P_F < 0.1$, 'repair' when $0.1 \geq P_F < 0.2$, and 'major rehabilitation' when $P_F \geq 0.2$. The shift of the expected cost of 'no information' between P_F = 0.1 and P_F = 0.2 results in a higher expected VoI at P_F = 0.2.

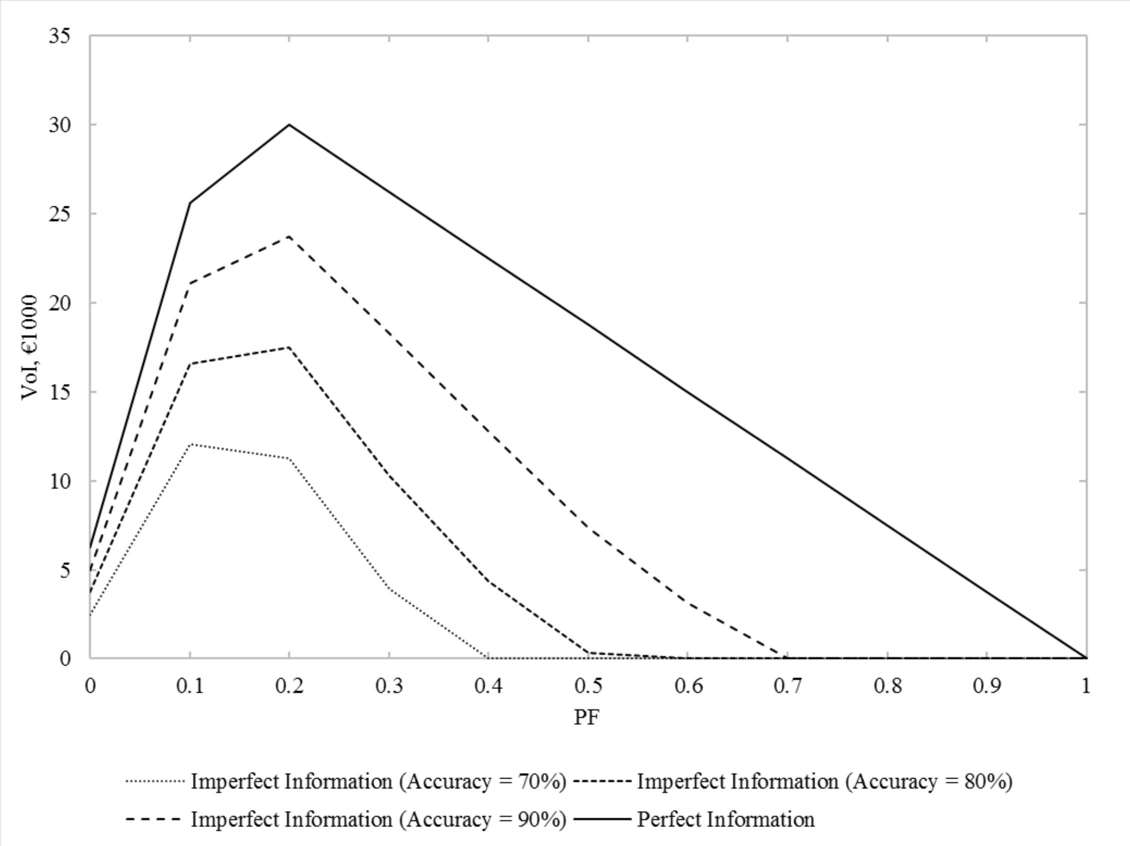

Figure 2b. Expected VoI conditional on the probability of failure, P_F.

This example indicates that a rational assessment of the VoI of visual inspection requires a full decision model, including an accurate assessment of the prior probability of the bridge states, the likelihood of inspector assigned condition ratings and the economic setting surrounding the maintenance action alternatives. If any of these elements are excluded from the decision model, an objective estimate of the VoI cannot be determined. The principal method of bridge inspection is carried out using visual means and determining the value it provides has the potential of widespread applications to infrastructure asset managers in optimising inspection practices within different BMS.

4.0 Value of visual inspection to infrastructure asset managers

The hierarchy of roads in the Republic of Ireland comprises Motorways, National roads, Regional roads, and Local roads. Non-national regional and local roads in Ireland account for 94% of the country's roads and carry approximately 54% of all road traffic (DTTAS, 2016). These roads provide mobility within and between local areas driving local economic activity. They also provide vital links to Ireland's strategic national roads, ports, and airports, linking Ireland with the wider European economy. The maintenance of these infrastructure systems is essential from an economic, social and political perspective with €7.7million of state grants allocated to local authorities to carry out bridge rehabilitation works on regional and local roads in 2015 (O'Brien, 2015).

Condition Rating (CR)	Description
0	*No or insignificant damage.*
1	*Minor damage but no need of repair.*
2	*Some damage, repair needed when convenient. Component is still functioning as originally designed. Observe the condition development.*
3	*Significant damage, repair needed very soon. i.e. within next financial year*
4	*Damage is critical and it is necessary to execute repair works at once, or to carry out a detailed inspection to determine whether any rehabilitation works are required.*
5	*Ultimate damage. The component has failed or is in danger of total failure, possibly affecting the safety of traffic. It is necessary to implement emergency temporary repair work immediately or rehabilitation work without delay after the introduction of load limitation measures.*

Table 2. Condition rating descriptions (NRA, 2008).

Data for 449 bridges on regional roads and 828 bridges on local roads in County Cork, Ireland was considered for this section of study. These bridges are managed by a local authority operating the Eirspan BMS (Duffy, 2004). Additionally, data for 85 bridges for a bridge stock around Dublin is also considered. For each bridge, a visual inspection was carried out by a trained bridge inspector and a general condition rating was assigned as per Table 2. The cost of maintenance and repair works undertaken on each bridge in relation to the condition rating assigned is also provided. The distribution of condition ratings for three separate regions from which the bridge stocks are selected, is shown in Table 3. It can be seen that 7%, 29% and 26% of bridges were assigned a condition rating of 3 and over for the South Dublin; Cork regional; and Cork local road area respectively, suggesting that the Cork region is in significant need of investment in terms of bridge rehabilitation works.

	CR0	**CR1**	**CR2**	**CR3**	**CR4**	**CR5**
South Dublin local and regional roads (*n* = *85*)	0.11	0.54	0.28	0.06	0.01	0
Cork regional roads (*n* = *449*)	0.06	0.19	0.46	0.22	0.06	0.01
Cork local roads (*n* = *828*)	0.02	0.11	0.60	0.18	0.05	0.03

Table 3. Distribution of condition ratings.

The bridge condition state can take on six possible values, fixed by the BMS employed. The prior analysis will be based on a time-based maintenance strategy, whereby there is no information from inspections on the bridge state. A condition based maintenance strategy represents the pre-posterior case. The objective of a condition-based maintenance strategy is to provide information, in this case through visual inspection, regarding the condition state of a bridge. This information is combined with an existing prior belief on the degradation level of the bridge, to deliver a better estimate of the 'true' bridge state. The DM can then use this information to make informed decisions as set out in the BMS guidelines. The VoI provided by visual inspection is defined as the difference in the MEU of the condition-based maintenance strategy and the time-based maintenance strategy.

It is a common perception that a condition-based maintenance strategy provides a greater value that a time-based maintenance strategy, as a better estimate of the bridge state, should lead to improved maintenance decisions. However, the benefit that visual inspection information provides is heavily dependent on an accurate description of the model parameters. A measure on the merits that visual inspection provides to infrastructure asset managers operating a BMS is provided here. How this value is influenced by the accuracy and precision of inspector assigned condition ratings, the prior probability of the bridge state and uncertainties in the condition rating scale are also illustrated. The time-based and the condition-based maintenance strategy are specified as the prior case and the pre-posterior case, respectively.

4. 1 Variables involved in the Model

The IDs are solved using the LIMID algorithm. The conditional probability distribution of each node is given as a conditional probability table. The Cork regional road area is chosen for the 'typical case' in the analysis.

4.1.1 Bridge state

The change in bridge state over time is represented by $X = \{x_1, x_2, ..., x_n\}$, where *n* is the number of possible condition states. The degradation over time is represented by the stochastic process $\{X_t, t = 0,1,2,...\}$, where X_t describes the state of the bridge at time *t*. It is assumed that a bridge deteriorates sequentially between the condition states, with 0 being the best state. The probability that the bridge is in state *i* at time *t* is represented by the following probability distribution: $\pi_t(i) = \Pr(X_t = i)$. The bridge state vector is defined as $\pi_t = \{\pi_t(0), \pi_t(1), ..., \pi_t(N)\}$; $\pi_t(i) \geq 0$; $\forall_i = 0,1,...,N$; $\sum_{i=0}^{N} \pi_t(i) = 1$, where π_t describes the probability distribution of the bridge state at time *t* (Srinivasan & Kumar, 2013). At time $t = 0$, the DM's belief π_0 characterises the prior knowledge regarding the condition of the bridge before the beginning of the decision-making period. In this analysis, the condition rating data from the Cork regional road dataset is used to define a prior probability vector for the bridge state, given as, π = [0.063 0.192 0.458 0.219 0.058 0.011].

4.1.2 Condition Rating

A trained inspector conducts a visual inspection on a bridge and assigns a condition rating as per Table 4. This process is represented as $\{CR_t, t = 0,1,2,...\}$ with a finite observation space $CR = \{1,2,...,m\}$, where *m* is the number of condition states. In order to relate the information received from visual inspection to the state of the asset, an information matrix describing the error associated with visual inspection must be defined. Visual inspection is highly subjective and can lead to variable results that depend on multiple factors (Moore et al., 2001). To accurately define an information matrix, a study could be completed, in which multiple bridge inspectors inspect bridges of each condition rating, whereby the condition rating has previously been deterministically defined through an in-depth expert-level inspection. This data could then be used to accurately define probability distributions of assigning the correct condition rating given the 'true' bridge state (Moore et al., 2001). As this data is not available here and for most bridge stock under practical conditions, it is assumed that the probability of an inspector assigning a correct condition rating follows a normal distribution $N(\mu, \sigma)$ with mean μ and unit standard deviation $\sigma = 1$ over the finite outcome space $CR = \{0,1,2,3,4,5\}$ (Graybeal et al., 2002).

This normal distribution describes the error (area underneath the curve) in the ability of an inspector to assign the correct condition rating. On the basis of this, an $n \times m$ information matrix, $Y = [y_{ik}]$, $k \in m$, $i \in n$, is assigned, where y_{ik} represents the conditional probability of receiving condition rating *k*, given that the current state is *i*, i.e., $y_{ik} = \Pr(CR_t = K \mid X_t = i)$ (Srinivasan & Kumar, 2013). The information matrix is given as:

Y =

0.3989	0.242	0.054	0.0044	0.0001	0
0.242	0.3989	0.242	0.054	0.0044	0.0001
0.054	0.242	0.3989	0.242	0.054	0.0044
0.0044	0.054	0.242	0.3989	0.242	0.054
0.0001	0.0044	0.054	0.242	0.3989	0.242
0	0.0001	0.0044	0.054	0.242	0.3989

and is based on limited and existing information on the topic. From the early days of treating uncertainties around human effects on decisions on infrastructure in a systematic manner (Stewart, 1992) to date (Malings & Pozzi, 2016), the importance of field data and the lack of it have been highlighted, At this stage, most databases available to the authors are not mature enough to develop benchmarked information matrices, although over time this situation is expected to be improved.

4.1.3 Decision alternatives

The decision space for the decision node D_i is defined first. Let $\{D_t, t = 0,1,2,...\}$ be the decision process to control the evolution of the bridge state, where $d \in D_t$ indicates the maintenance decision made at time t. For the BMS in this study, $D = \{d_0, d_1, d_2, d_3, d_4, d_5\}$, where d_0 = *'do nothing'*, d_1 = *'minor remedial works'*, d_2 = *'minor repair works'*, d_3 = *'minor repairs and preventative measures'*, d_4 = *'extensive repairs'*, and d_5 = *'replacement/extensive rehabilitation'*.

4.1.4 Cost matrix

The utility node is represented in terms of cost, which is a function of the bridge state and the decision alternative chosen. The cost function $C(i,d)$ represents the cost incurred when the asset is in state *i* and the decision *d* is taken. Given prior π_t the expected immediate cost incurred at time *t* is $C(d)=\sum_{i=1}^{N}\pi_t(i)C(i,d)$. The cost matrix is defined based on the following assumptions:

- The cost of each decision alternative is defined as the mean repair cost conditional on the condition rating assigned, i.e. if a bridge is assigned a condition rating of CR2, the mean repair cost is €11,690.
- The probability of bridge failure for each bridge state is given by the following vector P_F = [0 0.1 0.2 0.5 0.75 1]. Thus, if a bridge is defined as being in the worst state x_5, it is assumed to lead to sure failure. This probability assignment is for demonstrative purposes only.
- The cost of bridge failure is €250,000.
- The cost of a visual inspection strategy is €500/bridge.

The cost matrix for the analysis is given as:

C =

	$P_F = 0$	$P_F = 0.1$	$P_F = 0.2$	$P_F = 0.5$	$P_F = 0.75$	$P_F = 1$
x_0	2030	27030	52030	127030	189530	250000
x_1	4480	4480	544800	129480	191980	250000
x_2	11690	11690	11690	136690	199190	250000
x_3	16480	16480	16480	16480	203980	250000
x_4	31530	31530	31530	31530	31530	250000
x_5	50760	50760	50760	50760	50760	50760

Indirect costs can vary significantly (Pakrashi et al., 2011) and thus a consideration of such variation can make the comparison for inspection uninterpretable. Under such circumstances, for this example, the relative contributions of indirect costs are assumed to be of similar level.

4.2 Results

The results for the typical case using the Cork regional road data are given in Table 6. As anticipated, a perfect inspection has the lowest expected cost of €12,339. An inspection strategy is only worth undertaking if it costs less than its VoI and in this case, the estimated value is €6,876, which is related to the case of imperfect information.

Case	**Optimal Strategy**	**E[C] (€)**	**VoI (€)**
No Information (prior)	d_3	29,972	-
Perfect Information	$(x_0, d_0), (x_1, d_1), (x_2, d_2), (x_3, d_3), (x_4, d_4), (x_5, d_5)$	12,339	17,633
Imperfect Information	$(x_0, d_2), (x_1, d_3), (x_2, d_3), (x_3, d_3), (x_4, d_4), (x_5, d_4)$	23,096	6,876

Table 4. LIMID outputs.

In the case of no information the strategy with the minimum expected cost is d_3. With perfect information regarding the condition state, the optimal strategy takes the form of an identity matrix (Table 6). Imperfect information via visual inspection deduces a change in the above identity matrix, with the following strategy $D_{Imperfect\_information} = [(x_0, d_2), (x_1, d_3), (x_2, d_3), (x_3, d_3), (x_4, d_4), (x_5, d_4)]$ giving the lowest expected cost. As a result, visual inspection may not be suitable for certain databases and conditions, which will be investigated in the next section. These ratings can be improved in real situations by sharing more databases, which has started gaining popularity. Such information can be also be related to capacities and this allows clustering of bridges (Hanley & Pakrashi, 2015) or transition of ratings over time (Reale & O'Connor, 2011), both of which are signatures of the collective performance of a bridge stock.

4.3 Factors influencing the value provided by visual inspection

4.3.1 Condition Rating Accuracy and Precision

Accuracy is a measure of how close an assigned condition rating value is to the actual 'true' bridge state. One of the key challenges with visual inspection is that bridge inspectors grade the degradation differently based on their perception of the level of degradation. For example, one inspector may have an optimistic perception and grade a bridge as *CR3*, while another may be more pessimistic and grade the same bridge as *CR4*. In order to understand the impact of accuracy, the parameter *CR* was varied, from a pessimistic view to an optimistic view by varying the mean of the normal distribution with constant unit standard deviation over the finite outcome space $CR = \{0,1,2,3,4,5\}$. The mean is shifted from the true value, in both the positive and negative direction, characterising, to varying degrees, a pessimistic and optimistic inspector, respectively.

The amount of the shift represents the accuracy of the measurement. For example, in the analysis, a pessimistic inspector would assign a condition rating to a bridge in state x_1 as $N(1.9,1)$ in the worst case of pessimism, where N is a normal distribution with mean and standard deviation as the two arguments respectively. Figure 3 estimates VoI as a function of visual inspection accuracy. As the inspector becomes more pessimistic, the expected VoI decreases linearly. In the most optimistic case the expected VoI is € 8,375, which decreases to €6,876 for a neutral inspector and further decreases to €5,071 in the most pessimistic case. For the most optimistic inspector the optimal strategy $D_{optimistic} = [(x_0, d_2), (x_1, d_2), (x_2, d_3), (x_3, d_3), (x_4, d_3), (x_5, d_4)]$ is risk-seeking while the optimal strategy for a pessimistic inspector is more risk-adverse, corresponding to $D_{pesimistic} = [(x_0, d_3), (x_1, d_3), (x_2, d_3), (x_3, d_4), (x_4, d_5), (x_5, d_5)]$.

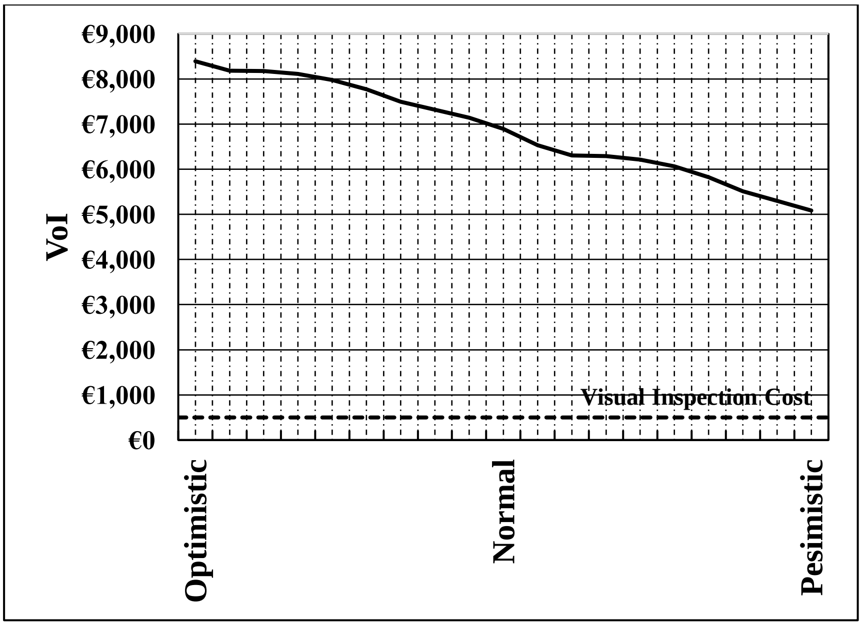

Figure 3. Investigation of the VoI as a function of visual inspection accuracy.

Precision refers to the closeness of two or more measurements to each other. In relation to visual inspection, precision is a measure of the repeatability of inspection. Poor precision results from random errors which results in poor repeatability. Precision is independent of accuracy and can be described by varying the standard deviation of the distribution for each condition rating. The standard deviation defines the width of the distribution, describing how much variation can occur between successive measurements. Figure 4 describes the estimated VoI as a function of visual inspection precision σ. The trend is monotonic but not linear, indicating that the worse the precision the lower the VoI. A high value of €17,633 is associated to the value of perfect information, whereby maintenance decisions are made with perfect information on the condition state of the asset, and diminishes towards zero as the precision of visual inspection degrades to $\sigma = 9.5$. The optimum precision occurs at $\sigma = 4.7$ (Figure 4).

Only a visual inspection strategy presenting a VoI higher than the cost of visual inspection (€500) is rationally suitable for implementation. However, given the significantly high values related to lack of precision at which the VoI becomes less than the cost indicates that in this case an inspection is almost always beneficial. This may not be necessarily at the same level for other bridge stocks and the VoI may be lower than the visual inspection cost for particularly challenging set of bridges with access and equipment aspects, where the design of inspection programme will be of importance. For practical applications, very high standard deviation will not be expected from inspections and consequently the comparison will be relevant within the sharply decreasing part of the bar-chart of Figure 4.

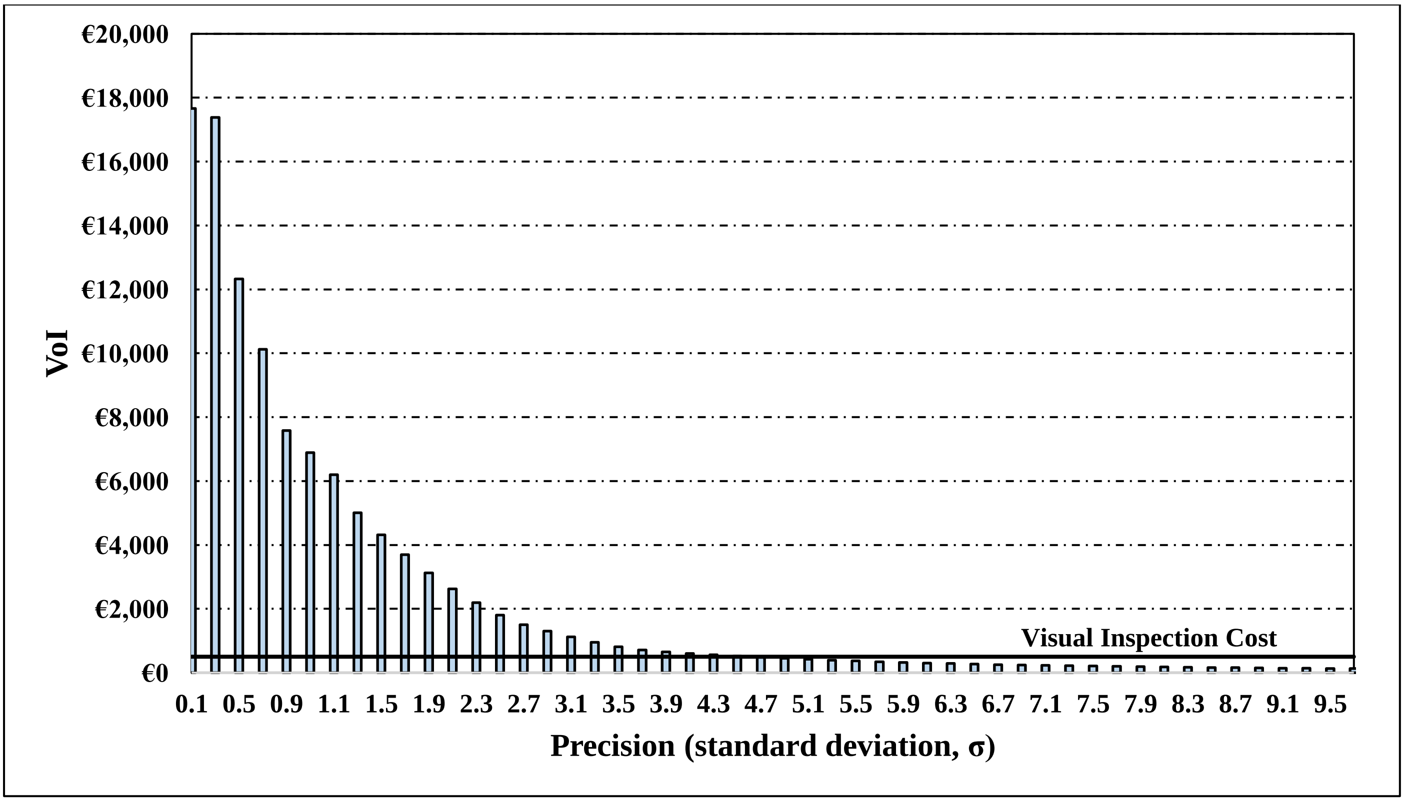

Figure 4. Investigation of the VoI as a function of visual inspection precision.

4.3.2 Prior Bridge State

Depending on the prior condition state of a bridge stock, visual inspection may give rise to different results for VoI. To examine the effect that the prior bridge state has on the VoI of visual inspection, the analysis was run whereby the prior state took on each possible distribution in Table 5. The likelihood of assigned condition ratings and the cost matrix were kept constant.

	CR0	**CR1**	**CR2**	**CR3**	**CR4**	**CR5**
Prior state probability distribution over the finite outcome space CR = {0, 1, 2, 3, 4, 5}	N (0, 1)	N (1,1)	N (2,1)	N (3,1)	N (4, 1)	N (5,1)

Table 5. Probability distributions for prior bridge state.

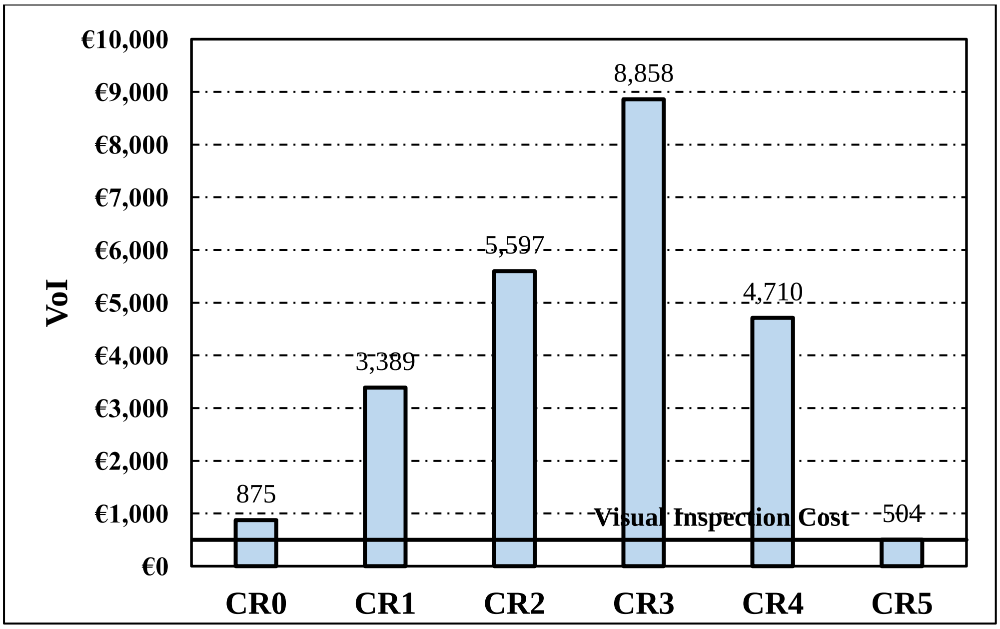

Figure 5. Impact of the prior bridge state on the VoI.

It is observed from Figure 5, that visual inspection provides the greatest VoI for CR3. The VoI is lowest for CR5 as the cost of perfect information $C_{perfect\_information\_CR5}$ = €41,208 converges to the cost of major rehabilitation $C_{Major\_rehabilitation}$ = €50,760. Bridge stocks, in reality, exhibit different prior state probability distributions depending on the type of road, bridge age, exposure conditions, state investment in bridge rehabilitation works, etc. The analysis was repeated using prior probability distributions for four different road types as outlined in Table 6. For this purpose, a significantly larger stock with 32250 bridges in Portugal was considered with real distributions of bridge conditions.

	CR0	**CR1**	**CR2**	**CR3**	**CR4**	**CR5**
Cork regional roads (*n = 449*)	0.06	0.19	0.46	0.22	0.06	0.01
Cork local roads (*n = 828*)	0.02	0.11	0.60	0.18	0.05	0.03
South Dublin local and regional roads (*n = 85*)	0.11	0.54	0.28	0.06	0.01	0
Portuguese roads (*n = 32250*)	0.08	0.56	0.30	0.05	0.01	0.001

Table 6. Distribution of condition ratings for different road types.

Figure 6 indicates the value that visual inspection provides is heavily dependent on the prior probability distribution of the bridge stock. Visual inspection provides the greatest benefit for bridge stocks with a high proportion of bridges with a CR2 rating such as the Cork regional and local roads. The VoI for the Dublin and Portuguese roads, which both had a high proportion of bridges with a CR1 rating was significantly lower, but still economically viable for a visual inspection strategy at a cost of €500. It also indicates how the proposed method can be applied to different bridge stocks of disparate sizes and how they can be compared in terms of the estimated value of their visual information.

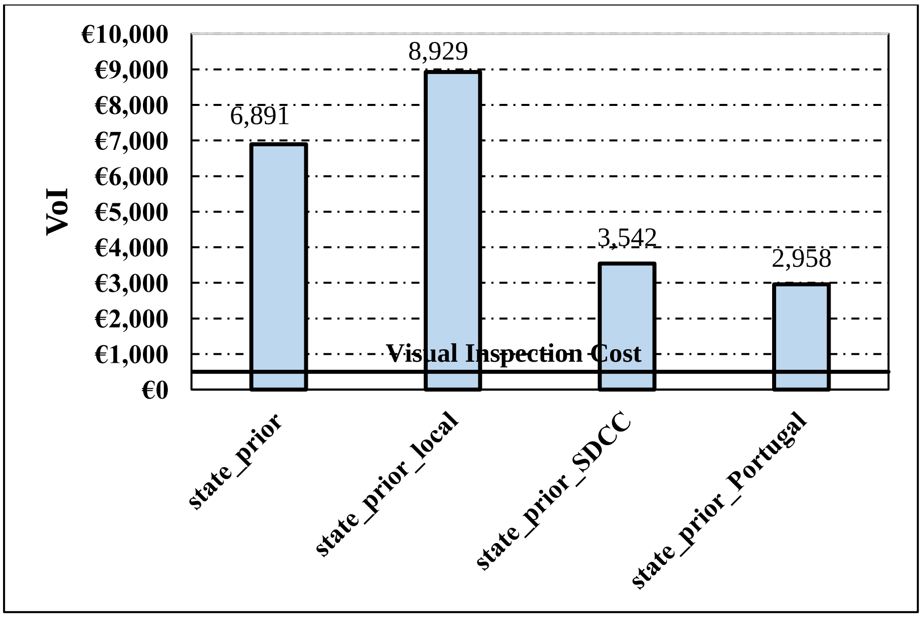

Figure 6. Effect of the prior bridge state of on the estimates of VoI for different bridge stocks.

4.3.3 Uncertainty in the Condition Rating Scale

Due to the nature of bridges in Ireland, a trend emerges in terms of the distribution of bridge condition states for local and regional roads. Ireland has an aging bridge stock and limited investment is available for bridge rehabilitation. As a result, the majority of bridges fall into the category of CR1, CR2 and CR3. It is investigated in Figure 7 if value is added to a visual inspection strategy where there is a finer resolution in the condition rating scale for various combinations of CR1, CR2, CR3 and CR4. For each application, the prior bridge state has equal probability of being in each state along the condition rating scale. i.e. for the typical case π_t = [0.167 0.167 0.167 0.167 0.167 0.167]. The cost matrix is altered based on the precision level achieved in visual inspection. The likelihood of inspector assigned condition ratings follows the same format as outlined in this paper but the matrix is contracted or expanded based on the precision level of the condition rating scale.

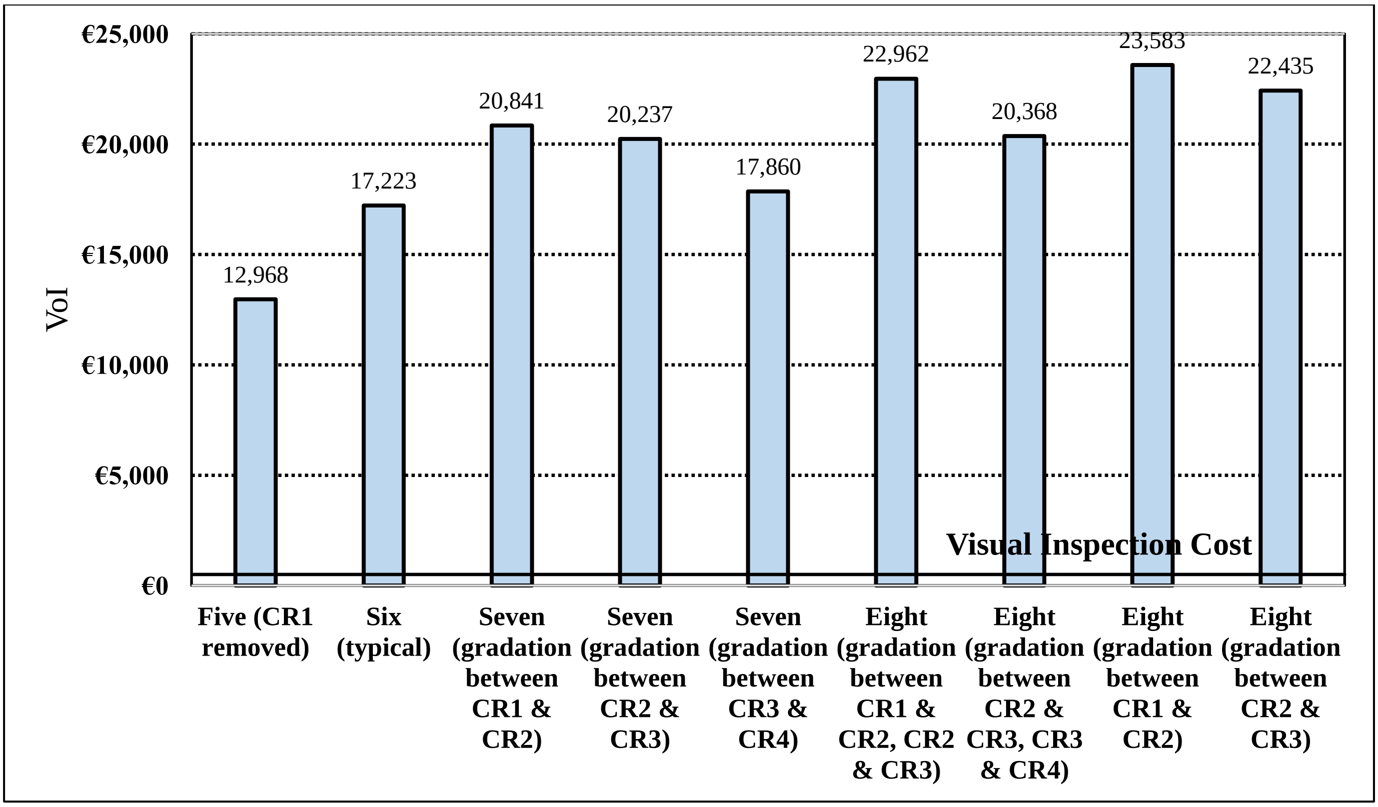

Figure 7. Effect of condition rating scale on VoI.

A negative impact on value was observed when CR1 was removed from the condition rating scale. A small drop in value was also observed when an additional rating was added between CR3 and CR4. The value improved from the typical case for all other cases with the greatest improvement in value observed when two additional rating were added between CR1 and CR2. This coincides with Figure 6, whereby the greatest VoI was shown for bridge stocks with a high proportion of bridges in the CR2 category. In addition to assessing the actual effect on the condition rating scale on VoI, this study also provides demonstrative evidence to adapt the proposed method for practical assessment and integration of varied bridge stocks with different inspection ratings.

5.0 Conclusions

The value of implementing a visual inspection strategy in a BMS was estimated employing the VoI methodology and several insights into visual inspection based decision making for bridge maintenance were investigated through analysis of various scenarios. Several real bridge stocks and related data were used in this regard. The estimated VoIs of no information, perfect information and imperfect information were calculated with county Cork in Republic of Ireland as a case study. The change in the optimal strategy based on perfect information and imperfect information from the prior state was also illustrated. The analysis is dependent on the characterisation of the parameters in the model, including the assumed probabilistic models of the prior bridge state, the likelihood of inspector assigned condition ratings and the economic setting surrounding the cost matrix for maintenance decision alternatives. The effect that the underlying uncertainties of the parameters have on the benefit provided by visual inspection was highlighted through numerical investigations. It was found that an optimistic inspection results in a higher VoI than a pessimistic inspection and more optimistic inspections lead to relatively more risk-seeking optimal maintenance strategies. As an inspector becomes more pessimistic, the VoI reduces and the optimal maintenance strategy becomes more risk-adverse. The additional information must have enough accuracy to alter that belief, else the decision maker has the potential to make wrong choices or will be better off with a preventive maintenance strategy. The prior perception of an inspector on the degradation of an asset significantly affects the value provided and information from multiple inspectors inspecting the same bridge could offer value in terms of reducing bias. Analysing the impact of precision of visual inspection with regard to the value provided, it was found that as precision decreases the value delivered by visual inspection decreases monotonically, but in a nonlinear fashion.

A visual inspection strategy presenting a VoI higher than the cost of visual inspection is rationally suitable for implementation in a BMS. Analyses on the prior state distribution indicate that the greatest value is provided for bridge stocks with specific priors, given the rating method is known. By analysing real bridge stocks, it was observed that the greatest benefit was provided for bridges in local and regional roads, which had a high proportion of bridges in the CR2 condition state. In contrast, a lower value was seen for the Dublin and Portuguese datasets, whose prior distribution had the majority of bridges in the CR1 state. Where a high proportion of bridges are in the CR3 or CR2 condition state, the benefit is observed to be greatest by adopting a visual inspection strategy. This was investigated further by investigating if value is added to visual inspection if the condition rating scale is presented in a different resolution. A negative impact on value was shown when the condition rating scale was narrowed by removing CR1. The highest increase in value was observed when two additional ratings were added in between CR1 and CR2, where the VoI increased significantly from the typical scenario. The applicability of VoI for visual inspections of bridges depend on the input parameters like the prior degradation model, the prior bridge state distribution, the likelihood of inspector assigned condition ratings and the economic setting surrounding the cost values of the maintenance action alternatives. Accurate determination of these parameters obtained from several bridge stocks over an appropriately representative length of time can provide better estimates and stabilities around such values.

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References

Ang, A. H.-S., & Tang, W. H. (1975). *Probability concepts in engineering planning and design*. New York: Wiley.

ASCE. (2013). Report Card for America's Infrastructure. Retrieved from http://www.infrastructurereportcard.org/

Attoh-Okine, N. O., & Bowers, S. (2006). A Bayesian belief network model of bridge deterioration. *Proceedings of the Institution of Civil Engineers - Journal of Bridge Engineering, 159*(2), 69-76.

Beck, J.L. & Au, S.K. (2002). Bayesian updating of structural models and reliability using Markov Chain Monte Carlo Simulation. *ASCE Journal of Engineering Mechanics*, *128(4)*, 380–391.

Benjamin, J., & Cornell, C. A. (1970). *Probability, statistics, and decision for civil engineers*. New York: McGraw-Hill.

Bensi, M., Der Kiureghian, A., & Straub, D. (2013). Efficient Bayesian network modeling of systems. *Journal of Reliability Engineering and System Safety, 112*(2013), 200-213.

Bensi, M., Der Kiureghian, A., & Straub, D. (2015). Framework for post-earthquake risk assessment and decision making for infrastructure systems. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 1*(1), 04014003-1-17.

Bensi, M. T. (2010). *A Bayesian Network methodology for infrastructure seismic risk assessment and decision support.* PhD Thesis, University of California, Berkeley, CA, USA.

Biondini, F., & Frangopol, D. M. (2016). Life-cycle performance of deteriorating structural systems under uncertainty: Review. *ASCE Journal of Structural Engineering, 142*(9), F4016001-1-17.

Browne, T. M., Collins, T. J., Garlich, M. J., O'Leary, J. E., Stromberg, D. G., & Heringhaus, K. C. (2010). *Underwater bridge inspection*. Report No. FHWA-NHI-10-027 C, Federal Highway Adminitration, Washington DC, USA.

Chase, S. B., Adu-Gyamfi, Y., Aktan, A. E., & Minaie, E. (2016). *Synthesis of national and international methodologies used for bridge health indices*, Report No. FHWA-HRT-15-081, Federal Highway Administration, McLean VA, USA.

De Leon, D., Lopez, A., & Esteva, L. (2015). *Value of Information on the risk/benefit of infrastructure under strong winds in Mexico*. Paper presented at the 12th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP12), Vancouver, Canada.

DeGroot, M. H. (1984). Changes in utility as information. *Theory and Decision, 17*(3), 287-303.

Der Kiureghian, A., & Ditlevsen, O. (2007). *Aleatory or epistemic? Does it matter?* Paper presented at the Special Workshop on Risk Acceptance and Risk Communication, Stanford University.

Deshmukh, P., & Bernhardt, S. K. L. (2000). *Quantifying uncertainty in bridge condition assessment data.* Paper presented at the Mid-continent Transportation Symposium 2000 Proceedings.

DTTAS. (2016). Department of Transport Tourism and Sport: Regional and Local Roads. Retrieved from http://www.dttas.ie/roads/english/regional-and-local-roads

Duffy, L. (2004). Development of Eirspan: Ireland's bridge management system. *Proceedings of the Institution of Civil Engineers - Journal of Bridge Engineering, 157*(BE3), 139-146.

Estes, A. C., Frangopol, D. M., & Foltz, S. D. (2004). Using visual inspection results to update reliability analyses of highway bridges and river lock structures. *Journal of Structural Safety and Reliability, 26*(3), 319-333.

Gattulli, V., & Chiaramonte, L. (2005). Condition assessment by visual inspection for a bridge management system. *Journal of Computer-Aided Civil and Infrastructure Engineering, 20*(2005), 95-107.

Goulet, J.-A., & Smith, I. F. C. (2013). Categories of SHM deployments: Technologies and capabilities. *Journal of Structural Engineering, 20*(11), 1-15.

Goulet, J. A., Der Kiureghian, A., & Lia, B. (2015). Pre-posterior optimization of sequence of measurement and intervention actions under structural reliability constraint. *Journal of Structural Safety, 52*(A), 1-9.

Graybeal, B. A., Phares, B. M., Rolander, D. D., Moore, M., & Washer, G. (2002). Visual inspection of highway bridges. *Journal of Nondestructive Evaluation, 21*(3).

Hanley, C., & Pakrashi V. (2015). Reliability Analysis of a Bridge Network in Ireland. Proceedings of the ICE, Bridge Engineering, 168 (5):442-456.

Jensen, F. V., & Nielsen, T. D. (2007). *Bayesian Networks and Decision Graphs* (Second ed.): Springer.

Koller, D., & Friedman, N. (2009). *Probabilistic graphical models: principles and techniques*. Cambridge, Massachusetts, London, England: The MIT Press.

Konakli, K., Sudret, B., & Faber, M. H. (2015). Numerical Investigations into the value of information in lifecycle analysis of structural systems. *Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 2(3)*, B40150071-13.

Kosgodagan, A., Morales-Nápoles, O., Maljaars, J., Yeung, T., & Castanier, B. (2015). *Bayesian Networks to quantify transition rates in degradation modeling: Application to a set of steel bridges in The Netherlands*. Paper presented at the 12th International Conference on Applications of Statistics and Probability in Civil Engineering, Vancouver, Canada.

Krause, A. (2008). *Optimizing sensing theory and applications.* PhD Thesis, Carnegie Mellon University, PA, USA.

Li L., Sun, L., & Ning, G. (2014). Deterioration prediction of urban bridges on network level using Markov-Chain model. *Mathematical Problems in Engineering*, 2014, Article ID 728107, 10 pages.

Lindley, D. V. (1956). On the measure of the information provided by an experiment. *Annuals of Mathematical Statistics, 27*(4), 986-1005.

Luque, J., & Straub, D. (2015). *Probabilistic modeling of system deterioration with inspection and monitoring data using Bayesian Networks*. Paper presented at the 12th International Conference on Applications of Statistics and Probability in Civil Engineering, Vancouver, Canada.

Madanat, S. (1993). Optimal infrastructure management decisions under uncertainty. *Journal of Transportation Research Part C: Emerging Technologies., 1*(1), 77-88.

Madsen, H. O., Sørensen, J. D., & Olesen, R. (1989). *Optimal inspection planning for fatigue damage of offshore structures.* Paper presented at the 5th International Conference on Structural Safety and Reliability.

Malings, C. & Pozzi, M. (2016). Value of information for spatially distributed systems: Application to sensor placement. *Reliability Engineering & System Safety*, 154, pp.219–233.

Malings, C., & Pozzi, M. (2015). *Sensor network optimization using Bayesian Networks, Decision Graphs, and value of information.* Paper presented at the 12th International Conference on Applications of Statistics and Probability in Civil Engineering, Vamcover, Canada.

Memarzadeh, M. & Pozzi, M. (2016). Value of information in sequential decision making: Component inspection, permanent monitoring and system-level scheduling. Reliability Engineering and System Safety, 154, pp.137–151.

Mirzaei, Z., Adey, B. T., Klatter, L., & Thompson, P. D. (2014). *Overview of existing bridge management systems*. International Association for Bridge Maintenance And Safety (IABMAS).

Morbin R., Zanini M.A., Pellegrino C., Zhang H., & Modena C. (2015) A probabilistic strategy for seismic assessment and FRP retrofitting of existing bridges. *Bulletin of Earthquake Engineering*, 13(8): 2411-2428.

Moore, M. E., Phares, B. M., Graybeal, B. A., Rolander, D. D., & Washer, G. A. (2001). *Reliability of visual inspection for highway bridges*. Report No. FHWA-RD-01-020, Federal Highway Administration, McLean, VA, USA.

Murphy, K. (2001). The Bayes Net Toolbox for Matlab. *Department of Computer Science, University of California, Berkley.*

NRA. (2008). *Eirspan: System Manual No. 3 Principal Inspection*.

O'Brien, T. (2015). Funding for local and regional roads cut by nearly €40m. *The Irish Times*. Retrieved from http://www.irishtimes.com/news/ireland/irish-news/funding-for-local-and-regional-roads-cut-by-nearly-40m-1.2090023

Pakrashi, V., Kelly, J., & Ghosh, B. (2011). Sustainable prioritisation of bridge rehabilitation comparing road user cost, Transportation Research Board Annual Meeting, 2011.

Pakrashi, V., Kelly, J., & O'Connor, A. (2012). Direct and probabilistic interrelationships between half-cell potential and resisitivity test results for durability ranking, IABMAS 2012, Stresa, Italy.

Pozzi, M., & Der Kiureghian, A. (2011). Assessing the value of information for long-term structural health monitoring. *Journal of Health Monitoring of Structural and Biological Systems, 7984*, 1-14.

Pozzi, M., & Der Kiureghian, A. (2012). *Assessing the value of alternative bridge health monitoring systems*. Paper presented at the 6th International IABMAS Conference, Stresa, Lake Maggiore, Italy.

Pozzi, M., Zonta, D., Wang, W., & Chen, G. (2010). *A framework for evaluating the impact of structural health monitoring on bridge management*. Paper presented at the 5th International Conference on Bridge Maintenance, Safety and Management (IABMAS 2010), Philadelphia.

Rafiq, M. I., Chryssanthopoulos, M. K., & Sathananthan, S. (2015). Bridge condition modelling and prediction using dynamic Bayesian belief networks. *Journal of Structure and Infrastructure Engineering, 11*(1), 38-50.

Raiffa, H., & Schlaifer, R. (1961). *Applied statistical decision theory*. Boston: Division of Research Graduate School of Business Administration Harvard University.

Reale, T., & OConnor, A. (2011). Cross-entropy as an optimization method for bridge condition transition probability determination. *ASCE Journal of Transportation Engineering*, *138(6)*, 741–750.

Saydam, D., Frangopol, D., & Dong, Y. (2013). Assessment of risk using bridge element condition ratings. *ASCE Journal of Infrastructure Systems, 19*(3),252-265 .

Srinivasan, R. P., Kumar A. (2013). Value of condition monitoring in infrastructure maintenance. *Journal of Computers & Industrial Engineering, 66*(2), 233-241.

Stewart, M.G., 1992. Modelling human error rates for human reliability analysis of a structural design task. *Reliability Engineering & System Safety*, 36(2), pp.171–180.

Straub, D. (2009). Stochastic modeling of deterioration processes through dynamic Bayesian networks. *ASCE Journal of Engineering Mechanics, 135*(10), 1089-1099.

Straub, D. (2014). Value of information analysis with structural reliability methods. *Journal of Structural Safety, 49*, 75-86.

Straub, D., & Faber, M. H. (2005). Risk based inspection planning for structural systems. *Journal of Structural Safety, 27*(4), 335-355.

Sánchez-Silva, M., Frangopol, D. M., Padgett, J., & Soliman, M. (2016). Maintenance and operation of infrastructure systems: Review. *Journal of Structural Engineering, 142*(9), F4016004-1-16.

Sørensen, J. D., & Thoft-Christensen, P. (1986). Optimal strategy for inspection and repair of structural systems. *Civil Engineering Systems*, *4*(2), 94-100.

Tang, W. (1973). Probabilistic updating of flaw information. *Journal of Testing and EvaluationJournal of Testing and Evaluation, 1*(6), 459-467.

Vaghef, K., de Melo e Silva, H. A., Harris, D. K., & M. Ahlborn, T. (2011). *Application of thermal IR imagery for concrete bridge inspection*. Paper presented at the PCI Convention and National Bridge Conference.

Von Neumann, J., & Morgenstern, O. (1953). *Theory of games and economic behaviour* (Third ed.): Princeton University Press.

Wang, N. (2010). *Reliability-based condition assessment of existing highway bridges.* PhD Thesis, Georgia Institute of Technology, GA, USA.

Washer, G. A., & Fuchs, P. A. (2015). *Developments in the use of infrared thermography for the condition assessment of concrete*. Paper presented at the International Symposium Non-Destructive Testing in Civil Engineering, Berlin, Germany.

Wellalage, N. K. W., Zhang, T., & Dwight, R. (2014). Calibrating Markov chain-based deterioration models for predicting future conditions of railway bridge elements. *ASCE Journal of Bridge Engineering, 20*(2), 04014060-1-13.

Weninger-Vycudil, A., Hanley, C., Deix, S., O'Connor, A., & Pakrashi V. (2015). Cross-asset management for road infrastructure networks. *Proceedings of the Institution of Engineers – Transport*, *168(5)*, 442-456.

Zanini, M.A., Faleschini, F., & Pellegrino, C.. (2016). Bridge residual service-life prediction through Bayesian visual inspection and data updating. *Structure and Infrastructure Engineering*, *Ahead of Print,*DOI:info http://dx.doi.org/10.1080/15732479.2016.1225311.

Zink, J., & Lovelace, B. (2015). *Unmanned aerial vehicle bridge inspection demonstration project*. Report No. MN/RC 2015-40, Minnesota Department of Transportation, St. Paul, Minnesota, USA.

Znidaric, A., Pakrashi, V., O' Connor, A., & O' Brien, E. (2011). A review of road structure data in six European countries. *Proceedings of the ICE, Journal of Urban Design and Planning*, *164(4)*, 225-232.

Zonta, D., Glisic, B., & Adriaenssens, S. (2014). Value of information: Impact of monitoring on decision-making. *Journal of Structural Control and Health Monitoring, 2014*(21), 1034-1056.