# Value of information: A roadmap to quantifying the benefit of structural health monitoring

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**Abstract**: The concept of value of information (VoI) enables quantification of the benefits provided by structural health monitoring (SHM) systems – in principle. Its implementation is challenging, as it requires an explicit modelling of the structural system's life cycle, in particular of the decisions that are taken based on the SHM information. In this paper, we approach the VoI analysis through an influence diagram (ID), which supports the modelling process. We provide a simple example for illustration and discuss challenges associated with real-life implementation.

## 1 Introduction

Structural health monitoring (SHM) systems provide information on the state of structures, their performance and the demands they are subjected to. In this way, SHM can support the prediction of the infrastructure's future performance and the planning of preventive and corrective actions. In the recent past, sensor technology, data transmission and processing have advanced markedly, and as a result more and more structures are equipped with SHM systems. As the technology matures, owners and operators of these structures are focusing their attention on the utilization of the collected data and are increasingly concerned with the benefit-cost ratio of the SHM systems. The underlying questions are: What is the value of the information provided by the SHM? And how can it be maximized? The answers to these questions are intricate, because the Value of Information (VoI) depends on:

- the future usage and performance of the structures and associated costs and benefits,
- the inherent capabilities of the SHM system and the data processing,
- the possible outcomes of the SHM and
- the future decisions associated with those outcomes, in particular on maintenance, repair and rebuild actions.

Because of this complexity, the VoI has in practice been addressed mainly on a qualitative level, often in a rather ad-hoc manner. In principle, Bayesian decision analysis offers a framework for quantifying the VoI (Raiffa and Schlaifer 1961; Straub 2014). However, the direct implementation of the framework requires a complete probabilistic modelling of the structural performance, demands and the SHM system performance, as well as a-priori identification of rules for preventive or corrective actions to be taken based on the possible SHM outcomes. As a consequence, the quantitative framework has in practice been implemented only for special cases with limited complexity and good availability of models, such as the planning of inspections in offshore structures (Pedersen et al. 1992; Faber et al. 2005; Straub and Faber 2005). A small number of publications have recently demonstrated the applicability of the framework on idealized structural systems (Pozzi and Der Kiureghian 2011; Faber and Thöns 2013; Konakli et al. 2015; Thöns et al. 2015; Luque and Straub 2017). These studies provide useful insights, but are not directly transferable to practice because of the necessary simplifying assumptions adopted.

A key question is thus how the theoretical frameworks can be used to benefit the analysis of SHM systems in real-world structures and infrastructure systems. This necessitates capturing the complexity of the asset management process, without making the modeling overly demanding (see e.g. Zonta et al. 2014). As a step towards this aim, we represent the VoI quantification process through an influence diagram (ID). This ID provides a structured overview, which facilitates the communication among experts involved in the process and the organization of the different models and their interfaces. We demonstrate that the ID provides a unifying framework that is consistent with the theory, but is intended to be flexible enough to allow for different types of models and degrees of detailing to be combined within a single analysis. The working process of the ID is illustrated with examples from different application domains. A conceptual numerical example is introduced, whose results are presented and discussed in Section 3.

The contribution closes with a discussion of main difficulties involved in practical applications. Examples include the handling of spatially-temporally distributed information and decisions, and the inclusion of unanticipated scenarios within the quantitative framework.

## 1.1 Influence diagrams

We introduce the framework for a VoI analysis through an influence diagram (ID). IDs are a structured graphical form of representing decision processes under uncertainty (Shachter 1986). A detailed introduction to IDs is provided in (Jensen and Nielsen 2007).

IDs have the following basic characteristics: square nodes represent decisions, round nodes represent parameters that are commonly uncertain (random variables), and diamond-shaped nodes represent cost, consequences or more generally utilities. The directed links (arcs) between the nodes represent the dependence structure among the variables and parameters. In a special case, links pointing to a decision node describe the flow of information. Ideally, all links follow the causal direction, if such exists. As an example, the links point from the structural condition to the indicators to the observations, which may appear counterintuitive at first because the flow of information is from observations to structural condition. However, it is clearly the condition of the structure that causally affects the observation, and not vice-versa. Note that causality is not a strict requirement, but non-causal IDs are likely to lead to modelling errors (Pearl 2009).

## 2 A framework for value of information analysis

The SHM analysis process is summarized by the ID of Figure 1. The elements of the analysis are discussed individually in the following. It is important to realize that it may not be essential for the VoI analysis to carry out in great depths every part of the analysis, as would be necessary when assessing and optimizing decisions related to the design, repair or maintenance. For example, to assess if a structure has sufficient reliability, a detailed probabilistic and structural model is typically required. Simplified models may however be used when determining the VoI, because this requires only an understanding of the effect of the SHM on the reliability.

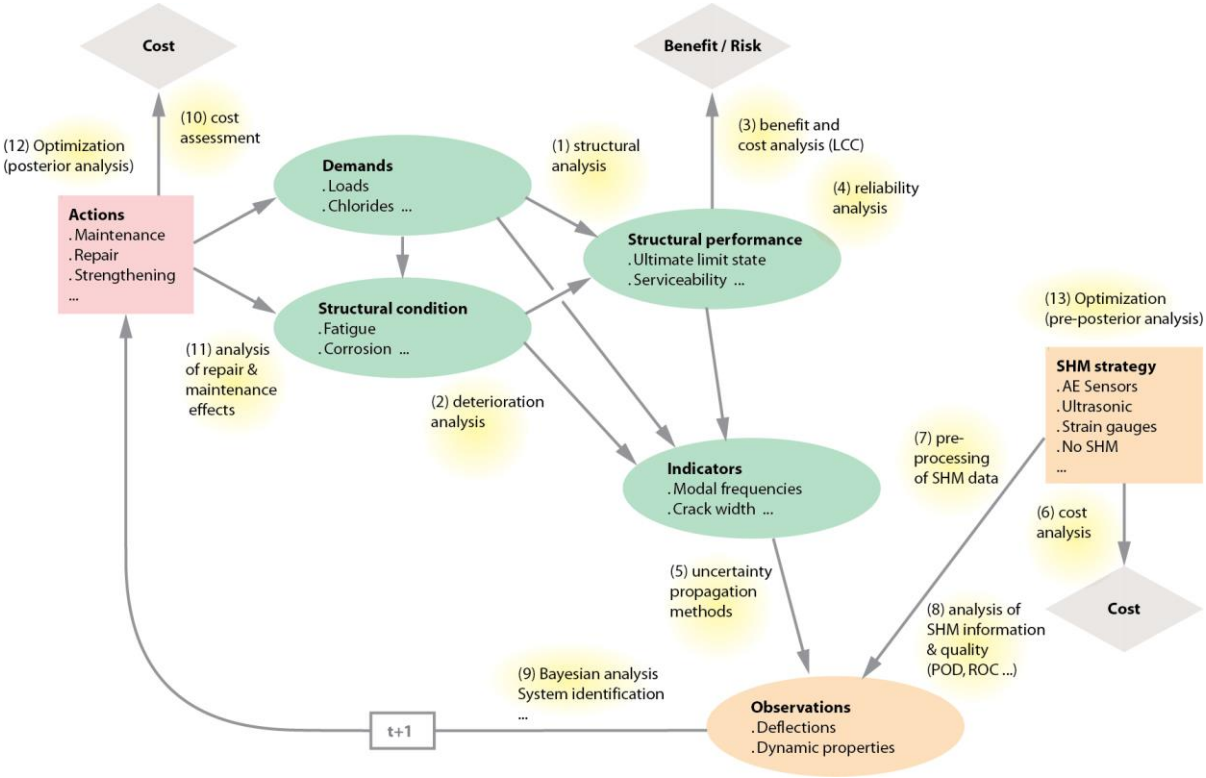


*Figure 1: Influence diagram (ID) of the SHM analysis process. Green colours indicate parameters and models related to the structure, orange colours indicate those related to the SHM, red colour indicates repair, maintenance and related actions. The yellow bubbles are the analysis methods and tools used in the different parts of the process. The box [t+1] indicates that the link is from one time step to the next, hence this ID represents a decision process in time. An earlier version of this ID is presented in (Straub and Chatzi 2016).*

To quantify the SHM VoI, the crucial aspect is to model the entire process, even if that requires making some rather crude simplifications on some parts of the process. Nevertheless, procedures that include only selected steps, even if they do not quantify the VoI, can in many situations provide the necessary decision support (e.g. Courage et al. 2016); for example they can prioritize different SHM strategies and can give a qualitative measure of their effectiveness.

We illustrate the framework by sketching the assessment of the VoI obtained from an SHM system installed on a bridge structure subject to corrosion and other types of deterioration. In practice, the use of SHM in such systems is mostly limited to special cases, e.g. bridges that exhibit structural deficiencies or that are subject to increased loads. However, there is a large body of research on developing such systems, and road agencies are currently considering their more widespread use (Haardt and Holst 2017). This application is an example of SHM systems installed on structures for optimizing asset management.

In addition, we provide a simple numerical example, to reveal the workings of the VoI quantification and to demonstrate that it can be based on a simplified modelling of the system and still enable meaningful conclusions. The numerical example is constructed so that all random variables have a binary outcome space, and all decisions have only two alternatives. In real applications, most parameters are continuous or multi-state, but this simple binary representation is selected to facilitate the interpretation of the example.

The numerical example has been implemented in the freely available Genie software (Genie 2016) and is available for download from www.era.bgu.tum.de/supplementary-materials.

## 2.1 Demands

Engineering structures are subject to uncertain demands $\mathbf{D}(t)$ over time $t$. These include the loads on the structure; e.g. traffic, wind or temperature for the bridge structure. They can also be environmental factors that can cause or foster deterioration, such as salinity, which can lead to chloride-induced corrosion of the reinforcement. Demands can be influenced by the decisions (actions) made during the lifetime of the structure[1], e.g. a protective layer may be added to reduce chloride ingress into the concrete. In a probabilistic analysis, demands are fully described by stochastic processes, but in most cases a simplified model based on random variables suffices (Melchers 1999).

*Numerical example*: The structure can be subject to the anticipated "normal" demands over the lifetime of the structure, $D = 0$, or it is subject to abnormal (larger) demands, $D = 1$. Probabilities are $p_D(0) = 0.95$ and $p_D(1) = 0.05$.

## 2.2 Structural condition

The structural condition is affected by the demands on the structure and the maintenance and retrofitting/repair actions taken during the service life[2]. Ideally, the structural condition is described by physical parameters, such as crack width or corrosion loss, since these can be directly related to the measured quantities. However, in practice the structural condition is mostly described by abstract damage parameters, such as the Palmgren-Miner damage for fatigue, or a condition rating in a bridge management system. In most cases, the damage is described for components or parts of the structure, possibly aggregated into a system condition rating. For the VoI analysis, one needs to include only the condition of the elements on which the SHM might provide information.

In a probabilistic setting, the structural condition is described by the uncertain condition parameters $\mathbf{C}(t)$, which form a stochastic process. In many instances, the stochastic process is replaced by a damage model whose parameters are random variables. For the bridge example, parametric models for reinforcement corrosion exist (Schiessl et al. 2006).

*Numerical example*: The structural condition is represented by a binary random variable $C_t$ at each discrete time step $t$. It can be undamaged ($C_t = 0$) or damaged ($C_t = 1$). The probabilities are defined conditional on the demand, the retrofitting actions and the condition in the previous time step $C_{t-1}$.

[1] Demands are also affected by the initial design decisions. Since we restrict ourselves to decisions made during the service life of the structure, this is not included here.

[2] Additionally, the structural condition is strongly affected by the initial quality of the structure and its materials. This might be assessed by monitoring (quality control), but we do not address this situation here.

## 2.3 Structural performance

The structural performance is expressed through the probability of the system states that in turn determine benefits, costs and other consequences. Most structures provide a benefit as long as their use is not impaired. The benefit may be reduced if the usage of the system is no longer possible or must be restricted. Additional consequences occur if the system fails (fully or partially). These system states are commonly described by limit state functions. In the example of the bridge, relevant structural performance states that lead to consequences can be visible corrosion, spalling of the concrete, failure of parts or the entire bridge.

Probabilistically, the structural performance is summarized by the probability of the system states. It can be defined as a deterministic or stochastic function of system demand and structural condition. In the case of the bridge structure, the structural performance can be obtained either directly from the system condition for states such as "visible corrosion" or "concrete spalling", or through a structural model for failure states such as "partial collapse" or "complete collapse".

*Numerical example*: The structural performance is here described by the binary random variable $B_t$ at each discrete time step $t$, with states normal performance ($B_t = 0$) and failed ($B_t = 1$). The probability of $B_t$ is defined conditional on the structural condition $C_t$ and the demand $D$.

## 2.4 Benefit and risk

Benefits and risk[3] quantify the consequences of structural performance (the system states). The consequences are associated with different attributes, such as cost, financial benefits, safety, environmental impacts, and should be quantified in respective units, such as monetary values, expected number of fatalities and injuries, travel time, $CO_2$ emissions (JCSS 2008). In order to quantify the VoI in a single numeric value, it is necessary to express all consequences in the same metric, e.g. monetary values. If this is not desirable, it is possible to express consequences through multiple attributes. However, this hinders a fully quantitative VoI analysis, because multi-attribute decision analysis does not (yet) facilitate a VoI calculation (Roijers et al. 2013).

Since costs and benefits occur at varying times over the service life, they must be discounted, typically to present values. Discounting factors commonly used in life-cycle analyses also apply here (Rackwitz et al. 2005).

For the bridge example, the benefit may be reduced if weight restrictions are imposed or if the bridge has to be closed for traffic. Additional costs occur if the bridge is damaged or collapses, which can also lead to consequences for people.

*Numerical example*: Normal performance ($B_t = 0$) is associated with a benefit $U = 1$ and structural failure ($B_t = 1$) leads to an expected cost of $100$ (i.e. the utility is $U = -100$). These costs are representative for a time period $\Delta T$. In a real application, discounting of the costs must be included.

## 2.5 Indicators

SHM typically cannot measure relevant model parameters or system states directly, but relies on indirect inference. For example, dynamic properties of a structural system can provide information on its condition. *Indicators* are the quantities that are obtained from the SHM system,

[3] Strictly, the risk is the expected consequence of structural damage states, hence it combines the possible consequences of system states (as defined here) with the probability $p_{B_t}$ of these system states (the structural performance parameters).

which are related to the demand, condition or performance of the structure. If one of the relevant parameters can be measured directly, the indicator is identical to the parameter.

In principle, it is not necessary to model indicators explicitly, since they can be included in the likelihood function describing the SHM outcomes (Section 2.7). However, it is useful to define the indicators, since this facilitates a better understanding of the two sources of uncertainty associated with SHM results: (1) the fact that it is the indicators that are measured and not the parameters of interest themselves; (2) the measurement and estimation errors, which are related to how well a SHM technology can determine the indicator.

*Numerical example*: We assume that a damage ($C_t = 1$) can lead to changes in the dynamic properties of the system, which may be picked up by the SHM system. These dynamic properties are thus an indicator of the damage. We consider that with some probability the dynamic properties of the system change because of other factors (e.g. temperature) that are not relevant for its integrity, which might give rise to false alarms.

## 2.6 SHM technologies

SHM technologies describe the options for monitoring the structure. One option is always the null-option, not to perform any monitoring. This option is included to provide a reference against which the VoI is computed In the bridge application, alternative options could be the installation of a set of accelerometers, a set of strain gauges or a weight-in-motion device, or the combination of two or more techniques (e.g. Cross et al. 2013). The SHM technology also includes the procedures, methods and algorithms adopted to extract information from the data.

*Numerical example*: We here consider only the choice between a monitoring system and none.

## 2.7 SHM outcomes

Most SHM systems provide continuous data streams with potentially large amount of data. To make use of these data, they are aggregated and processed by suitable algorithms into summarizing statistics and assessments. These include binary outcomes (e.g. a damage/no-damage indication), scalar and vector values (e.g. maximum deflections, strains or loads), or time-series of relevant parameters.

In theory, Bayesian analysis methods provide the most complete and consistent approach to the processing of the data. Many advanced algorithms are based on the Bayesian paradigm, including Markov Chain Monte Carlo (MCMC) methods (e.g. Ching et al. 2006), algorithms based on the Kalman filter (e.g. Chatzi and Smyth 2009), algorithms using structural reliability methods (Straub et al. 2016) or asymptotic methods (Papadimitriou et al. 2001). Nevertheless, in practice data is often interpreted through simpler or less formalized procedures, e.g. by setting thresholds on summary statistics, or by expert assessment. The processing can be performed online (automatically) or offline.

In the bridge example, accelerometers or strain gauges could be utilized to determine dynamic properties of the bridge, in an output-only structural identification (e.g. Peeters and De Roeck 1999).

*Numerical example*: Based on the dynamic system identification, the SHM method either indicates an anomaly or not. This binary outcome is chosen for simplicity, but it is also reflecting the fact that a more detailed description of inspection outcomes would anyway need to be associated with a limited number of action alternatives.

## 2.8 Actions

Actions encompass all decisions and activities that are informed by the SHM outcomes, in particular repair, maintenance, retrofitting or replacement decisions. The modelling of these actions is central to a VoI analysis of a deteriorating system, because the value of the SHM for the structure comes entirely from an improved decision making on these actions, informed by the SHM outcome[4].

In practice, asset managers often find it difficult to specify a-priori how exactly the SHM outcomes will be utilized in the decision making process. It is then necessary to make at least simplifying assumptions on decisions taken based on the SHM outcomes, possibly utilizing experience with structures in which SHM systems are already installed.

In the bridge example, possible actions include mild repairs (e.g. corrosion protection paint), strengthening or retrofitting of the structure (e.g. post-tensioning) on the component or system level, measures to limit or eliminate deterioration (e.g. concrete cover improvements or anodic protection), as well as emergency measures (e.g. load restrictions or complete closure).

*Numerical example*: There are only two alternatives; (a) the structure is retrofitted or (b) no action is taken.

## 2.9 Costs

A VoI analysis requires quantification of all costs that are affected by, or associated with, SHM. Besides the risks and benefits related to structural performance (Section 2.4), these include the SHM cost (including data analysis and interpretation) and the cost of actions triggered by the SHM outcomes. In agreement with Section 2.4, costs should be expressed in monetary terms and should be discounted.

Costs of SHM system hardware are known at least approximately at the time of making the decision on SHM adoption. However, care is required to account properly for the total life-cycle cost of these systems, since their life-time is often limited and they can require substantial maintenance. The analyst also needs to quantify the cost of possible action alternatives, such as repair or maintenance. Experiences from other structures could provide estimates.

*Numerical example*: Costs of do-nothing alternatives are zero, the cost of installing and operating the SHM is 0.01, the cost of retrofitting is 1. (Compare these to the potential total life-cycle benefit of 2 and the cost of failure 100, Section 2.4).

## 2.10 Influence diagram in time

The influence diagram of Figure 1 reflects the decision making process in time in a simplified manner. The link from “SHM outcome” to “action”, in which the time count is increased by one, indicates that one deals with a sequential decision making process. To make the time dependence explicit, the ID could be unrolled; in doing so, copies of the nodes at the multiple points in time are introduced (Jensen and Nielsen 2007). Some of the nodes are not repeated in time. In particular the decision “SHM technologies” is typically made once, but affects the outcomes of all subsequent time periods. In addition to copies of the nodes at different points in time, the full ID will also include additional links among nodes at different points in time. For example, the condition at a time $t$ will be defined conditional on the condition at the previous time step $t-1$.

[4] Additional value may be generated if the information provided by the SHM is utilized to improve design and management of other structures.

For the VoI analysis, the number of time periods in the model determines the computational effort. In the general case, this effort increases exponentially with the number of time steps, so that one has an interest in keeping it small. For a fast VoI analysis, it can be sufficient to consider only a small number of steps, for example by discretising the whole life of the structure into 5 year intervals.

*Numerical example*: For simplicity, only two time periods are considered. The first corresponds to the time prior to the action, i.e. the period in which the SHM is installed and data is collected. The second period represents the complete time interval following the decision on whether or not to retrofit the structure. An additional ID is available as supplementary material demonstrating the extension of the model to four time periods.

# 3 VoI analysis

Once the model with all its components following Section 0 is established, the VoI analysis is performed. In a nutshell, it consists of maximizing the expected utility, or minimizing the expected cost, conditional on the available SHM solutions. This process can be understood quite intuitively through the so-called backward induction approach, in which the problem is represented by means of a decision tree (see e.g. Straub 2014 for the correspondence between an ID and a decision tree). This approach is also known as the *extensive form* in the literature on preposterior analysis (Raiffa and Schlaifer 1961). In practice, backward induction is only applicable to problems with limited number of decision alternatives, due to the exponential growth of the tree. For models with many decisions, the normal form of the analysis, which allows to optimize decision policies, is preferable (e.g. Bismut et al. 2017).

Details of the VoI computations are beyond the scope of this paper, the reader is referred to the literature (e.g., Pozzi and Der Kiureghian 2011; Straub 2014). For the numerical example provided with this paper, the analysis is not computationally demanding and can be performed with the Genie software.

The *net VoI* is defined as the difference in maximum expected utility of the decision to install the monitoring system and the maximum expected utility without the monitoring system:

$$net\ VoI = \mathrm{E}\left[U \middle| d_{opt,SHM}, SHM\right] - \mathrm{E}\left[U \middle| d_{opt,no\ SHM}, No\ SHM\right] \tag{1}$$

$d_{opt,SHM}$ and $d_{opt,no\ SHM}$ are the respective optimal decision policies and $\mathrm{E}[U|.]$ is the conditional expected utility. An example of a decision policy associated with an SHM installation is "repair the structure if the SHM identifies a problem".

The VoI is defined as the net VoI without the cost of the monitoring system. While the net VoI can be negative (if the cost of the monitoring system is larger than its benefit), the computed VoI cannot take negative values.

## 3.1 Results of the numerical example

### *3.1.1 Value of information*

For the numerical example, the expected utility is computed with and without the SHM system. These are $1.311$ and $1.298$, respectively, and it follows from Eq. 1 that $net\ VoI = 1.311 - 1.298 = 0.013$. The net VoI includes the cost of the SHM. By excluding the cost of the SHM, which is $0.01$, one obtains $VoI = 0.013 + 0.01 = 0.023$.

Since the net VoI is positive, it pays off to install the SHM. Its benefit/cost ratio is $\frac{0.023}{0.01} = 2.3$.

### *3.1.2 Value of partial perfect information*

Introducing a link from structural condition to the action mimics the situation in which one has perfect information about the structural condition when deciding on whether or not to strengthen the structure. This corresponds to partial perfect information (as the future condition and demands are still uncertain). The expected utility computed with this ID is $1.473$, hence the value of partial perfect information is $VPPI = 1.473 - 1.298 = 0.175$. This is the maximum value achievable with any SHM.

This result indicates that the potential benefit from an improved SHM is still large, as the VoI achieved with the considered SHM is only $0.023/0.175 = 13\%$ of the potential maximum value.

### *3.1.3 Improvement potential*

The difference between the VoI and the VPPI is due to the imperfect assessment of the structural condition. This imperfection is caused by the indicator, which is not a perfect reflection of the true condition, and by the SHM outcome, which is not a perfect measurement of the indicator. To understand the relative contribution of the two sources of uncertainty, we perform two additional computations in which either the indicator or the SHM is modelled as perfect. (Perfect implies that the conditional probabilities are either zero or one.) The results are summarized in Table 1.

*Table 1: Value of information under different (hypothetical) situations. Value in parenthesis indicate the value relative to the value of partial perfect information.*

| Partial perfect information | Current situation | Perfect indicator | Perfect SHM |
|---|---|---|---|
| 0.175 (100%) | 0.023 (13%) | 0.079 (45%) | 0.062 (35%) |

Table 1 shows that the detrimental effect of the imperfection in the indicator is slightly larger than the effect of the imperfection in the SHM. With the indicator “dynamic properties of the system”, only up to 35% of the potential maximum VoI can be extracted (with a perfect SHM). This suggests that additional indicators should be considered, with corresponding monitoring systems to measure them.

## 4 Challenges in real-world applications

The ID facilitates the modelling and presentation of the VoI process. Nevertheless, multiple challenges remain related to the modelling, the computation and the communication of the VoI. The computational burden can be significant to intractable, but in the short term most of the computational issues can be solved more efficiently by altering modelling choices rather than by improving algorithms. The communication of the VoI concept to the end user is often fairly straightforward, because the VoI emphasizes the “bangs for the buck” principle. It is often more difficult to communicate it to the engineer who is not familiar with an analytical, quantitative approach to modelling decisions (actions). We hope that the ID helps to make such modelling more accessible. Arguably the biggest challenges to the VoI assessment lie in the modelling; some of them are discussed in the remainder of this section.

As emphasized in this paper, the modelling process can potentially be quite simple, see also (Zonta et al. 2014). In practice, it requires significant experience by the analyst to identify a model that is simple yet consistent in reflecting the effect of the monitoring on the life-cycle cost of the structure. Additionally, for some effects no simple models have been identified yet – for example, it remains unclear how the effect that the monitoring of individual structural

elements has on the reliability of correlated, non-monitored elements can be quantified in a simple manner.

In many applications, the SHM is installed not least to identify any type of abnormalities, which can indicate a possibly unforeseen damaging mechanism (the "unknown unknowns" as opposed to the "known unknowns"). It is still unclear how such unforeseen events can be included in a VoI analysis. One path in this direction might lie in considering the population of similar structures and establishing incident rates on this basis; unfortunately, this approach is not directly applicable to the analysis of novel systems and prototypes. A related, if less drastic challenge, lies in the difficulty to predict future developments of technology, which can affect the future actions taken on the structure. These are associated with construction and monitoring technology, as well as analysis capabilities.

In many instances, the results of the SHM are interpreted by experienced engineers, who combine them with additional information, which is often qualitative, such as visual inspection results or knowledge about the contractor's quality. This type of information can be difficult to formalize prior to making the observation. This poses challenges to the VoI modelling process, in particular at the nodes "SHM outcome" and "Actions" in the ID, which have not been addressed in research thus far.

Overall, many of these questions might be addressed by investigating the actual decisions made in practice based on SHM. If data on existing systems were available, realistic probabilities as required for the VoI analysis could be determined empirically. Such an approach was followed by Sättele et al. (2015) for the analysis of warning systems. However, such investigations require significant efforts and the willingness of infrastructure owners to systematically collect and analyse their data and decisions.

# 5 Conclusion

Value of Information (VoI) analysis provides a formal framework for assessing the effect and benefit of SHM. An influence diagram, which provides a concise overview on the uncertain conditions and decisions that determine the VoI, can structure the analysis. When performing the VoI analysis at a detailed level, the modelling process and the computations can be demanding. However, in many instances a simplified model is sufficient to obtain a reasonably accurate estimate of the VoI.

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