Integration of information quality assessment in bridge resilience management

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ABSTRACT: Bridge conditions assessment is increasingly relying on Structural Health Monitoring (SHM) which allows the continuous acquisition of information on the structural state and overcomes problems that affect visual inspection such as subjectivity of the assessment, and difficulty to access hidden damages. However, the quality of SHM data is scarcely considered when information extracted from data is used to support management decisions, even though it plays an important role in the optimization of the management strategy and relevant decision-making process. In this article, a proposal to integrate the assessment of SHM information quality into bridge condition assessment management is presented. Mainly are discussed a general bridge management assessment procedure, and a decision-making scheme based on the Value of Information analysis to quantify the Value of Information Quality Assessment (IQA), and the impact of SHM IQA on bridge performance indicators..

1 INTRODUCTION

Modern bridges, constructed primarily in the past century, are aging worldwide and require maintenance. It is a challenge to extend their lifetime due to population growth, and increased natural risks from climate change.

Transportation is a necessity for the economy, the appropriate operation of modern society, and its continuous welfare (Schroten et al., 2019). However, due to the scarcity of resources required for adequate maintenance, preserving the required functionality level of aging critical infrastructures such as bridges is problematic. The average annual loss on transport infrastructure due to floods during the years 2010 to 2015 (*European Environment Agency*, 2019) represents an average annual loss of 13.3 billion euros, with a constant upward trend in the coming years. Therefore, one main objective of the European Union (EU) is to preserve transport infrastructures appropriately functional. This led the EU, for example, to invest solely €38 billion in maintenance (Schroten et al., 2019). These figures call for the development of a strategy to optimize bridge integrity management accounting for our scarce capacity to precisely predict the occurrence, long-term evolution, and spatial distribution of disruptive events.

In the last 30 years, research efforts have been devoted to a change of perspective from a condition-based to a risk-based approach in pursuit of efficient bridge integrity management subject to limited budgets. This is demonstrated by the extensive literature on this theme resumed in (Makhoul & Argyroudis, 2018) and by the several research projects funded by the EU, such as COST TU1406 (Casas & Matos, 2021). However, risk-based approaches to bridge integrity management do not account for the need to improve the recovery phase after the disruption thereby reducing the indirect consequences related to its loss of functionality ((Bruneau et al., 2003), (Faber, 2007), (Cimellaro et al., 2009), (Linkov et al., 2014), (Sharma et al., 2018), (Faber, 2018)).

Furthermore, interconnections between networks and domains are neglected most of the time. This does not replicate the real world which is shaped by increasingly interconnected technological, economical, sociological, and ecological networks ((Havlin et al., 2012), (Linkov et al., 2014)). Thus, a systemic approach is needed to account for these interconnections allowing us to describe the resilience across and within these domains.

In (Faber, 2018) a systemic approach was suggested for sustainable and resilient engineered systems. It allows for building decision support and management tools using an indicator-based approach, which was suggested for interconnected subsystems (i.e., physical, social, and economical). In (Turksezer et al., 2020) the concept of resilience indicators was used to define the characteristics of the managed system in terms of physical, information, and organizational subsystems. In this framework, the management of the system operated by the organizational subsystem is supported by the information flow managed by the information subsystem. However, in this, as in many other approaches, information quality is not considered, implicitly assuming that the available information possesses the required quality to support decisions. Studies addressing information quality and discussing the role of information quality in resilience management are still absent (Makhoul & Argyroudis, 2018), (Makhoul & Argyroudis, 2019), (Faber, 2018), (*Disaster Resilience: A National Imperative*, 2012)). The scope of this article is to propose a step toward this direction through the integration of information quality into a framework for managing the resilience of bridge infrastructure.

This article recalls in Section 2 indicators for data quality (DQ) assessment previously published ((Makhoul, 2022), (Makhoul & Limongelli, 2022)) and in Section 3 their deterministic and probabilistic metrics (Makhoul, 2022). In Section 4, which constitutes the core of the paper, a possible framework based on Value of Information (VoI) analysis is proposed to account for SHM information quality in the management of bridge condition assessment. Finally, the integration of SHM information quality assessment into VoI analysis and the impact of SHM information quality on bridge performance indicators are briefly discussed.

2 SELECTION OF INDICATORS FOR QUALITY ASSESSMENT OF SHM DATA

Data quality indicators for structural health monitoring were suggested in (Makhoul, 2022) and (Makhoul & Limongelli, 2022). Those indicators were clustered and assigned sub-indicators to describe their different aspects. Overall, six indicators, and five sub-indicators were designated as presented in Table 1 with their allocated definitions. The indicators were grouped into three phases of data management (i.e., acquisition, processing and sharing, and Supporting decisions). The classification aims to highlight proper data quality aspects for each one of the SHM data management phases.

Table 1. Data quality indicators and sub-indicators.

Data management phase	Indicator	Definition
Acquisition	**Correctness**	**data is accurate, precise, and consistent**
	Accuracy	the measured value of data is close to the real-world
	Precision	the measured data values are close to each other
	Consistency	the measured data is free of internal contradictions with respect to a rule.
	Redundancy	the measured data is not unique (multiple sets of data exist).
Processing and sharing	**Accessibility**	**the measured data is available and can be shared reliably**
	Interoperability	the measured data is concise and interpretable by machines
	Security	the access to data can be restricted to other parties and kept secure.
	Traceability	the sources of data are known
Supporting decisions	**Timeliness**	**the data is up-to-date when needed**

Completeness	**all required data are available in the dataset**
Relevance	**the data is useful for the task at hand**

3 METRIC FOR THE GLOBAL QUALITY INDICATOR INDICATORS

The data quality metrics were reviewed (Makhoul, 2022), and two methods were suggested for assessing DQ metrics in SHM Context. Those methods are 1) A deterministic method, and a probabilistic method accounting for uncertainties.

3.1 *Deterministic metrics*

The deterministic method assigns data quality metrics using scales. Those scales range from 0 (i.e., the lowest quality) to 1 (i.e., the highest quality). Metrics are defined as discrete or continuous scales as follows.
The discrete scale, where the metric has at least two or more discrete values:

$$\text{metric} = \begin{cases} 1 & yes \\ 0 & no \end{cases} \tag{1}$$

$$\text{metric} = \begin{cases} 1 & yes \\ 0.5 & partially \\ 0 & no \end{cases} \tag{2}$$

where 'yes' and 'no' means that the data is accurate (for accuracy), or not, etc., and 'partially' means that the data partially possess the quality under consideration (e.g., 0.5).
The continuous scale, where the metric is defined as a percentage of the data having this quality (i.e., 50% of the data is accurate, etc.).
Then, (Makhoul, 2022) introduced a global metric accounting for all quality attributes. This DQ is computed using the equation:

$$\text{DQ} = \sum_u \omega_u * DQ_u \tag{3}$$

Where DQ_u is the metric for the u^{th} quality attribute and ω_u the relative normalized weight.
The normalized weights are calculated by:

$$\omega_u = \frac{S_u}{\sum_u S_u} \tag{4}$$

Where S_u are the weights of the quality attributes which, for example, might be based on expert opinion. They enable us to distinguish between the importance levels of selected attributes. The decision-maker is required to allocate scales (S_u) to each quality indicator based on its assigned importance for the decision-making case at hand. The definition of the weights in equation (4) guarantees that the sum of all the weights equals 1:

$$\sum_u \omega_u = 1 \tag{5}$$

This global metric is used to assess the level of data quality by suggesting adequate thresholds.

3.2 *Probabilistic metrics*

Probabilistic metrics were proposed in (Makhoul, 2022) in the form of probability distribution functions. They were offered for the cases of permanent and occasional monitoring to account for different data flows (Table 2). The probabilistic approach assigns an adequate probability distribution function to the indicator metrics. As discussed in (Makhoul, 2022) probabilistic metrics varies based on the type of data and associated uncertainties. In SHM, the probability distribution function assigned is highly dependent on the flow of the SHM data. The flow is scarce in the case of occasional SHM measurements, thus the data is discrete and the binomial distribution can be used (Faber, 2012). The flow is abundant in the case of permanent SHM measurements, thus the data is continuous and the normal distribution can be used (Faber, 2012).

Table 2. The probabilistic metrics for DQ for permanent and occasional SHM.

Indicators				
Measurement	**Accuracy**	**Precision**	**Consistency**	**Completeness**
Permanent	A = R – M ~ N (μ, σ)	σ_d	Co ~ N(μ_{co}, σ_{co})	C ~ N (μ_c, σ_c)
Occasional	A = R – M ~ B (n, p)	σ_d	Co ~ B(n_{co}, p_{co})	C ~ B (n_c, p_c)
Indicators				
Measurement	**Timeliness**	**Accessibility**	**Redundancy**	**Relevancy**
Permanent	$Q_{Time} = 1$	Ac ~ N (μ_c, σ_c)	R ~ N (μ_r, σ_r)	Re ~N (μ_{re}, σ_{re})
Occasional	$Q_{Time}(T) = e^{-\lambda \cdot T}$	Ac ~ B (n_c, p_c)	R ~ B (n_r, p_r)	Re ~B (n_{re}, p_{re})

4 ACCOUNTING FOR DATA QUALITY OF SHM IN THE LIFE CYCLE ASSESSMENT MANAGEMENT

In this section, the integration of SHM information quality assessment into bridge condition assessment is proposed. In Section 4.1, a general bridge management assessment procedure considering the SHM information quality is presented. Then in Section 4.2, the integration of SHM information assessment into the Value of Information analysis is presented. Finally, in Section 4.3, the impact of SHM information quality assessment on the estimation of bridge performance indicators is briefly discussed.

4.1 *GENERAL BRIDGE MANAGEMENT ASSESSMENT PROCEDURE CONSIDERING THE SHM DATA QUALITY*

A General Assessment Procedure (GAP) for the existing structure was presented in (ISO 13822, 2010). Herein an Updated General Assessment Procedure (UGAP) that includes the assessment of SHM information quality in the process is introduced (Makhoul, 2023). It is presented in Fig. 1. This step was included after the inspection tests such as surveillance, visual, etc. The outcome of the VoI analysis may lead – or not – to perform an Information Quality Assessment (IQA). Two outcomes are possible i.e., whether the value of information equals zero, then the IQA is skipped, and GAP is followed straightforwardly. If the IQA leads to a value of information greater than zero, then IQA is performed on the collected information. The word 'inspections' is generically used herein to address the process of collecting information about the bridge condition. This process can be carried out through visual surveys, destructive and nondestructive testing, SHM, etc. The selection of the specific type of inspection can be carried out through a Value of Information analysis. However, herein the focus is on the integration of information quality assessment (IQA) into condition assessment thereby the selection of the inspection type will not be addressed. Without loss of generality, it will be assumed that the inspection process is carried out through SHM. The management actions considered in the flowchart in (figure 1) can be operation actions (i.e., monitoring, and change in use) or construction actions (i.e., rehabilitation such as repair or upgrading, and demolition). In the following, they will be generically addressed as 'interventions'.

4.2 *VALUE OF INFORMATION ANALYSIS ACCOUNTING FOR THE SHM INFORMATION QUALITY ASSESSMENT*

The suggested decision-making framework to assess the benefit of performing SHM IQA is based on VoI analysis. The approach is based on pre-posterior Bayesian analysis and expected value theory (Schlaifer & Howard, 1961), (Benjamin & Cornell, 1970), and (von Neumann & Morgenstern, 2007).

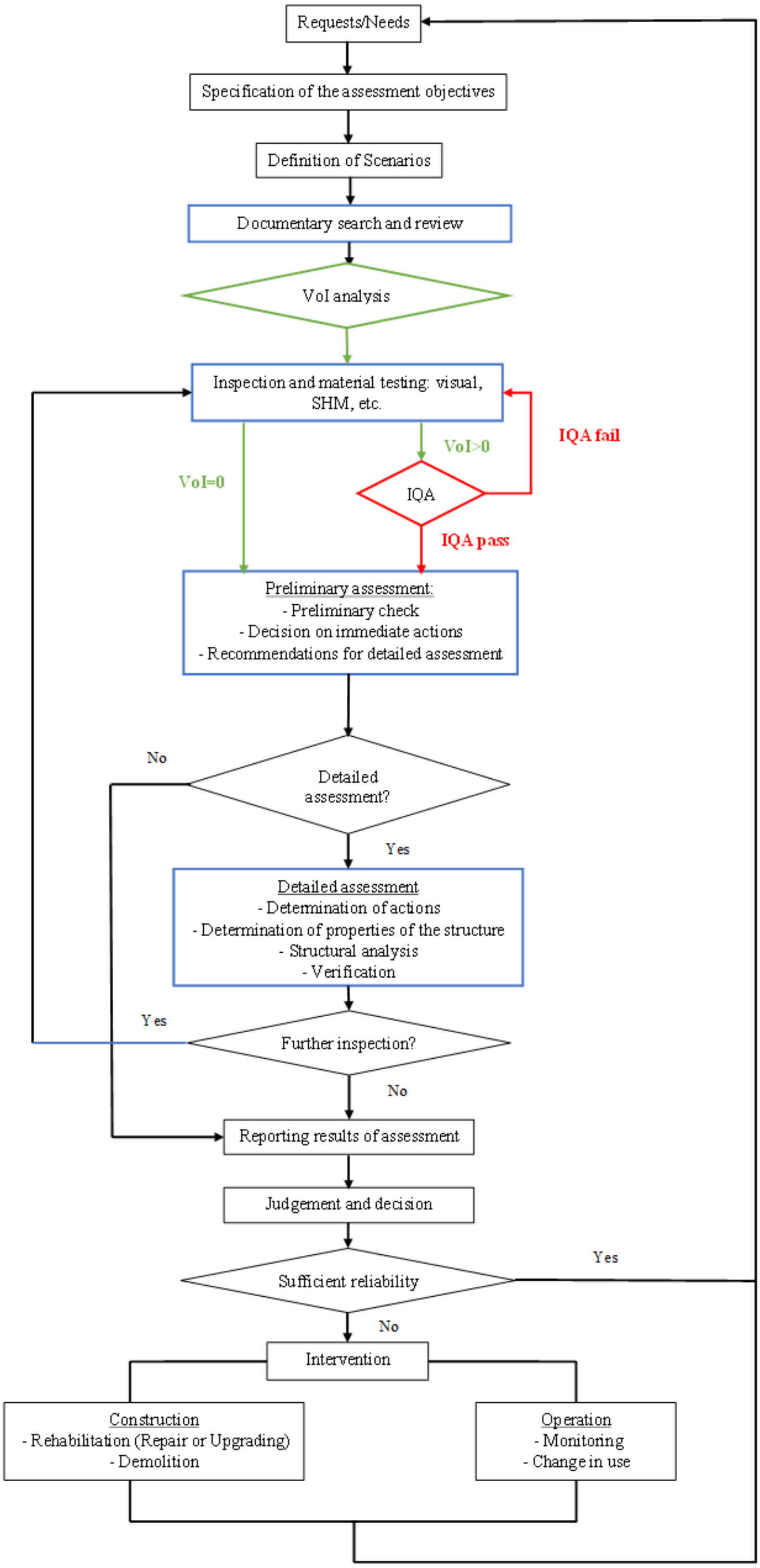

Figure 1. Flowchart for the updated general assessment procedure of existing structure considering the SHM IQA.

In figure 2 the process to quantify the VoI of IQA for information collected through inspections is represented through a decision tree. In reference (Giordano et al., 2023) the complete framework is described and applied using a machine-learning-based tool for the assessment of the information quality. Herein the decision tree that describes the VoI quantification is illustrated. Decision nodes are depicted by a square, and chance nodes by a circle. Branches stemming from squares represent decision alternatives, and branches stemming from circles represent states of nature. Herein the decisions are about the implementation of the information quality assessment (IQA), and of the intervention action (a). The upper branch of the tree represents the prior decision analysis where the selection of the optimal intervention is carried out without performing IQA. The bottom branch is the pre-posterior decision analysis where the decision about the intervention is performed with the support of IQA. The difference between the expected consequences of the optimal actions (schematically reported in equation 6) selected with the two types of decision analyses (prior and pre-posterior) quantifies the values of IQA. The process is detailed further in (Makhoul, 2023).

$$VoI = C_{preposterior} - C_{prior} \tag{6}$$

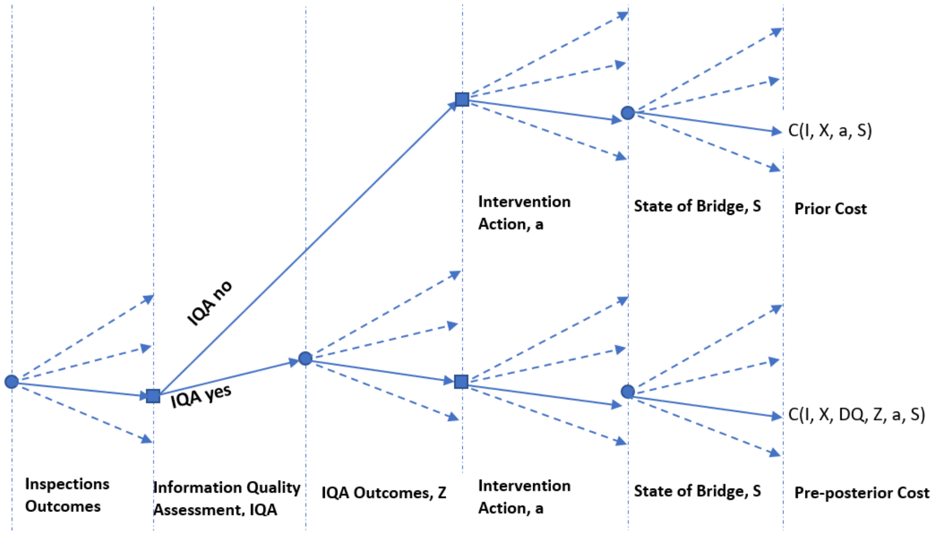

Figure 2. Decision tree for the quantification of the Value of Information Quality assessment (IQA)

4.3 *SYSTEM PERFORMANCE INDICATORS ACCOUNTING FOR SHM INFORMATION QUALITY*

Bridge performance can be analyzed using several available performance indicators, such as for instance risk and resilience. Herein reference is made to a generic performance indicator.

The structural performance – and thereby its indicators – will generally decrease in time due, for instance, to deterioration associated with insufficient maintenance.

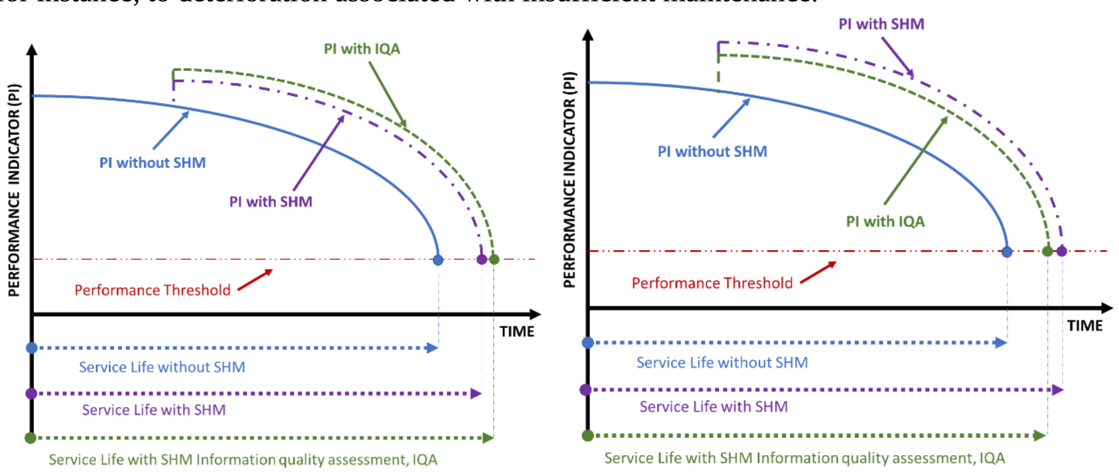

Figure 3. Performance indicator profile with and without SHM IQA: a) case of Service life longer with SHM and with SHM IQA, b) case of Service life greater with SHM but shorter without SHM IQA.

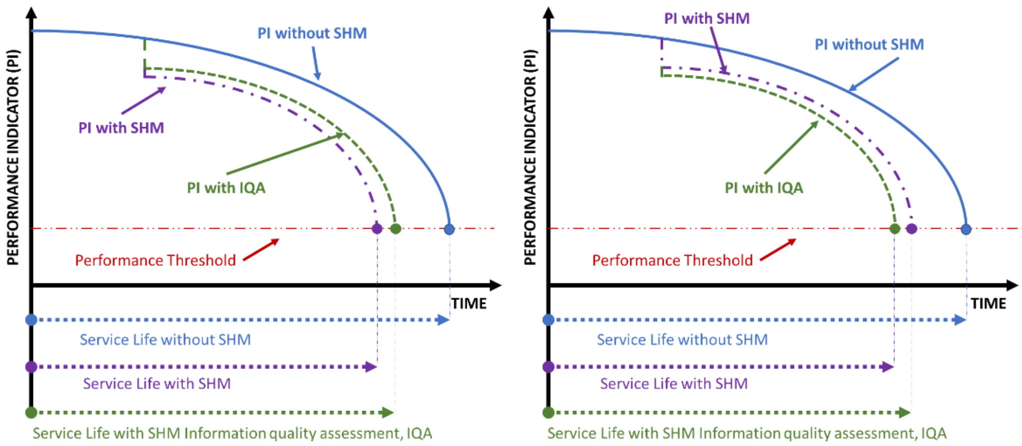

Figure 4. Resilience indicator profile with and without SHM IQA: a) case of Service life longer without SHM and longer with IQA than without IQA, b) case of Service life longer without SHM but shorter without IQA than with IQA.

The estimation of performance indicators can benefit from SHM information that provides an improved knowledge of the bridge condition (Bocchini et al., 2012) and (Capacci & Biondini, 2020). If also SHM IQA is carried out, a further update of the performance indicator can be carried out, leading to a different estimation of the service life as shown in (Figures 3 and 4).

5 CONCLUSIONS

Bridge conditions assessment is increasingly relying on Structural Health Monitoring (SHM). However, the quality of SHM information is rarely considered although it plays a vital role in management strategy optimization and relevant decision-making. To address this issue, this article suggests the integration of SHM information quality assessment on a Value of Information analysis base. The integration of SHM information quality assessment into VoI analysis and the quantification of resilience indicators and bridge service life are briefly discussed.

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