Published in *Journal of Civil Structural Health Monitoring* 10 (3) **2020** pp.485-496

A framework for assessing the value of information for health monitoring of scoured bridges

Giordano, P.F.[a,1], Prendergast, L.J.[b,2], Limongelli, M.P.[a,3]

[a] Department of Architecture,
Built Environment and Construction Engineering,
Politecnico di Milano,
20133 Piazza Leonardo da Vinci 32,
Milan,
Italy

[b] Department of Civil Engineering,
Faculty of Engineering,
University of Nottingham,
Nottingham,
NG7 2RD,
United Kingdom

[1]Corresponding author

Email: [1]pierfrancesco.giordano@polimi.it, [2]luke.prendergast@nottingham.ac.uk,
[3]mariagiuseppina.limongelli@polimi.it

Keywords: Scour, Structural Health Monitoring, Value of Information, Decision Making, Bridge Management

Abstract

It is generally accepted that climate-change is leading to increased frequency of extreme weather events worldwide, and this is placing heavier demands on an already aging infrastructure-network. Bridges are particularly vulnerable infrastructure assets that are prone to damage or failure from climate-related actions. In particular, bridges over waterways can be adversely affected by flooding, specifically the washing away of foundation soils, a mechanism known as scour erosion. Scour is the leading cause of failure for bridges with foundations in water as it can rapidly compromise foundation stiffness often resulting in unacceptable movements or even collapse. There is growing interest among asset managers in applying health monitoring approaches to assess the real-time performance of bridges under damaging actions, including scour. Sensor-based approaches involve the acquisition of data such as dynamic measurements, which can be used to infer the existence of scour or other damage without the

laborious requirements of undertaking visual inspections. In this paper, a framework is proposed to assess the benefit obtained from health monitoring systems as compared to the scenario where no monitoring system is employed on a bridge, to ascertain how useful these systems are at assisting decision-making. Decisions typically relate to the implementation of traffic restrictions or even partial or complete bridge closure in the event of damage being detected, which has associated consequences for a network. A case study is presented to demonstrate the approach postulated in this paper.

1. Introduction

Extreme weather events are becoming more frequent as a result of climate-change and this is putting increasing pressure on built infrastructure. In tandem with this, infrastructure networks worldwide are aging, and many are approaching the end of their original design lives. These two phenomena together mean it is now more important than ever to direct attention to the maintenance and management of the aging asset stock to ensure safe, reliable transport infrastructure exists for generations to come.

Bridges are one of the main infrastructure assets at significant risk from climate-induced loading. Bridges with foundations in water are susceptible to scour erosion [1], whereby adverse hydraulic actions remove soil from around and under foundations compromising stability and increasing the risk of failure [2]. The occurrence of scour can cause a reduction in the stiffness and capacity of a bridge foundation [3–5] and lead to sudden failure.

Scour is most commonly monitored by means of visual inspections, whereby divers inspect a given bridge's foundations periodically (typically at times when flooding is not occurring). Susceptible bridges are usually rated using a scale related to the perceived severity of the scour problem affecting their foundations. The main issues with this type of approach are the subjective nature of the rating schemes adopted by respective agencies, and the fact that inspections typically occur during non-flooded conditions (when scour holes may have re-filled post flooding). It is generally not possible to inspect structures during flooding due to safety reasons, as well as the fact that flooded water conditions tend to be turbid thus obscuring the view of the foundations. Furthermore, rating-based ranking measures tend to vary between agencies responsible for the bridges (e.g. national road and railway agencies) as well as from country to country. To improve on the drawbacks associated with visual-type inspections, a significant number of sensor-based systems have been developed in recent times to assist in remotely monitoring scour hole depth evolution. These systems include, among others: radar/electromagnetic systems [6–8], physical probe systems [9–11], and sound wave devices [7, 12]. Interested readers are referred to Refs. [13, 14] for a comprehensive discussion on these types of systems. While these sensor-systems have varying success at monitoring scour hole depth evolution near a foundation of interest, they generally provide limited useful information on the structural condition as a result of scour hole formation. This is critical as the presence of a given scour hole may have limited or significant impact on the stability and safety of affected structures, and this will vary depending on factors such as foundation depth and type, as well as structural configuration.

In recent times, the application of vibration-based damage detection and health monitoring [15] to bridge scour assessment has become popular in research with many publications investigating the performance of a variety of methods at detecting and monitoring scour. The benefit of systems of this nature for scour detection is that they use actual structural response measurements to infer changes in support conditions (e.g. losses in foundation stiffness) and so can obtain a direct indication of the effect of a scour hole on a given structure. The premise underlying these damage identification methods is that changes in stiffness due to scour modify the dynamic properties of a structure, therefore measuring changes in dynamic parameters can potentially indicate the presence of scour. A variety of vibration-based scour monitoring approaches are put forward in Refs. [5, 16–26]. It should be noted, however, that the adoption and deployment of health monitoring systems of this nature on a bridge can be expensive, therefore tools and methods to assess their benefit for emergency management of bridges on a given network are needed.

In this paper, a framework for assessing the benefit of installing a monitoring system as a decision support tool for emergency management of scoured bridges is proposed. The framework is based on the Value of Information (VoI) from Bayesian decision theory. A case study is undertaken to demonstrate the approach. The VoI can be understood as the maximum price a bridge operator should pay for the information from a Structural Health Monitoring (SHM) system: the SHM system should be installed only if the corresponding VoI is higher than the cost of the system itself. Moreover, the VoI can be considered as the money saved each time a decision maker interrogates the SHM system. Interested readers should refer to Refs. [27–36] for further details on VoI theory and applications.

The remainder of this paper is structured as follows. Section 2 presents the general framework for VoI analyses in the case of emergency management of structures; Section 3 presents the application of VoI analyses to scoured bridges; and Section 4 presents a case study demonstration of the approach.

2. General framework

The VoI is herein defined in the context of Bayesian decision theory, which was presented more than half a century ago by Raiffa and Schlaifer [37]. Bayesian decision theory is based on the Expected Utility Theorem by Van Morgenstern and Neumann [38] and on the Bayesian definition of probability [39] which represents a measure of the belief in the different states of a system: probabilities can be updated by means of the well-known Bayes' Theorem, when new information is obtained. Bayesian decision theory is based on the maximization of expected utility: a Bayesian decision maker associates a numerical utility to each of the possible consequences of an action, and a probability to each of the states of the system that may affect that utility. The utility expresses the desirability of a possible option in a decision scenario.

The classical formulation of the VoI is herein adapted to the management of civil structures in the aftermath of a disastrous event. For the purpose of the present paper, this will be specified as a severe flood affecting a given structure. According to the available information, three types of decision analyses are possible, namely prior analysis, posterior analysis and pre-posterior analysis. The terms prior and posterior refer to when an analysis is performed with respect to when information is acquired through a monitoring system. The term pre-posterior refers to when an analysis is performed before (pre) acquiring any SHM information. In this case, the analysis is carried out forecasting the information that will be acquired after (posterior) installing the monitoring system.

Prior decision analysis deals with decisions taken on the basis of the decision makers' prior knowledge and uses no additional information. In relation to bridge management, the decision maker might be concerned about the potential failure of a bridge caused by a disastrous event. Even if failure does not occur directly because of the event, it may occur at a later time due, for example, to traffic loads, or aftershocks in the case of earthquakes, or slowly evolving scour induced by the action of flowing water. It is assumed that following an event of intensity measure IM, which may induce one of L discrete damage states in a structure DS_l, $l = 1, \dots, L$, a choice has to be made among N actions A_n, $n = 1, \dots, N$. The expected cost of action A_n, given that the state of the system is DS_l, is obtained as

$$E[c(A_n)|DS_l] = c_F(A_n)P(F|A_n, DS_l) + c_{\bar{F}}(A_n)[1 - P(F|A_n, DS_l)] \quad (1)$$

where $P(F|A_n, DS_l)$ is the probability of bridge failure related to action A_n and damage state DS_l; $c_F(A_n)$ and $c_{\bar{F}}(A_n)$ are the costs associated with structural failure and survival, respectively, which change according to the action A_n. The quantity $E[c(A_n)|DS_l]$ represents the expected cost of action A_n in the ideal case where the decision maker knows with certainty the state of the structure DS_l. In real cases however, the knowledge of decision makers is affected by uncertainty, therefore each damage state has a certain probability of occurrence that, when dealing with disastrous events, depends on the intensity IM of the event. The expected cost of action A_n, given a certain IM, $E[c(A_n)|IM]$, is computed as the sum of the expected costs related to the occurrence of the possible damage states DS_l, $E[c(A_n)|DS_l]$, each weighted by their probability of occurrence following the event of intensity IM $P(DS_l|IM)$, as follows:

$$E[c(A_n)|IM] = \sum_{l=1}^{L} E[c(A_n)|DS_l]P(DS_l|IM) \quad (2)$$

Herein the utility is expressed as negative cost. Therefore, the prior decision is made according to the Expected Utility Theorem by selecting the action $\hat{A}$, which maximizes the utility, that is the action that corresponds to the minimum expected cost $c_1(IM)$, see Eq. 3 and Eq. 4.

Published in *Journal of Civil Structural Health Monitoring* 10 (3) **2020** pp.485-496

$$\hat{A} = \hat{A}(IM) = \arg\min_n E[c(A_n)|IM] \tag{3}$$

$$c_1(IM) = E\big[c(\hat{A})|IM\big] = \sum_{l=1}^{L} E\big[c(\hat{A})|DS_l\big]P[DS_l|IM] \tag{4}$$

The described prior decision problem is represented in Fig. 1 by means of a decision tree. Round nodes indicate a possible state of the system to which a probability of occurrence must be assigned; square nodes indicate a decision that is made based on the minimization of costs.

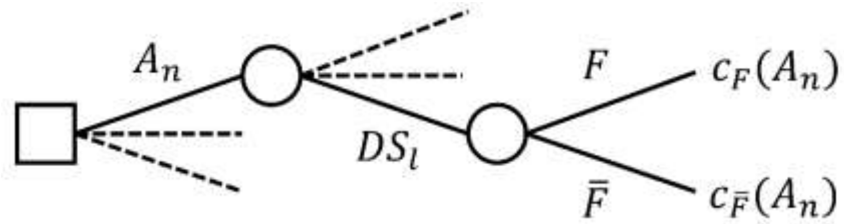

Fig 1. Decision tree for prior decision analysis

Posterior analysis is performed when new information on the state of the structure is obtained such as one of the possible outcomes O_j, $j = 1, \dots, J$, from an SHM system. This information is used to update the prior probabilities of damage states according to Bayes' theorem, which reads

$$P\big(DS_l\big|O_j, IM\big) = \frac{P\big(O_j|DS_l\big)P(DS_l|IM)}{P\big(O_j|IM\big)} \tag{5}$$

where $P\big(O_j|DS_l\big)$ is the probability of obtaining the outcome O_j when the state of the system is DS_l, which is obtained by so-called *likelihood functions*; $P\big(O_j|IM\big)$ is the total probability given by Eq. 6.

$$P\big(O_j|IM\big) = \sum_{l=1}^{L} P\big(O_j|DS_l\big)P(DS_l|IM) \tag{6}$$

The posterior expected cost of action A_n is computed similarly to Eq. 2, but using posterior probabilities of damage states, as follows:

$$E\left[c(A_n)\middle|O_j, IM\right] = \sum_{l=1}^{L} E[c(A_n)|DS_l]P\left(DS_l\middle|O_j, IM\right) \tag{7}$$

The decision is made by selecting the action $\breve{A}_{O_j}$ corresponding to the minimum expected cost $E\left[c\left(\breve{A}_{O_j}\right)|O_j, IM\right]$, as follows:

$$\breve{A}_{O_j} = \breve{A}\left(O_j, IM\right) = \arg\min_{n} E\left[c(A_n)\middle|O_j, IM\right] \tag{8}$$

$$E\left[c\left(\breve{A}_{O_j}\right)|O_j, IM\right] = \sum_{l=1}^{L} E\left[c\left(\breve{A}_{O_j}\right)|DS_l\right] P\left(DS_l\middle|O_j, IM\right) \tag{9}$$

In this case, the optimal action and the corresponding expected cost depend on both the intensity of the event IM and the outcome O_j.

The pre-posterior analysis is made prior to obtaining additional information. It is used to forecast the expected cost resulting from decision making when a certain information acquisition strategy is adopted. It consists of multiple posterior analyses, where the decision maker selects the optimal action for each possible outcome O_j of the selected acquisition strategy. The expected cost $c_0(IM)$ associated with the information acquisition strategy is computed by marginalizing the expected costs $E\left[c\left(\breve{A}_{O_j}\right)|O_j, IM\right]$ over the probabilities of occurrence $P\left(O_j|IM\right)$ of each possible outcome O_j, according to Eq. 10.

$$c_0(IM) = \sum_{j=1}^{J} E\left[c\left(\breve{A}_{O_j}\right)|O_j, IM\right] P\left(O_j|IM\right) \tag{10}$$

The pre-posterior decision analysis with information from SHM is represented in the decision tree in Fig. 2.

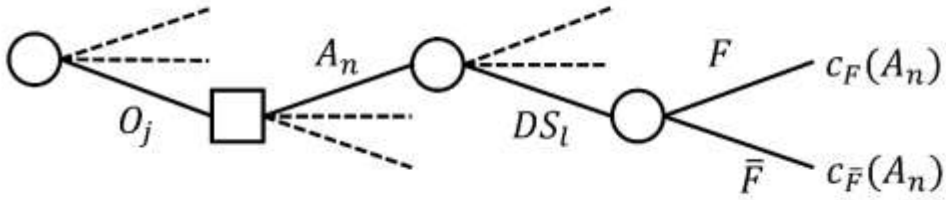

Fig. 2 Decision tree representing the pre-posterior decision analysis with information from SHM

The VoI for the decision-making process relevant to the choice of the action needed to manage the bridge after an event of intensity IM, $\mathrm{VoI}(IM)$, is obtained as the difference between the expected cost of the action taken without (prior) and with (pre-posterior) information, see Eq. 11.

$$\mathrm{VoI}(IM) = c_1(IM) - c_0(IM) \tag{11}$$

In general, the optimal action and the corresponding cost, for both prior and pre-posterior analyses, change according to IM that, before the occurrence of an event, is not known. The VoI over the reference period for which it is calculated, is obtained by marginalizing over the entire range of intensities, as follows:

$$\mathrm{VoI} = \int_{IM} \mathrm{VoI}(IM) f(IM) dIM \tag{12}$$

where $f(IM)$ is the probability density function (PDF) of the intensity measure IM over the reference period. The idea behind Eq. 12 is that the decision maker has at their disposal a statistical model providing the likelihood of a disastrous event occurring in a certain geographical area in a given reference time. Examples include seismic hazard functions for earthquakes or distributions of maximum annual flow for rivers. In Eq. 12, the contribution to the VoI of rare events, with relatively small values of PDF $f(IM)$ is negligible. In turn, terms of $\mathrm{VoI}(IM)$ corresponding to likely events, and therefore to high values of PDF, are dominant. In this way, accurate estimation of the VoI can be obtained before the installation of a SHM system.

It can be demonstrated (see e.g. Straub [29]) that the VoI is bounded between zero and the so-called Value of Perfect Information (*VoPI*), which is obtained, ideally, when the information acquired is not affected by uncertainty. Nevertheless, it has been shown recently [40, 41] that the VoI could be negative. This could occur, for example, if the person managing the bridge, i.e. the manager in charge of issuing traffic restrictions, is not the same person making the decision on acquiring new information, i.e. the owner who pays for the SHM system. Even if they share the same information, the perception of the costs associated with structural failure and survival might differ between the two individuals. In the VoI framework, this is modelled by two different utility functions that may lead to a negative VoI. In particular, the VoI could be negative in the owner's perspective if they are forced to accept an action - chosen by the manager - that they perceive as too risky due to their own risk averse nature. In this sense the VoI should not be intended as the absolute benefit associated with the support to decisions provided by the SHM system, but rather as the perception of this value on behalf of the different stakeholders involved in the decision process.

3. Application to scoured bridges

In this section, the methodology for assessing the VoI of SHM in emergency management is applied to bridges under scour hazard. Fig. 3 shows a flowchart of the general framework: the basic variables of the decision problem are indicated in blue; the probabilities are indicated in red.

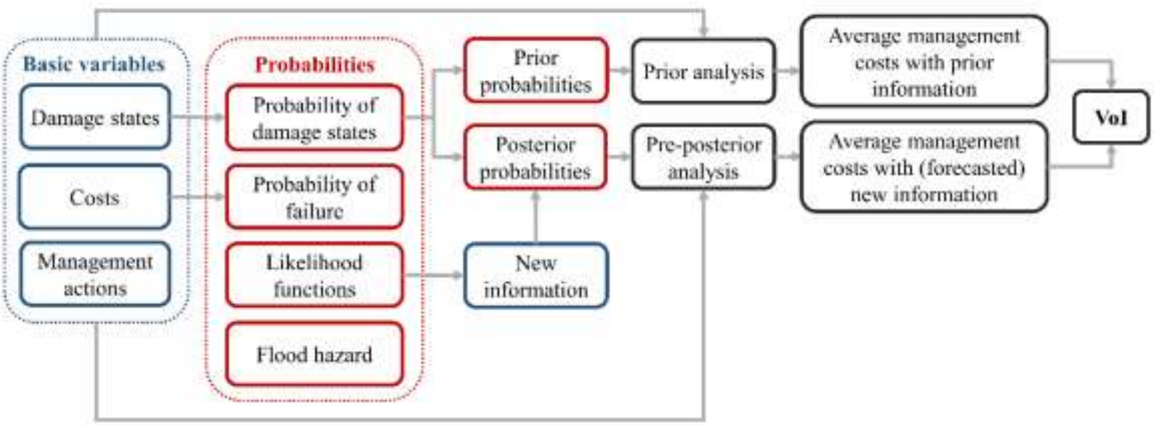

Fig. 3 Flowchart showing general methodology for assessing the VoI

The basic variables of the decision problem include the damage states of the system induced by scour, the possible bridge management actions, and the consequences associated with the different combinations of damage states of the system and actions. An understanding of likely damage states of the system under evolving scour is necessary, which refer to the condition of the bridge (and its elements) under various scour severities. Prior probabilities of the damage states can be calculated, which refer to the likelihood of obtaining a certain scour magnitude based on flow intensity and bridge geometrical conditions (using design formulae or otherwise). The probability of failure of the structure under various scour conditions should be calculated using assumed capacity models and estimates of demand on the system from external actions. Likelihood functions, which refer to the likely output from a SHM system (for example measurements of system frequency) under various scour scenarios, should be obtained in order to calculate the posterior probabilities of the damage states. The consequences of the actions chosen should be quantified, for example bridge closure or imposed traffic restrictions. Finally, the VoI can be obtained as a function of the hydraulic variables to ascertain the costs associated with implementing a SHM system or remaining without one. More detailed information on these elements is provided in the following subsections.

3.1 Damage states

The damage states affecting a structure, in their simplest form, can correspond to different scour depths developing at a critical pier, for example. These in turn can be related to a change in residual load bearing capacity of the given foundation. More advanced damage states including the development of cracks, differential settlement or partial collapse could also be defined, as expected to result from the development of a given scour hole. The probability that the structure is in a certain damage state depends on the scour depth produced by a flood event. In the next section the methodology to compute the prior probabilities of the different states of the bridge is described.

3.2 Prior probabilities

Several equations are reported in the literature for the computation of local scour depth y_s resulting from given flow and bridge geometrical conditions. A widely used equation is the Hydraulic Engineering Circular (HEC-18) design formula [42], which reads

$$\frac{y_s}{y_1} = 2.0\lambda K_1 K_2 K_3 K_4 \left(\frac{a}{y_1}\right)^{0.65} Fr_1^{0.43} \tag{13}$$

where y_1 is the flow depth upstream of a pier; K_1 is the correction coefficient for pier nose shape; K_2 is the correction coefficient for angle of attack of flow; K_3 is the correction coefficient for bed conditions; K_4 is the correction coefficient for armoring by bed material; a is pier width; $Fr_1 = V_1/\sqrt{gy_1}$ is the Froude Number, where V_1 is the mean velocity of flow upstream of the pier; g is the acceleration due to gravity; and λ is the model correction factor discussed in reference [43].

The quantities y_1 and V_1 can be computed according to the Eq. 14 and Eq. 15, respectively [44], where Q is the water flow; B is the average width of the channel; n is the Manning's coefficient; s is the slope of the channel; and λ_Q is a random variable accounting for the uncertainty in the flow [43].

$$y_1 = \left(\frac{\lambda_Q Q n}{B s^{0.5}}\right)^{3/5} \tag{14}$$

$$V_1 = \frac{\lambda_Q Q}{B y_1} \tag{15}$$

Each damage state corresponds to a threshold $th_l, l = 1, \dots, L$, for the scour depth, where $th_1 = 0$. The prior probabilities of the different damage states are obtained as follows

$$\begin{aligned} &P(DS_l|Q) = P[\{y_s \geq th_l\} \cap \{y_s < th_{l+1}\}] && for\ l \neq L \\ &P(DS_l|Q) = P(y_s \geq th_l) && for\ l = L \end{aligned} \tag{16}$$

3.3 Consequences

The computation of the consequences of bridge management actions is a complex task, which depends on the boundary conditions of the problem and, to some extent, on the expert judgement of the analyst [45]. Typically, in the context of bridge management, consequences are classified into direct consequences and indirect consequences [46]. Direct consequences are related to failures and damage resulting from the failure of the bridge itself, such as human losses, repairs and replacements. Indirect losses are generated by the reduced functionality of the transportation system, such as delays, re-routing and resulting pollution. Consequences are generally expressed in monetary terms, i.e. costs. Several equations exist in the literature to compute the consequences resulting from bridge failure, which include both indirect and direct consequences. For instance, in reference [47] the total failure costs are computed as the sum of rebuilding costs C_{RB}, running costs C_{RN}, costs related to time loss C_{TL}, and costs associated with loss of life C_{LL}. Rebuilding costs and loss of life costs are generally classified as direct, whereas running costs and time loss cost are generally considered as indirect costs.

3.4 Probabilities of failure

The probability of failure of a bridge under a scour hazard is a function of the capacity of the bridge (in its given state) and the demand imposed by external actions. A limit state function, or performance function, $g(X)$ may be generated in the form of Eq. (17).

$$g(X) = (C - D)\begin{cases} > 0 & safe\ state \\ = 0 & limit\ state \\ < 0 & failure\ state \end{cases} \tag{17}$$

where C is the capacity of the bridge for a given scour condition and D is the demand, comprising external actions. The capacity of the bridge can be quantified in several ways and is linked to the assumed mode of failure of the bridge. Bridges affected by scour actions can suffer a loss in vertical foundation capacity, therefore, a capacity distribution can be specified in terms of available vertical foundation resistance under scour. For a case like this, simplified design codes such as the American Petroleum Institute (API) [48] propose equations to calculate the available shaft and base resistance of pile groups, whereby scour leads to a reduction in this capacity via a decrease in available pile shaft shear area. Uncertainty can be incorporated via the specification of a distribution for the soil parameters contributing to the capacity which, in the case of the API formulation, are the bulk unit weight and the angle of internal friction. For a lateral bridge failure mechanism, the lateral capacity distribution of the bridge can be defined, once again, using simplified design assumptions from codes such as API or otherwise. In this case, failure can be defined as the loss in lateral resistance and can be quantified using lateral soil reaction-displacement (*p*-*y*) curve analyses [5, 49]. Uncertainty in the operational parameters defining *p*-*y* curves enables the specification of a capacity distribution. For each proposed failure mechanism, further uncertainty can be incorporated by postulating distributions for the bridge structural parameters (material and geometry) as appropriate.

The demand, D is a function of the externally applied actions affecting the bridge and comprises the dead load, any environmental variations, and applied traffic loading. Once the capacity and demand are defined, the performance function g can be obtained.

The probability of failure $P(F)$ can be calculated from the performance function generated for a given scour condition and failure mechanism using the expression in Eq. 18.

$$P(F) = P[g(X) \leq 0] \tag{18}$$

The value of $P(F)$ can be obtained by multiple reliability techniques, such as FORM, SORM and Monte Carlo simulations [50].

3.5 Likelihood functions

Likelihood functions are used to update prior probabilities of damage states as described in section 2. They describe the distribution of the outcome (indicator) provided by a monitoring system. For scour-related actions, a variety of indicators can be used to infer damage to the structure [51]. Scour causes a reduction in the stiffness of foundation elements. Therefore, a number of previous works have focussed on using changes in dynamic properties to infer scour presence. The fact that stiffness changes lead to changes in modal properties was the original motivation behind using dynamic measurements for damage detection [15]. The most straightforward modal property that is influenced by scour is the frequency of vibration of the structure, which decreases with the increase of scour depth [3]. Therefore, it is sensible to suggest that observing frequency shifts could infer the presence of scour. While this is a simple concept, there exists significant uncertainty in this process, most notably due to uncertainties in operating soil conditions and stiffness at interfaces, geometrical and material properties of structural elements, and environmental influences such as temperature [52, 53]. For this reason, there exists a distribution of likely frequency values that may be retrieved from measurements obtained under a given scour condition. The likelihood function is defined as a likely distribution of frequencies that could be measured by a sensor placed on a bridge in the event of scour with a certain depth magnitude affecting the bridge. To generate likelihood functions, in the absence of real SHM information measured on a scoured bridge, finite-element models can be used accounting for the various sources of uncertainty that influence the problem (e.g. material and geometrical properties, noise in sensors, model uncertainty, environmental and operational factors, etc.).

3.6 Flood hazard

As discussed in Section 2, the VoI depends on the distribution of the intensity of the event IM that, for the case of a scour hazard, can be represented by the maximum annual flow. Prior to the installation of a monitoring system, the magnitude of any future maximum annual flow is not known a priori. However, its probability distribution can be obtained by statistical inference on a sample of annual maxima. The VoI obtained by Eq. 11 as a function of IM can be integrated over the PDF of the annual maximum flow according to Eq. 12. This VoI can be interpreted as the money saved each year by using SHM information and it should be compared with the equivalent annual cost (including the annual share of the installation and decommissioning costs) of the SHM system.

4. Demonstration of the approach

The proposed framework to compute the benefit of installing a SHM system for scoured bridges is demonstrated in this section for a generic bridge. The validity of the results obtained is limited to this example that has scope only to illustrate the application of the procedure. It is supposed that the operator of a bridge is concerned about the traffic restrictions to be imposed in the aftermath of a severe flood. Hence, they are considering the adoption of an automatic vibration-based SHM system to support decision-making during emergency operations. In this demonstration, it is supposed that the bridge manager and the owner are the same person. In this respect, the possibility of obtaining negative VoI is prevented. Utility is expressed as negative cost. The decision problem in the absence of SHM information, i.e. the prior decision problem, is represented by the decision tree in Fig. 4.

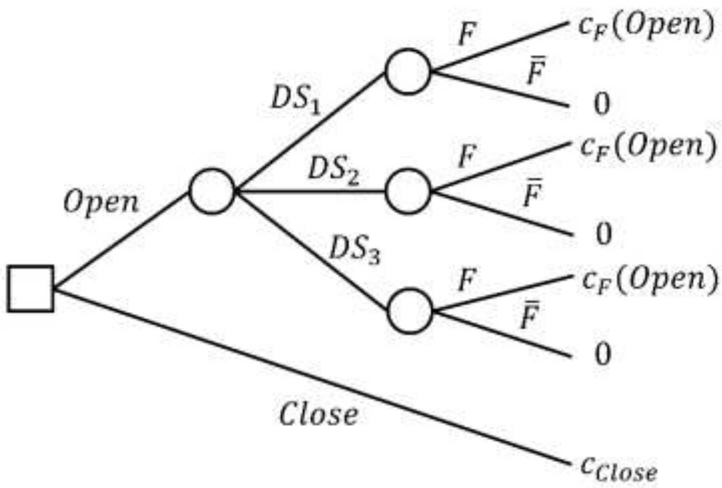

Fig. 4 Decision tree representing the prior decision analysis

Two possible traffic management actions are considered, namely “leave the bridge open” and “close the bridge” indicated in the decision tree as *Open* and *Close*, respectively.

The damage state of the bridge due to scour is discretized into three levels: (i) no damage/minor damage, DS_1; (ii) medium damage, DS_2; (iii) severe damage, DS_3. The damage states correspond to different scour depths, which in turn are related to different residual load bearing capacities of the bridge pier foundation. The probability that the structure is in a certain damage state depends on the scour depth y_s produced by a flood event, whose intensity is represented by the flow Q (see Eq. 13 to Eq. 15). Given the uncertainty of the parameters involved, to each value of the flow corresponds a distribution of the scour depth. For this case study the parameters reported in Table 1 were assumed.

Table 1 Input variables used in the calculation of the distribution of scour depth

Variable	Unit	Distribution	Mean	CoV	Reference
K_1	-	Det.	1	-	-
K_2	-	Det.	1	-	-
K_3	-	Uniform	1.2	0.048	[54]
K_4	-	Det.	1	-	-
a	m	Det.	1.2	-	-
B	m	Lognormal	50	0.05	Assumed
s	-	Lognormal	0.003	0.05	Assumed
λ_Q	-	Normal	1	0.05	[43]
λ	-	Lognormal	0.412	0.646	[43]
n	-	Lognormal	0.035	0.28	[55]

Fig. 5 displays the distribution of the scour depth obtained by a Monte Carlo simulation with 10,000 random samples considering a flow Q=500 m^3/s. Thresholds th_2 and th_3 refer to scour depths corresponding to the proposed damage levels DS_2 and DS_3 (discussed in more detail below).

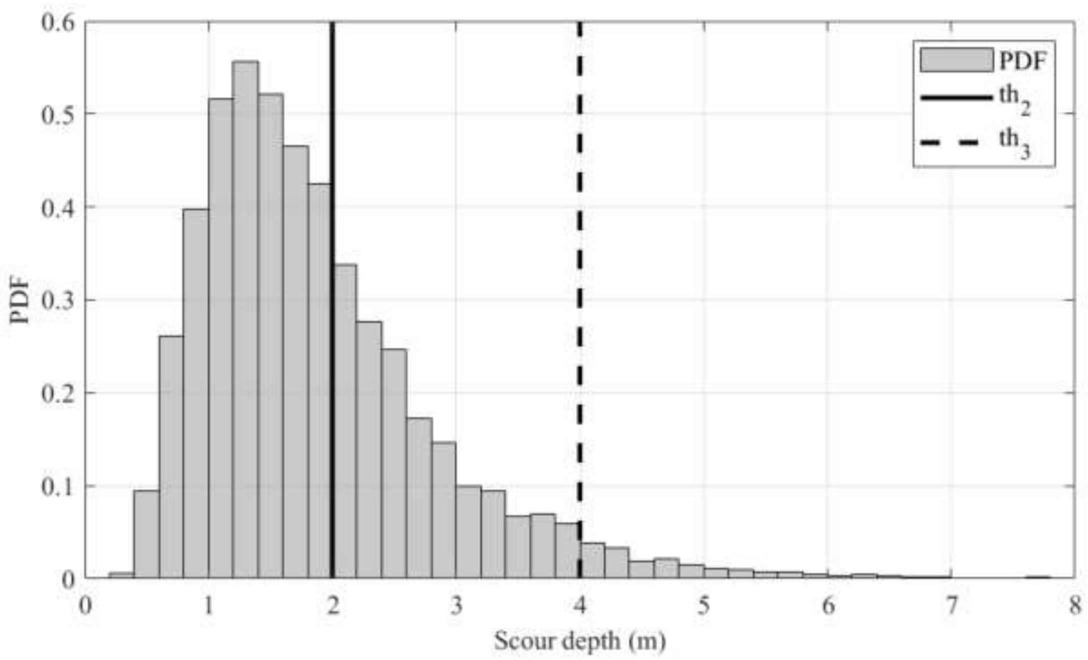

Fig. 5 Distribution of the scour depth for Q=500m^3/s

The Gumbel distribution is commonly employed to represent the distribution of the maximum value of the flood flows that occur within a year [56]. Thus, the probability distribution of the maximum annual flow is assumed as a Gumbel distribution with mean 500 m^3/s and CoV of 0.10, as shown in Fig. 6.

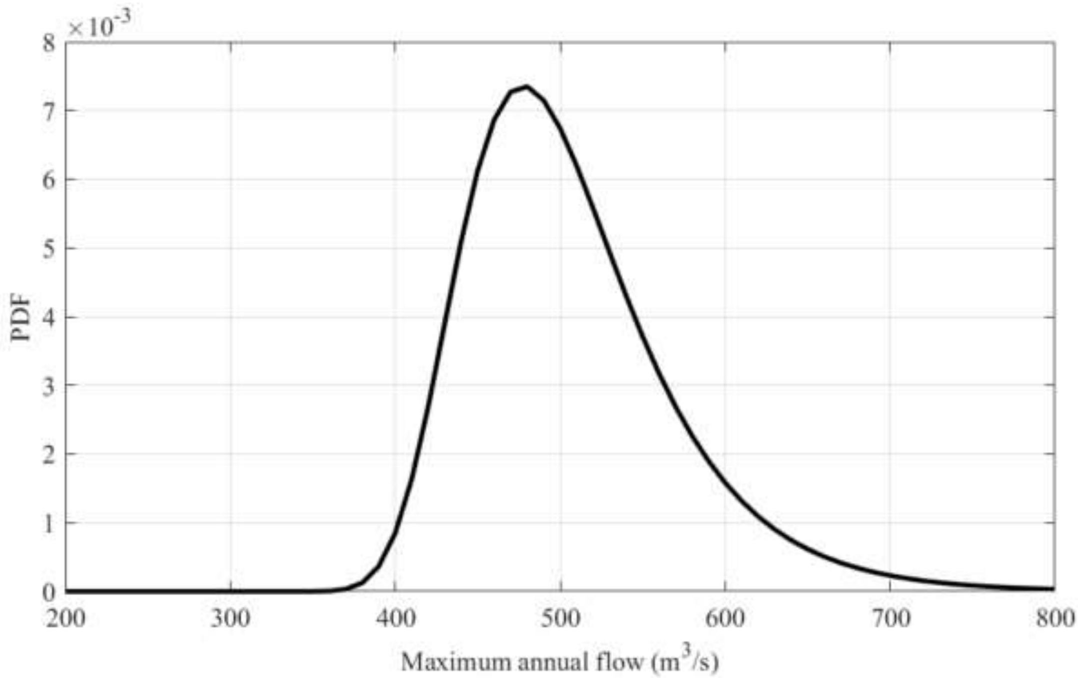

Fig. 6 Distribution of annual maximum flow rate

Three damage levels have been considered defining three threshold values of the scour depth i.e. $th_1 = 0$, $th_2 = 2$ m, and $th_3 = 4$ m. Damage state DS_1 occurs for $0 \leq y_s < 2$ m; damage state DS_2 occurs for scour depths in the interval $2 \leq y_s < 4$ m; damage state DS_3 occurs for $y_s \geq 4$ m. The probabilities of the damage states change according to the value of the flow. For instance, for Q=500 m^3/s the probabilities of the damage states read $P(DS_1) = 0.640$, $P(DS_2) = 0.322$, and $P(DS_3) = 0.038$. In relation to the selected action and to its damage state, the bridge might fail under external actions, such as traffic loads and/or the hydrodynamic force of flowing water. In this demonstration, the following probabilities of failure are associated with the action *Open*: $P(F|DS_1) = 0.0001$, $P(F|DS_2) = 0.01$, and $P(F|DS_3) = 0.8$. In a real application, a reliability analysis should be carried out to determine these probabilities (values adopted in this case are for demonstration only).

The costs of bridge failure and survival for action $A_n = Open$ are $c_F(Open) = 1{,}500{,}000$ € and $c_{\bar{F}}(Open) = 0$, respectively. The expected cost of the action *Close*, c_{Close}, is fixed under the hypothesis that it can generate only indirect consequences and it is taken as 55,000€. The expected costs of the two actions *Open* and *Close* computed by means of Eq. 2 as a function of the flow are shown in Fig. 9(a). The expected cost of action *Open* depends on the prior probabilities of the different damage states, which in turn depend on the magnitude of the flow. As the water flow increases, the probability of the bridge becoming damaged increases. So, the expected cost of the action *Open* increases. The upper bound of the expected cost of the action *Open* is reached when the damage state DS_3 is certain, i.e. $P(DS_3) = 1$, and it is computed according to Eq. 1 as $c_F(Open) \times P(F|DS_3) = 1{,}500{,}000$ € $\times\, 0.8 = 1{,}200{,}000$€. The prior probabilities of damage states are obtained by Monte Carlo simulation with 10,000 samples of random variables. According to the prior analysis, rational decision makers should close the bridge in the case where flow exceeds (approximately) 540 m^3/s, that is the value at which the expected costs of the two actions coincide.

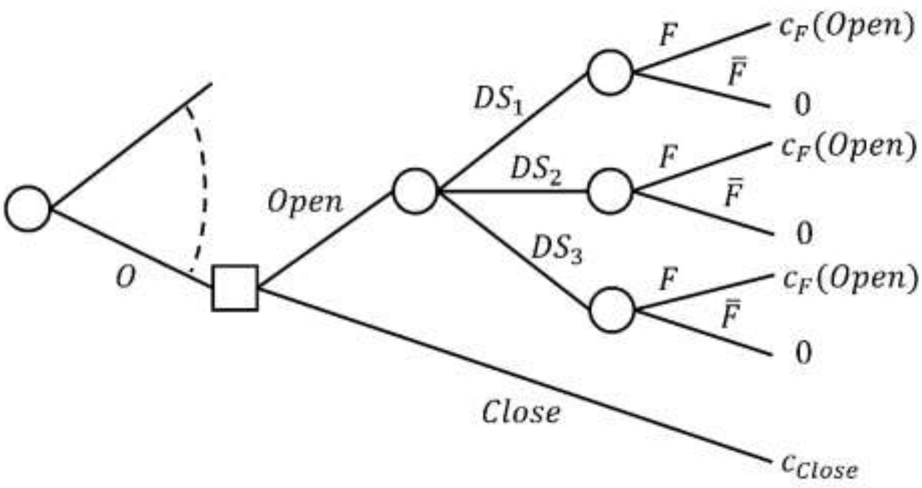

Fig. 7 Decision tree representing the decision analysis with information from SHM for the case study

It is now assumed that the decision maker is interested in knowing the expected costs of actions when using SHM information, prior to installing such a system, see Fig. 7. This expected cost can be computed by applying Eq. 10. The damage-sensitive feature used by the decision maker is the first natural frequency of the bridge, which is expected to decrease when scour is present [20]. This parameter can be estimated by means of several Operational Modal Analysis (OMA) techniques. The estimated values of natural frequencies are typically affected by multiple sources of uncertainties. These uncertainties are accounted for in the definition of the likelihood functions, which can be interpreted as the probability distribution function of the first natural frequency in correspondence to the three damage states (see section 3.5). Herein, it is assumed that the distribution of the first natural frequency corresponding to damage states DS_1, DS_2 and DS_3 of this generic bridge can be described by a Lognormal distribution with mean value 1.6 Hz, 1.3 Hz, and 1 Hz, respectively, and 0.05 CoV, as shown in Fig. 8. In this case, a continuous output is obtained from the SHM system and therefore the sum in Eq. 10 is replaced by an integral.

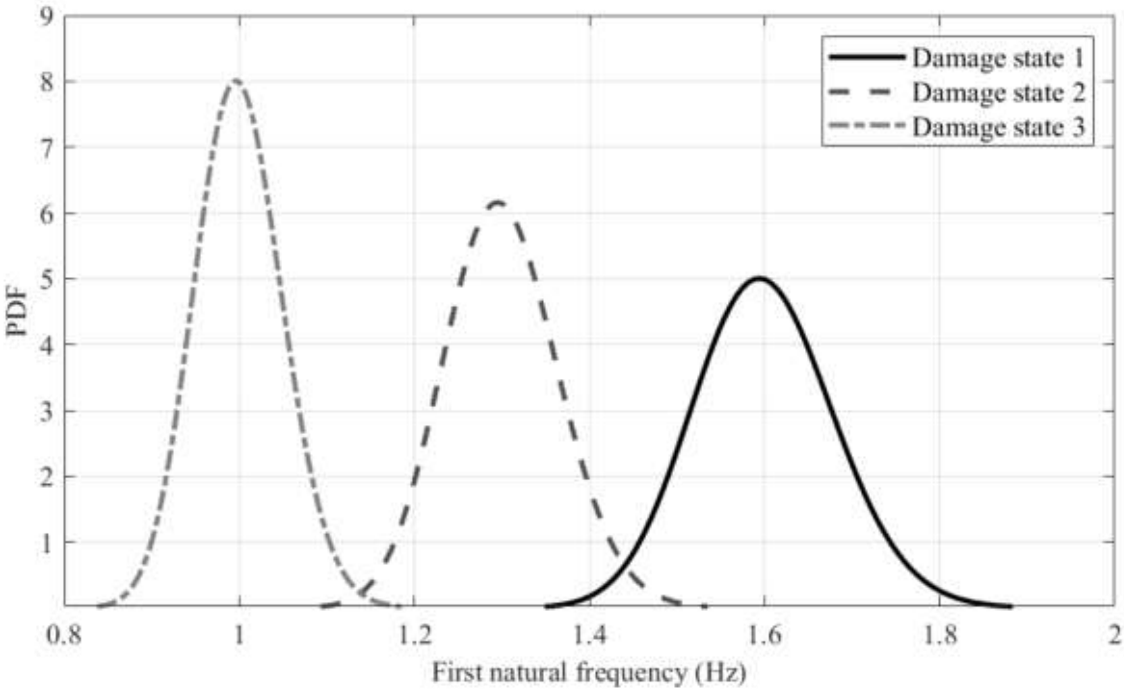

Fig. 8 Likelihood functions

The VoI as a function of the flow is computed according to Eq. 11. The results are displayed in Fig. 9(b). It is observed that the VoI is maximum when the two actions *Open* and *Close* have the same expected costs. In fact, the benefit of collecting information on the condition of the bridge is maximum when the uncertainty on the selection of the optimal action is large, that is when alternative actions correspond to similar expected costs. The VoI is integrated over the probability distribution of the maximum annual flow to remove the dependence on the intensity measure, according to Eq. 12, obtaining an expected cost of about 43,000 €. The SHM system should be employed if its (annual) cost is lower than the computed VoI.

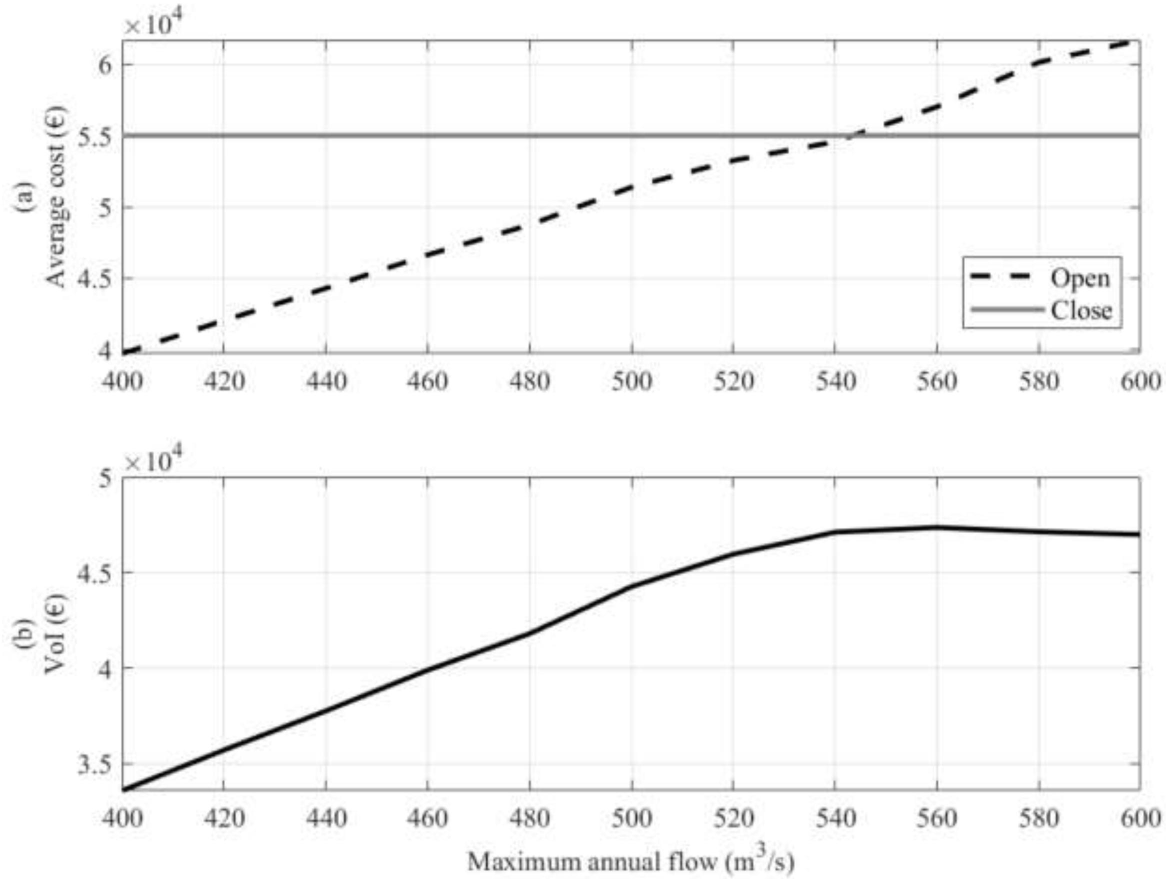

Fig. 9 (a) Prior average costs of actions; (b) VoI as a function of the flow rate

5. Conclusions

In this paper, a framework to assess the benefit of SHM information in the context of bridges damaged by scour erosion is presented and a brief example (case study) is demonstrated. The framework is based on the VoI from Bayesian decision theory, which is adapted herein to the case of emergency management of structures in the aftermath of a flood. The purpose of the paper is to introduce the concept of VoI in this context with a view to assisting asset managers in decision-making related to whether to close or keep open bridges that have been damaged in the aftermath of a flood event.

Intermediate bridge management actions, such as imposing traffic restrictions, can also be considered in the decision problem. The framework is demonstrated and the relevant steps in the process described.

The elements of a VoI analysis for scour monitoring are identified and described. These include: (i) identifying the possible damage states caused by scour, which are related to different scour depths affecting a given foundation; (ii) the prior probabilities of scour occurrence; (iii) the bridge management actions that the decision maker might take after a severe flood event, i.e. imposing traffic restrictions; (iv) the costs associated with different combinations of damage states and bridge management actions; (v) the probability of failure of the scoured bridge under external actions; and (vi) the *likelihood functions* used to update the prior probabilities of damage states according to Bayes' theorem, which represents the probability of observing a certain scour monitoring outcome (e.g. bridge frequency), given a certain damage state (scour condition). A simple but exhaustive numerical example is presented, including all the relevant elements of a VoI analysis. In this case demonstration, the operator of a bridge is concerned about traffic management after a severe flood and for this reason they are considering the adoption of a vibration-based SHM system to facilitate emergency operations. It is observed that the expected costs of bridge management actions increase as the intensity of the water flow increases since severe damage states are more likely to occur as a result (when damage is scour development). When the expected costs of actions reach similar values, the VoI is maximum. In this situation, additional information on the actual state of the bridge is particularly useful to select the optimal action. The VoI is computed by accounting for the distributions of maximum annual flow of the river and is used by the operator of the bridge as an upper bound for a cost-effective SHM system. The presented framework will be of use to decision-makers who must make informed decisions about management of bridges during severe flood events and allows the incorporation of uncertainties associated with the measured data and the resulting consequences of a given action. The framework should inform on the benefits (or not) of installing a sensor system on a given bridge based on the VoI this provides (relative to the absence of such information).

Acknowledgements

This study was partially funded by the Italian Civil Protection Department within the project DPC-RELUIS 2019 - RS4 'Monitoring and satellite data'. The second author would like to thank the Faculty of Engineering, University of Nottingham for funding to enable this collaboration.

Compliance with Ethical Standards

The authors declare that they have no conflict of interest.

References

1. Hamill L (1999) Bridge Hydraulics. E.& F.N. Spon, London
2. Maddison B (2012) Scour failure of bridges. Proc ICE - Forensic Eng 165:39–52
3. Prendergast LJ, Hester D, Gavin K, O'Sullivan JJ (2013) An investigation of the changes in the natural frequency of a pile affected by scour. J Sound Vib 332:6685–6702. https://doi.org/http://dx.doi.org/10.1016/j.jsv.2013.08.020i
4. Prendergast LJ, Hester D, Gavin K (2016) Determining the presence of scour around bridge foundations using vehicle-induced vibrations. J Bridg Eng 21:. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000931
5. Klinga J V., Alipour A (2015) Assessment of structural integrity of bridges under extreme scour conditions. Eng Struct 82:55–71. https://doi.org/10.1016/j.engstruct.2014.07.021
6. Forde MC, McCann DM, Clark MR, et al (1999) Radar measurement of bridge scour. NDT&E Int 32:481–492
7. Anderson NL, Ismael AM, Thitimakorn T (2007) Ground-Penetrating Radar : A Tool for Monitoring Bridge Scour. Environ Eng Geosci XIII:1–10
8. Yu X (2009) Time Domain Reflectometry Automatic Bridge Scour Measurement System: Principles and Potentials. Struct Heal Monit 8:463–476. https://doi.org/10.1177/1475921709340965

9. Hunt BE (2009) NCHRP synthesis 396: Monitoring Scour Critical Bridges - A Synthesis of Highway Practice. Washington, DC

10. De Falco F, Mele R (2002) The monitoring of bridges for scour by sonar and sedimetri. NDT&E Int 35:117–123

11. Zarafshan A, Iranmanesh A, Ansari F (2012) Vibration-Based Method and Sensor for Monitoring of Bridge Scour. J Bridg Eng 17:829–838. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000362.

12. Nassif H, Ertekin AO, Davis J (2002) Evaluation of Bridge Scour Monitoring Methods. Trenton, NJ

13. Prendergast LJ, Gavin K (2014) A review of bridge scour monitoring techniques. J Rock Mech Geotech Eng 6:138–149. https://doi.org/10.1016/j.jrmge.2014.01.007

14. Fisher M, Chowdhury MN, Khan A a., Atamturktur S (2013) An evaluation of scour measurement devices. Flow Meas Instrum 33:55–67. https://doi.org/10.1016/j.flowmeasinst.2013.05.001

15. Doebling S, Farrar C, Prime MB, Shevitz DW (1996) Damage identification and health monitoring of structural and mechanical systems from changes in their vibration characteristics: a literature review. Los Alamos, New Mexico

16. Chen C-C, Wu W-H, Shih F, Wang S-W (2014) Scour evaluation for foundation of a cable-stayed bridge based on ambient vibration measurements of superstructure. NDT E Int 66:16–27. https://doi.org/10.1016/j.ndteint.2014.04.005

17. Bao T, Andrew Swartz R, Vitton S, et al (2017) Critical insights for advanced bridge scour detection using the natural frequency. J Sound Vib 386:116–133. https://doi.org/10.1016/j.jsv.2016.06.039

18. Bao T, Liu Z (2016) Vibration-based bridge scour detection: A review. Struct Control Heal Monit

19. Foti S, Sabia D (2011) Influence of Foundation Scour on the Dynamic Response of an Existing

Bridge. J Bridg Eng 16:295–304. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000146.

20. Prendergast LJ, Gavin K, Hester D (2017) Isolating the location of scour-induced stiffness loss in bridges using local modal behaviour. J Civ Struct Heal Monit 7:483–503. https://doi.org/10.1007/s13349-017-0238-3

21. Fitzgerald PC, Malekjafarian A, Cantero D, et al (2019) Drive-by scour monitoring of railway bridges using a wavelet-based approach. Eng Struct 191:1–11. https://doi.org/10.1016/j.engstruct.2019.04.046

22. Fitzgerald PC, Malekjafarian A, Bhowmik B, et al (2019) Scour Damage Detection and Structural Health Monitoring of a Laboratory-Scaled Bridge Using a Vibration Energy Harvesting Device. Sensors 19:

23. Xiong W, Cai CS, Kong B, et al (2017) Identification of bridge scour depth by tracing dynamic behaviors of superstructures. KSCE J Civ Eng 1–12. https://doi.org/10.1007/s12205-017-1409-9

24. Xiong W, Kong B, Tang P, Ye J (2018) Vibration-Based Identification for the Presence of Scouring of Cable-Stayed Bridges. J Aerosp Eng 31:. https://doi.org/10.1061/(ASCE)AS.1943-5525.0000826.

25. Xiong W, Cai CS, Kong B, et al (2019) Bridge Scour Identification and Field Application Based on Ambient Vibration Measurements of Superstructures. J Mar Sci Eng 7:1–24

26. Prendergast LJ, Hester D, Gavin K (2016) Development of a Vehicle-Bridge-Soil Dynamic Interaction Model for Scour Damage Modelling. Shock Vib 2016:. https://doi.org/10.1155/2016/7871089

27. Pozzi M, Der Kiureghian A (2011) Assessing the value of information for long-term structural health monitoring. SPIE Press, San Diego, CA

28. Pozzi M, Zonta D, Wang W, Chen G (2010) A framework for evaluating the impact of structural health monitoring on bridge management. In: Bridge Maintenance, Safety, Management and Life-Cycle Optimization: Proceedings of the Fifth International IABMAS

Conference. CRC Press, Philadelphia

29. Straub D (2014) Value of information analysis with structural reliability methods. Struct Saf 49:75–85

30. Thons S, Faber M (2013) Assessing the value of structural health monitoring. In: ICOSSAR. New York, NY

31. Zonta D, Glisic B, Adriaenssens S (2014) Value of information: impact of monitoring on decision-making. Struct Control Heal Monit 21:1043–1056

32. Thöns S, Stewart MG (2019) On decision optimality of terrorism risk mitigation measures for iconic bridges. Reliab Eng Syst Saf 188:574–583. https://doi.org/10.1016/j.ress.2019.03.049

33. Long L, Döhler M, Thöns S (2020) Determination of structural and damage detection system influencing parameters on the value of information. Struct Heal Monit. https://doi.org/10.1177/1475921719900918

34. Skokandić D, Ivanković AM, Thöns S (2019) Quantifying the Value of B-WIM : Assessing Costs and Benefits for Value of Information Analysis. In: IABSE Symposium

35. Bayane I, Long L, Thöns S, Brühwiler E (2019) Quantification of the conditional value of SHM data for the fatigue safety evaluation of a road viaduct. In: 13th International Conference on Applications of Statistics and Probability in Civil Engineering (ICASP). Seoul, Korea

36. Iannacone L, Gardoni P, Giordano PF, Limongelli MP (2019) Decision making based on the value of information of different inspection methods. In: F-K. Chang, A. Guemes, & F. Kopsaftopoulos (Eds.), Structural Health Monitoring 2019: Enabling Intelligent Life-Cycle Health Management for Industry Internet of Things (IIOT) - Proceedings of the 12th International Workshop on Structural Health Monitoring. DEStech Publications Inc.

37. Raiffa H, Schlaifer R (1961) Applied Statistical Decision Theory. John Wiley & Sons, New York

38. Von Neumann, J., Morgenstern O (1947) Theory of Games and Economic Behaviour. Princeton University Press, New Jersey

39. Bayes T (1763) An essay toward solving a problem in the doctrine of chances. Philos Trans R Soc London 53:370–418

40. Bolognani D, Verzobio A, Tomelli D, et al (2017) Quantifying the benefit of SHM: what if the manager is not the owner? In: 11th International Workshop on Structural Health Monitoring

41. Verzobio A, Bolognani D, Zonta D, Quigley J (2019) Quantifying the benefit of SHM: can the VoI be negative? In: 13th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP13. Seoul, Korea

42. Richardson EV, Harrison LJ, Richardson JR, Davis SR (1993) Evaluating Scour at Bridges

43. Ghosn M, Moses F, Wang J (2003) Design of Highway Bridges for Extreme Events , National Cooperative Highway Research Program, NCHRP REPORT 489

44. BD 97/12 (2012) The assessment of scour and other hydraulic actions at highway structures. Design manual for roads and bridges, highway structures: Inspection and maintenance assessment (Vol. 3, Section 4, Part 21). London

45. Imam B, Chryssanthopoulos MK (2012) Causes and Consequences of Metallic Bridge Failures. Struct Eng Int 22:93–98

46. Faber MH (2008) Risk Assessment in Engineering: Principles, System Representation & Risk Criteria

47. National Academies of Sciences Engineering and Medicine (NASEM) (2007) Risk-Based Management Guidelines for Scour at Bridges with Unknown Foundations. Washington, DC

48. API (2007) RP2A: Recommended practice for planning, designing and constructing offshore platforms - Working stress design. Washington, DC

49. Chortis G, Askarinejad A, Prendergast LJ, et al (2020) Influence of scour depth and type on p – y curves for monopiles in sand under monotonic lateral loading in a geotechnical centrifuge. Ocean Eng (In Press): https://doi.org/10.1016/j.oceaneng.2019.106838

50. Ditlevsen O, Madsen H (1996) Structural Reliability Methods. John Wiley & Sons, Ltd,

Chichester

51. Prendergast LJ, Limongelli MP, Ademovic N, et al (2018) Structural Health Monitoring for Performance Assessment of Bridges under Flooding and Seismic Actions. Struct Eng Int 28:296–307

52. Sohn H (2007) Effects of environmental and operational variability on structural health monitoring. Philos Trans A Math Phys Eng Sci 365:539–560. https://doi.org/10.1098/rsta.2006.1935

53. Malekjafarian A, Prendergast LJ, OBrien EJ (2019) Use of mode shape ratios for pier scour monitoring in two-span integral bridges under changing environmental conditions. Can J Civ Eng In Press:

54. Johnson PA, Dock DA (1998) Probabilistic Bridge Scour Estimates. J Hydraul Eng 124:750. https://doi.org/10.1061/(ASCE)0733-9429(1998)124:7(750)

55. Hydraulic Engineering Centre (1986) Accuracy of Computed Water Surface Profiles. Davis, CA

56. World Meteorological Organization (2008) Guide to Hydrological Practices (WMO No. 168) Volume 2 - Chapter 5: Extreme Value Analysis. Geneva