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Framework to evaluate the value of monitoring-technique information for structural performance monitoring

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ABSTRACT

The management of existing civil infrastructure is becoming more crucial as a large share of bridges is approaching their theoretical end of service duration. Structural performance monitoring aims to verify bridge safety at a given time, and it should be differentiated from structural health monitoring, which aims at detecting structural damage. Possible monitoring techniques include bridge load testing, non-destructive testing, and continuous monitoring of structural behaviour, environmental conditions, and load levels. Nonetheless, selecting the optimal combination of monitoring techniques is challenging as each method provides unique but also redundant information. This study proposes a framework to assess the value of information from multiple bridge monitoring techniques. This framework enables defining the appropriate set of monitoring techniques to ensure that the collected information will potentially correct engineering decisions regarding structural safety. A full-scale bridge in Switzerland is used for validating the framework predictions. Combining four monitoring techniques, the expected average increase of degrees of compliance of structural verification is estimated to 19%, which is consistent with the 36% obtained after performing these monitoring techniques. The methodology supports decision-makers in selecting an optimal combination of monitoring techniques for structural performance monitoring by maximizing the value of information.

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Bridge assessment; bridge load testing; existing bridges; non-destructive evaluation; structural health monitoring; structural identification; value of information; weigh-in-motion

1. Introduction

In developed countries, most infrastructure was built in the second half of the twentieth Century. Most bridges are approaching their intended service duration (Biondini & Frangopol, 2016). Managing existing civil infrastructure is challenging because of evolving functional requirements, insufficient concrete and steel durability, and climate change (Yang & Frangopol, 2018, 2019). Neglecting infrastructure maintenance has been highlighted as one of the main limiting factors of economic growth in many countries (Schwab & Sala-I-Martin, 2017). Infrastructure safety assessments are crucial as these evaluations influence the infrastructure-network resilience and environmental impacts of asset management (Bocchini, Frangopol, Ummenhofer, & Zinke, 2014; Frangopol & Liu, 2007).

Infrastructure conditions are typically evaluated based on visual inspection, which is repeated every few years by road agencies (Schellenberg, Vogel, Chèvre, & Alvarez, 2013). However, the limitations of these qualitative inspections are well-known (Agdas, Rice, Martinez, & Lasa, 2016; Bertola & Brühwiler, Bertola & Brühwiler, 2023). For instance, some critical structural elements (i.e., prestressed tendons in concrete) may be embedded in the structure or are not accessible and thus cannot be visually inspected (Abdel-Jaber & Glisic, 2019; Jeon, Lee, Lon, & Shim, 2019).

To overcome the limitations of visual inspections, the deployment of monitoring systems to collect data on structural behaviour and conditions has attracted a lot of interest, see for example (Brownjohn, 2007; Catbas, Susoy, & Frangopol, 2008; Cross, Koo, Brownjohn, & Worden, 2013) among others. As structural models are inherently conservative (Proverbio, Vernay, et al., 2018), collecting monitoring data helps unlock untapped reserve capacities of existing infrastructure, thus improving decision-making without putting users at risk (Aktan, Bartoli, & Karaman, 2019; Smith, 2016). A better knowledge of structural performance can be leveraged to extend service durations and prioritize maintenance activities (Bocchini et al., 2014; Frangopol, Strauss, & Kim, 2008).

Two main structural-monitoring strategies should be differentiated (Figure 1). First, field measurements are used to estimate the structural capacity at a given time accurately, called structural performance monitoring (SPM) (Feng, Kim, Yi, & Chen, 2004). This strategy involves measuring the structure over a given period of time (from a few minutes to a few months) to update the safety assessment with monitoring data. The second strategy involves assessing the decrease in the structural performance over time due to the deterioration of the materials, called structural health monitoring (SHM) or damage detection (Farrar & Worden, 2010; Worden & Dulieu-Barton, 2004). These two strategies

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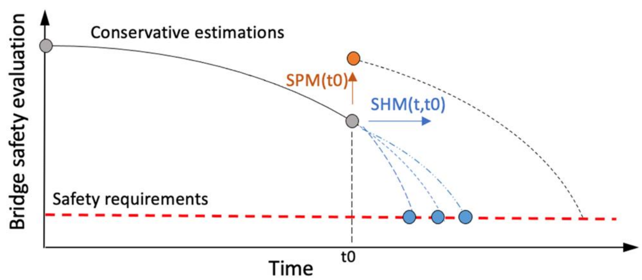

Figure 1. Influences of estimations from structural performance monitoring (SPM) and structural health monitoring (SHM) on bridge performance.

can be regrouped under the name of non-destructive evaluation (NDE) (Zheng & Ellingwood, 1998). As the same sensors (i.e., accelerometers, thermocouples, and strain gauges) are used for both monitoring strategies (Capellari, Chatzi, Mariani, & Azam, 2017; Wong, 2007), the two strategies are sometimes not clearly differentiated in the literature.

SPM can involve several monitoring techniques (MT) to achieve its goal of estimating structural capacity more accurately. These techniques include non-destructive testing (NDT), weight-in-motion (WIM), continuous monitoring of structural behaviour (over a short and predefined period of time), and bridge load testing. In NDT, instruments are locally deployed to temporarily measure the structural response under a known test setup (Kot et al., 2021; Lee, Kalos, & Shin, 2014). WIM stations measure axle and gross vehicle weights as vehicles pass through the measurement site, and this information is used to extrapolate maximum traffic demand (OBrien, Brownjohn, Hester, Huseynov, & Casero, 2021; Treacy, Brühwiler, & Caprani, 2014). Bridge weight in motion (BWIM) uses monitoring systems, such as strain gauges, to infer actual traffic load effects based on sensor measurements (Lydon, Taylor, Robinson, Mufti, & Brien, 2016; Ojio, Carey, OBrien, Doherty, & Taylor, 2016). The continuous-monitoring technique involves placing sensors and measuring the actual behaviour of the bridge elements due to the real operational (i.e., traffic) and environmental conditions for a given time (usually several months or years) (Oskoui, Taylor, & Ansari, 2019; Sawicki & Brühwiler, 2022; Wang, Niederleithinger, & Hindersmann, 2022).

In bridge load testing, static and dynamic excitations (Brownjohn, De Stefano, Xu, Wenzel, & Aktan, 2011; Cao, Koh, & Smith, 2019) are used to characterize the structural and material properties (i.e., the structural rigidity and the boundary conditions) of the bridge (Alampalli et al., 2021; Lantsoght, van der Veen, de Boer, & Hordijk, 2017). As each MT provides unique information, a combination of MTs is often recommended to maximize the information gain (Bertola, Henriques, & Brühwiler, 2023, Bertola, Henriques, Schumacher, & Brühwiler, 2022). MTs are often not combined for SPM. The first reason is that performing multiple techniques requires a large number of sensors and data-interpretation tools and may thus be expensive. Another reason is the difficulty in predicting the mutual and redundant information from multiple techniques. Selecting the optimal set of MTs is thus a complex task and must often be economically justified.

Researchers have first investigated optimal sensor networks to maximize the information gain during monitoring. (Bertola, Cinelli, Casset, Corrente, & Smith, 2019; Ercan & Papadimitriou, 2021). Strategies have been developed to predict the information gain of monitoring systems based on information-entropy criteria (Argyris, Papadimitriou, & Panetsos, 2017; Bertola, Papadopoulou, Vernay, & Smith, 2017b; Papadimitriou, 2004). The information entropy, also called Shannon entropy, is a metric measuring the disorder in information content. Optimal sensor placement is obtained by optimizing the sensor configuration that will provide the maximal information on the system uncertainties (Papadimitriou, 2004; Papadimitriou, Beck, & Au, 2000). In other words, the information gain of sensor configurations is evaluated based on uncertainty reduction (i.e., bridge properties identification) rather than the impacts of precise parameter values on bridge-safety evaluations.

Recently, efforts have been made to quantify the value of information (VoI) by comparing maintenance interventions with and without including expected information gain, see for example (Giordano, Quqa, & Limongelli, 2023; Pozzi & Der Kiureghian, 2011; Straub et al., 2017; Zhang, Qin, Lu, Liu, & Faber, 2022; Zonta, Glisic, & Adriaenssens, 2014) among others. One recent progress is the development of frameworks to quantify the VoI for sequential point-in-time decision-making for infrastructure management (Giordano et al., 2023; Larsson Ivanov, Björnsson, Honfi, & Leander, 2022; Verzobio, Bolognani, Quigley, & Zonta, 2022). The COST Action TU 1402 was a joint effort between academia, industry and authorities to provide complementary material for the quantification of the VoI of NDE between 2014 and 2019 (COST Action TU1402,1402,1402, 2014). Three guidelines were introduced for operators (Sousa, Wenzel, & Thöns, 2019b, 2019a), practising engineers (Diamantidis, Sykora, & Sousa, 2019), and scientists (Thöns, 2019).

Although insightful frameworks have been provided, they often rely upon simplified assumptions with respect to maintenance actions, hypothetical information gain, and numerical examples (Kamariotis, Chatzi, & Straub, 2022; Thöns, 2018). Further to this, a recent special issue has been released and aimed at demonstrating the practical feasibility of the VoI for infrastructure management through full-scale case studies (Sousa, Köhler, & Casas, 2022). Despite these efforts, a challenge lies in the integration of the expected information gain from multiple MTs in the VoI frameworks (Zhang, Lu, Qin, Thöns, & Faber, 2021). This work aims at providing novel approaches to tackle this challenge using results from a full-scale bridge case study in Switzerland.

This paper presents a novel framework to evaluate the value of information of a combination of MTs for SPM (VoI-based design of SPM) (Section 2). A combination means that several MTs will be performed on the bridge sequentially. The concept of the VoI in the context of SPM is first introduced. Then, methodologies are introduced to quantify the VoI depending if the MT provides a direct or indirect measure of structural properties (forward or inverse problem). These methodologies enable quantifying the VoI of SPM when several MTs can be performed. Results of a large monitoring campaign between 2016 and 2019 on a bridge in Switzerland have been used to validate VoI predictions of MTs using field measurements (Section 3). A discussion on the difference between information gain and VoI is made in Section 4.

2. Framework to evaluate the value of information of monitoring techniques for structural performance monitoring

2.1. Background

2.1.1. Error-domain model falsification (EDMF)

Error-domain model falsification (EDMF), is a probabilistic methodology for data interpretation of structural system (Goulet & Smith, 2013). This data-interpretation methodology is similar to Bayesian model updating and has been shown to provide robust identification (Pai & Smith, 2021, 2022). EDMF requires several steps. First, a model class is defined, which involves both the creation of a parametric behavior model of the structural system through the selection of its most critical behavior-sensitive characteristics (i.e., material properties, geometry, boundary conditions, etc.), their plausible ranges, as well as the quantification of non-parametric model uncertainties ($U_{i,g}$) and measurement errors ($U_{i,y}$). The second step is the generation of a set of model instances from the model class, where each instance represents a unique combination of model-parameter values. Predictions of these model instances are then compared to the field measurements in the third step.

For a measurement location i, the prediction of a model instance $g_i(\Theta)$ is generated by assigning a unique combination of parameter values Θ. Let's defined R_i the true structural response at this location (unknown in practice). R_i is linked to the field measurements y_i and model prediction $g_i(\Theta)$ using Equation (1) with n_y the number of measurements:

$$g_i(\Theta) + U_{i,g} = R_i = y_i + U_{i,y} \ \forall i \in \{1, \ldots, n_y\} \quad (1)$$

Distributions of model $U_{i,g}$ and measurement $U_{i,y}$ uncertainties are usually combined in a unique source of uncertainty $U_{i,c}$ using Monte-Carlo sampling (Robert-Nicoud, Raphael, & Smith, 2005b). Equation (1) is then transformed into Equation (2). The left side of Equation (2) shows the discrepancy between the model-instance prediction and the sensor data at location, i and is called the residual, r_i:

$$g_i(\Theta) - y_i = r_i = U_{i,c} \ \forall i \in \{1, \ldots, n_y\} \quad (2)$$

The last step involves falsifying model instances that have predictions that differ significantly to the measurements. For each measurement, upper and lower falsification thresholds are defined using a level of confidence (typically set at 95%) on $U_{i,c}$ (J.-A. Goulet & Smith, 2013). If a model instance is associated with a residual value exceeding a threshold bound at least in one sensor location, this model instance is falsified. This falsification means that the associated combination of model parameter values is discarded. By falsifying the wrong model instances, the output of EDMF is a set of plausible model instances (i.e., plausible combinations of parameter values) among the initial population. Therefore, only a subset of initial parameter ranges remains plausible, and information is gained.

2.1.2. Hierarchical algorithm for sensor placement

The hierarchical algorithm for sensor placement enables to identify optimal sensor configuration (Bertola et al., 2017b; Papadopoulou, Raphael, Smith, & Sekhar, 2014). The information gain is evaluated by the ability of a sensor configuration to discriminate model instances and is tailored for EDMF. The algorithm helps obtain the measurements that maximize the number of falsified model instances to reduce parameter-value ranges after monitoring. The hierarchical algorithm uses joint entropy as the objective function (Papadopoulou, Raphael, Smith, & Sekhar, 2016), which is an improvement of the information entropy. Information entropy has been used for two decades as the objective function for optimal sensor placement. This metric measures the disorder either in posterior parameter distributions (Papadimitriou et al., 2000) or model-instance prediction distributions (Robert-Nicoud, Raphael, & Smith, 2005a). Due to the large combination number of potential sensor configurations, a greedy search optimization algorithm is chosen (Papadimitriou, 2004).

In EDMF context, the evaluation of information entropy enables measuring the variability of model-instance predictions at sensor locations for a given uncertainty level. In order words, a sensor location with a large information entropy associated, means that this location will maximize the discrimination of model instances, and is an attractive sensor location. To quantify the information entropy, a histogram of model prediction at each sensor location is generated. The range of model-instance predictions is subdivided into $N_{I,i}$ subsets with a subset width given by the difference between upper and lower threshold bounds obtained with combined uncertainty $U_{i,c}$ (Equation (2)). The probability that a particular model-instance prediction $g_{i,j}$ falls inside the jth subset is thus equal to $P(g_{i,j}) = m_{i,j} / \sum m_{i,j}$ with $m_{i,j}$ the number of model instances falling inside jth interval. The information entropy $H(g_i)$ of sensor location i is then evaluated by:

$$H(g_i) = -\sum_{j=1}^{N_{I,i}} P(g_{i,j}) \log_2 P(g_{i,j}) \quad (3)$$

When the behavior of complex systems (i.e., bridges) is monitored, the collected measurements between sensor locations are correlated. The selection of the optimal sensor placement based on the information-entropy metric leads to suboptimal sensor configurations (Bertola, Papadopoulou, Vernay, & Smith, 2017a). To account for the mutual information between locations, joint entropy is introduced as a new objective function for sensor placement (Papadopoulou et al., 2014). Joint entropy $H(g_{i,i+1})$ enables the evaluation of the information entropy amongst sets of predictions at sensor locations. For a set of two sensors, the metric is calculated using Equation (4). In this equation, $P(g_{i,j}, g_{i+1,k})$ id the joint probability that model-instance predictions fall inside the jth interval at sensor i and the kth interval at sensor $i+1$ with $k \in \{1, \ldots, N_{I,i+1}\}$ and $N_{I,i+1}$ is the maximum number of prediction intervals at the $i+1$ location and $i+1 \in \{1, \ldots, n_s\}$ with the number of potential sensor locations $n_{s:}$

$$H(g_{i,i+1}) = -\sum_{k=1}^{N_{I,i+1}} \sum_{j=1}^{N_{I,i}} P(g_{i,j}, g_{i+1,k}) \log_2 P(g_{i,j}, g_{i+1,k}) \tag{4}$$

Due to the redundancy in the information gained between sensors, the joint entropy is less than or equal to the sum of the individual information entropies at sensors i and $i+1$. Equation (4) can be transformed into Equation (5), where $I(g_{i,i+1})$ is the mutual information between sensor locations i and $i+1$. The prediction of the algorithm is terms of information gain has been validated by the observations for several case studies (Bertola, Costa, et al., 2020):

$$H(g_{i,i+1}) = H(g_i) + H(g_{i+1}) - I(g_{i,i+1}) \tag{5}$$

2.2. Framework

2.2.1. Structural performance monitoring and metric for structural verifications

SPM aims to conduct structural verifications based on updated structural properties and observed loading demand. This monitoring approach should be differentiated from SHM, which aims at damage detection and predictions of future service duration (Figure 1). All structural requirements can be verified as monitoring information can influence both demand (load level) and structural capacity. This monitoring strategy has thus a lot of use cases in practice since often structural deficiencies are initially estimated by engineers. SPM typically has the following procedure:

1. Examination of the existing structure without monitoring information.
2. Identification of structural deficiencies for all limit states.
3. Design of the appropriate monitoring system.
4. Performance of the monitoring campaign.
5. Interpretation of the data in terms of identified bridge property values.
6. Updating of structural models and structural capacity.

In this study, a framework is proposed for the third step of the SPM procedure (design of the appropriate monitoring system) when multiple MTs can be implemented (such as NDT, WIM, continuous monitoring, and bridge load testing in this study). Before assessing the value of information of MTs, the metric used to evaluate structural performance is introduced. Several metrics have been proposed in the literature (Ghosn, Dueñas-Osorio, et al., 2016; Ghosn, Frangopol, et al., 2016).

In Switzerland, structural safety is commonly calculated following the deterministic approach using the degree of compliance n (Brühwiler, Vogel, Lang, & Lüchinger, 2012), shown in Equation (6). When the degree of compliance has a value larger than 1.0, it means that structural safety is ensured. This deterministic metric is generic and can thus be applied to any structural verifications for serviceability limit states (SLS), ultimate limit states (ULS), and fatigue limit states (FLS). The proposed methodology could also be used for probabilistic structural evaluations (Cervenka, 2013; Gulvanessian, Calgaro, & Holický, 2012; Melchers & Beck, 2018; Straub, Schneider, Bismut, & Kim, 2020). The choice of a deterministic evaluation of the degree of compliance is twofold: first, it replicates the current practice of the evaluation of structural safety in Switzerland. Second, it allows for faster evaluations of the structural verification metric.

To calculate both structural capacity and load effects at a given location of the bridge, analytical or numerical models, such as finite element models, are required. For a given case study, such as a bridge, several structural verifications are usually made for each limit state. In such cases, a degree of compliance for each structural verification is derived:

$$degree\ of\ compliance \equiv n = Capacity/Demand \tag{6}$$

2.2.2. Value of information

The proposed method to select the appropriate monitoring system (step 3 of the SPM process) is based on the concept of the value of information (VoI). VoI analyses aim at quantifying the economic value of monitoring information by assessing how decision-making is impacted by the additional data. Therefore, this study aims at proposing a framework for VoI-based design of optimal monitoring-technique combination for SPM. In this study, the value of information approach combines the entropy-based metric (Section 2.2) for information gain estimations and code-based deterministic structural verification (Equation (6)). This approach is similar to the one used for sensor placement by Bertola, Proverbio, et al. (2020).

Decision-making in SPM is related to structural-safety assessments. In the present study, potential intervention actions involve either structural strengthening or doing nothing. Monitoring data provide valuable information if they can change the assessments of bridge safety for structural verifications that initially showed deficiencies. In such situations, a structural intervention would be made without monitoring data, but this intervention may be avoided thanks to monitoring. Monitoring data help re-evaluate the degrees of compliance (Equation (1)) by reducing uncertainties on three main aspects: material properties (i.e., elastic modulus, material strength), load effect levels (i.e., maximum stress difference due to operating traffic), and structural modelling (i.e., boundary conditions, transverse load distribution). Each MT reduces uncertainties on a subset of parameters of structural models that may influence the structural safety assessment by means of an associated monitoring cost. Maximizing the VoI of MTs for SPM involves defining which data collected by a combination of MTs is the most likely to affect structural-safety assessment with the smallest monitoring costs.

The VoI of a MT (or combination of techniques) for SPM is quantified using:

$$VoI_{SPM} = (C_{int} - C_{not}) * P(n \geq 1) - C_{mon} \tag{7}$$

in which, C_{int} represents the cost of interventions, C_{not} is the costs of doing nothing (assuming equal to zero and does not account for potential rehabilitation costs associated with interventions for the durability of non-structural elements), C_{mon} is the monitoring costs, and $P(n \geq 1)$ is the probability that the degree of compliance n will be higher than 1.0 after performing the MT. In such situations, the intervention is avoided, and C_{int} is thus saved (Bertola, Proverbio, et al., 2020).

In this study, the simplification that C_{int} is a constant and is not affected by the outcomes of the monitoring campaign is made. In practice, C_{int} may be slightly reduced if the degree of compliance is increased. Nonetheless, a significant part of C_{int} depends on labour and indirect (i.e., impact on traffic) costs which are mostly independent of the degree of compliance. The optimal combination of MTs is defined as the combination that maximizes $P(n \geq 1)$ with a minimal C_{mon}. As the evaluation of degrees of compliance is made deterministically (Equation (6)), $P(n \geq 1)$ is the probability distribution that degrees of compliance will be found larger than 1.0 using this deterministic evaluation of structural safety given the potential information gain from a MT:

It is important to notice that a bridge may present several structural verifications with deficiencies that are partially uncorrelated, for instance, between SLS (Serviceability Limit State) and ULS (Ultimate Limit State). In such cases, $P(n \geq 1)$ is multi-dimensional. For example, a bridge where two structural verifications are deficient ($n < 1$ for each verification): the bending-moment at support (ULS) and the maximum deflection (SLS). As these verifications mostly depend on the structural capacity and the structural rigidity respectively, bridge properties influencing these verifications are partially uncorrelated. In such case, $P(n \geq 1)$ is a two-dimensional space, and this probability is computed for each verification independently and then combined. In addition, several bridge properties affect each dimension of $P(n \geq 1)$, such as material properties (i.e., structural rigidity) and true load level (i.e., frequent and maximum axle loads).

Figure 2 shows the flowchart to quantify the VoI for SPM, where two MTs (bridge load testing and NDTs) are taken as illustrative examples (other MTs could be considered). The first stage involves evaluating structural performance without monitoring information. This evaluation is based on a visual inspection. The main structural characteristics and load levels are estimated based on recorded information on the bridge (i.e., construction drawings). Conservative values are assigned to bridge properties where precise information is not available. Several structural verifications are made for the serviceability, fatigue and ultimate limit states. Building a numerical model is often required to provide precise evaluations of structural safety, and results are expressed in terms of degrees of compliance (Equation (6)). At this stage, the first evaluation of bridge potential deficiencies is made. The potential structural strengthening is designed, and its costs C_{int} are estimated. If the bridge does not present structural deficiency, SPM is not economical and is not recommended.

The next stage involves defining the potential MTs for SPM that could be applied to reduce uncertainties on structural behaviour by identifying bridge properties, such as material properties, boundary conditions, and load levels. Estimations of sensor types, the number of devices, and the duration of monitoring are also made, leading to the evaluation of the monitoring costs C_{mon} for each MT. Then, the usefulness of each MT is evaluated, and this process is made in three steps, as presented in detail in Section 2.2.3. The first step involves estimating posterior parameter distributions after monitoring. This step may not be trivial, especially when monitoring provides indirect information on the above-mentioned bridge properties, such as during load testing. Then, the structural verifications are re-evaluated based on these posterior distributions. Finally, $P(n \geq 1)$ can be estimated by calculating the predictive distributions of the degrees of compliance.

The last step is selecting the appropriate combination of MTs (linear combination of monitoring outputs) that maximize the VoI for all structural deficiencies. As each MT provides unique information, the best technique will often differ between structural verifications of limit states. A combination of MTs is thus often recommended to maximize the VoI if multiple structural deficiencies were initially evaluated. If the VoI of a given set of MTs is negative, this means that the monitoring costs are not justified by the benefits of this monitoring campaign. This MT should thus not be performed or improved.

2.2.3. Predicting monitoring outcomes

The main challenge in estimating the VoI for SPM lies in the evaluation of $P(n \geq 1)$ based on potential monitoring outcomes. $P(n \geq 1)$ depends on the bridge properties that can be identified during monitoring, the precision of this identification (called the identification range), and remaining uncertainties. Quantification of the identification range depends if the monitoring provides information on the bridge parameters directly or indirectly. Direct parameter monitoring means that the sensing device measures the bridge property directly. For instance, a rebound hammer provides readings of the concrete compressive strength. Indirect monitoring implies that the sensor data must be interpreted to identify bridge properties. For instance, structural deflection (bridge behaviour) is measured during static load testing. Then the structural rigidity (bridge property) is evaluated using an inverse analysis (F. Catbas, Kijewski-Correa, Lynn, & Aktan, 2013; Smith, 2016). Two methodologies are presented below to evaluate $P(n \geq 1)$ for direct and indirect monitoring respectively.

Another challenge is to evaluate the impact of monitoring properties on the degrees of compliance. One solution is to use the numerical or analytical model and generate a population of samples with a unique combination of property values and evaluate the degree of compliance for each of them. This process may be computationally costly as sufficient number of samples should be generated to explore the multi-dimensional parameter spaces, especially if non-linear finite-element models are used (Bertola, Proverbio,

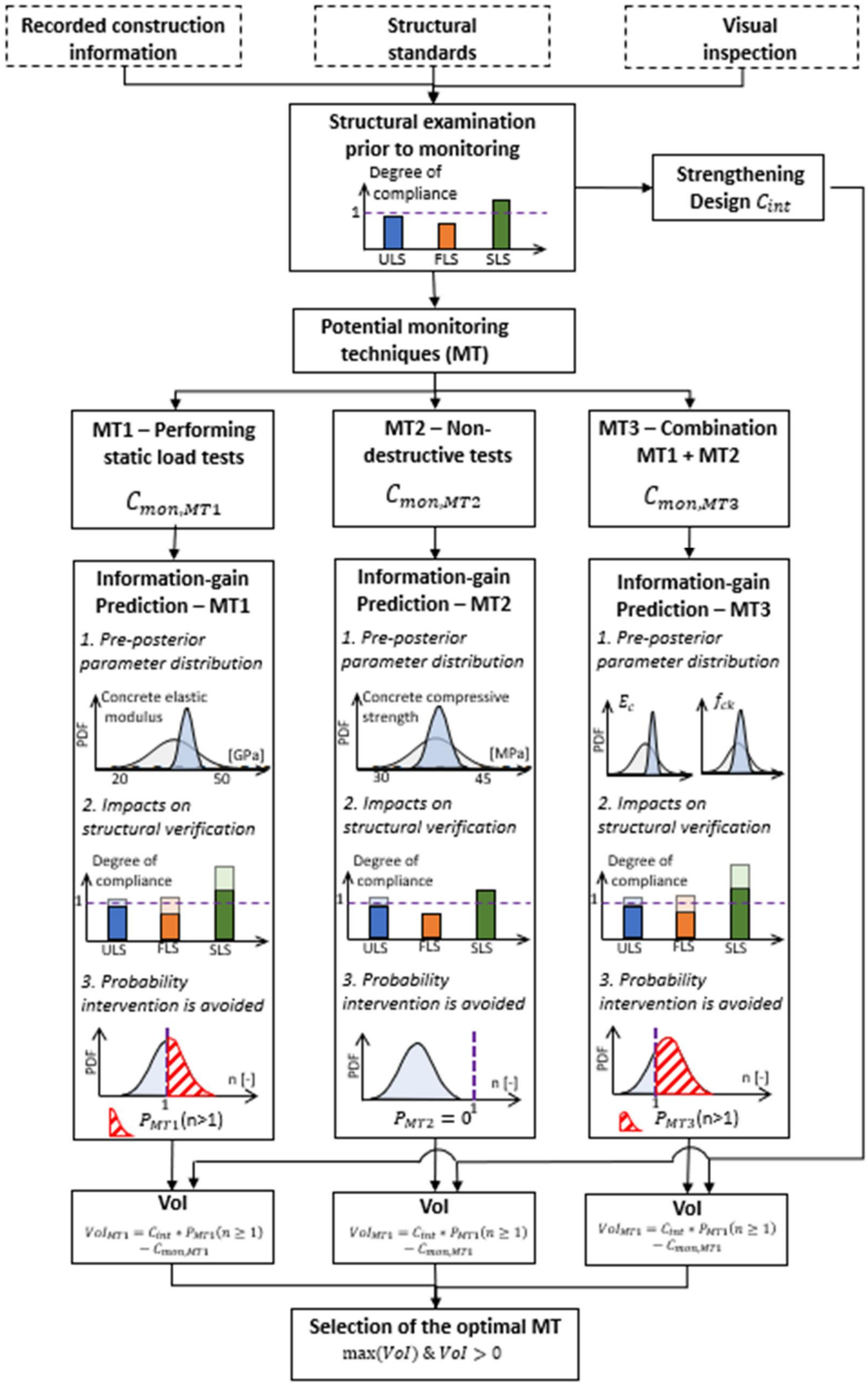

Figure 2. Flowchart of the methodology to assess the value of information of monitoring techniques.

et al., 2020). Using surrogate models is recommended to reduce the computational time of this step (Pai & Smith, 2021; Proverbio, Costa, et al., 2018).

When using direct measurements (i.e., using non-destructive tests), the identification range (measurement uncertainty) depends mostly on the repeatability of measurements that can be estimated based on sensor-supplier information and engineering judgment. The posterior parameter distribution is directly obtained by combining its prior distribution with the measurement uncertainty

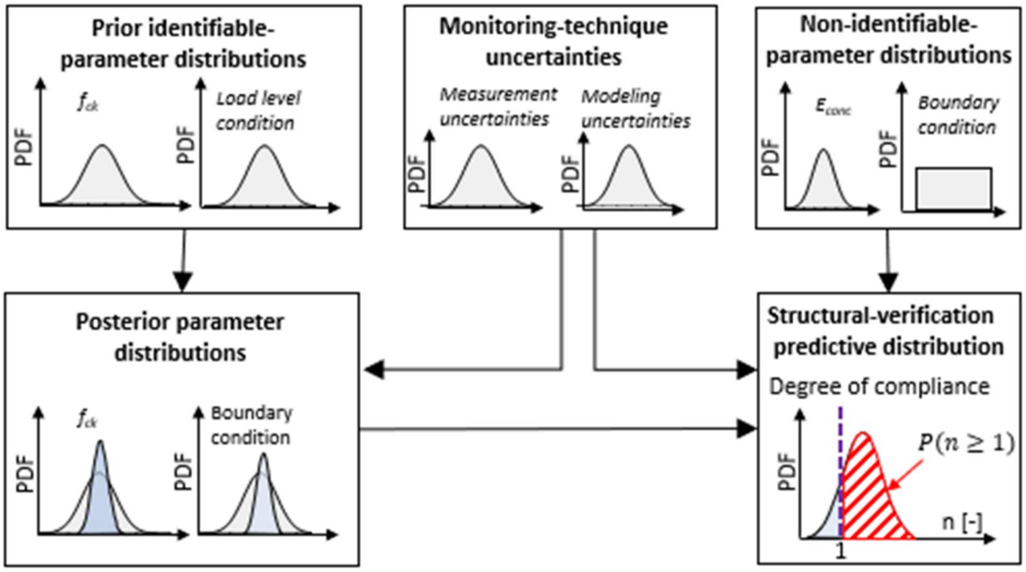

Figure 3. Detailed procedure to evaluate the value of information of a monitoring technique where parameter values of two parameters (E_{conc} and load level taken as illustrative examples) are directly measured (direct problem).

distribution using Monte-Carlo method (Figure 3). Then, by combining these posterior distributions with non-identified parameter prior distributions, and additional uncertainties (i.e., modelling uncertainties), a predictive distribution of a given degree of compliance is obtained. This combination is again computed using the Monte-Carlo method.

For indirect measurements (i.e., through an inverse analysis after bridge load testing), evaluating the posterior parameter distributions depends on the structural identification process between sensor data and model predictions. Defining the posterior parameter distributions thus depends on the sensor network that will be implemented, and the non-parametric uncertainties associated with the initial numerical models. The methodology to evaluate $P(n \geq 1)$ for the indirect MT is shown in Figure 4. Compared to Figure 3, the main difference lies in additional steps to obtain the posterior distribution. The combination of posterior distributions is computed using the same procedure described for direct measurements.

Sensor-placement methodologies provide information on the expected information gain, for instance, using the hierarchical algorithm as shown in Section 2.2 (Bertola et al., 2017b; Bertola, Proverbio, et al., 2020). First, the structural model is used to generate an initial set of model instances that are an instantiation of the model with a unique combination of bridge-parameter values that can be updated given the MT. The hierarchical algorithm evaluates the ability of a given sensor network to discriminate model instances based on the model and measurement uncertainties involved in the process. The initial model instance set is separated into multiple subsets. Each subset represents a possible outcome of parameter-value identification after monitoring.

Assuming that each model instance is equally possible, each outcome is assigned a probability calculated using the ratio between the number of model instances in the subset and the total number of model instances. Then, for each subset, parameter distributions can be recalculated using prior parameter values of model instances within the subset. A representive value of each parameter updated distribution is taken that is either the mean value for SLS verifications or the most conservative value for ULS and FLS. Then, the posterior distribution of the parameter is estimated given the subset representative value and its assigned probability. The predictive distribution of the degree of compliance is then calculated, including these posterior parameter distributions, remaining uncertainties and non-identifiable parameter prior distributions.

3. Case study

3.1. Presentation

In this section, a composite steel-concrete bridge used as a case study is introduced. This 195-meter-long viaduct is located in Switzerland and was built in 1959 (Figure 5). The composite superstructure involves a reinforced concrete (RC) slab monolithically connected to two steel box girders. The bridge has eight spans between 15.8 and 25.6 m. The RC slab has a total width of 12.7 m, and its thickness varies between 17 and 24 cm. The two steel girders have the same square sections of 1.30 m. In 2002, an intervention was made to strengthen the bridge. Longitudinal stiffeners were added to the steel box girders, and the Gerber's joints between the spans were fixed using steel connectors. It is worth mentioning that it is one of the first steel-concrete composite bridges in Switzerland and is important from a historical perspective (Mankar, Bayane, Sørensen, & Brühwiler, 2019).

Multiple MTs have been implemented on the bridge, and they are presented in the next paragraph. Measurements were collected between 2016 and 2019. A complete presentation of the monitoring system and the data collection is presented in (Bayane, Pai, Smith, & Brühwiler, 2021; Bertola

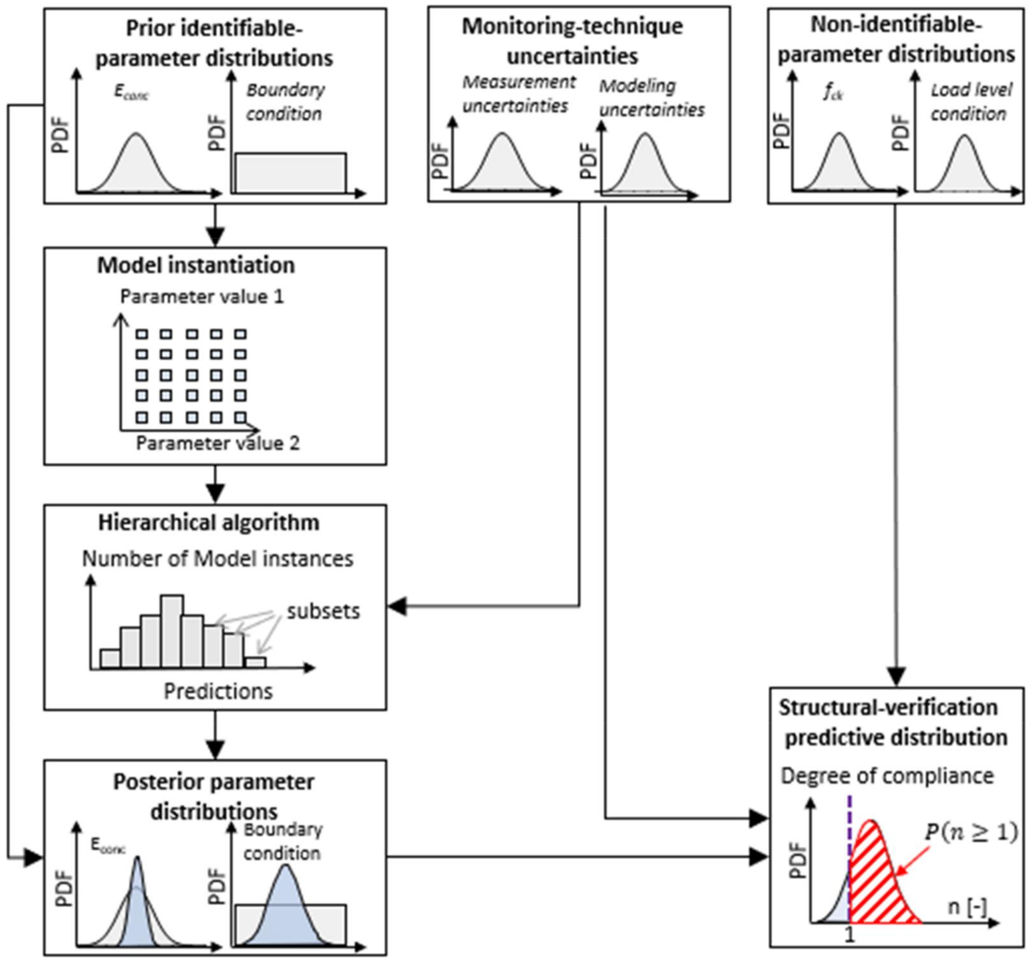

Figure 4. Detailed procedure to evaluate the value of information of a monitoring technique where parameter values are indirectly measured (inverse problem).

et al., 2023). The first MT involves NDTs (rebound hammer and sound velocity measurements). A static load test (second MT implemented) was performed on the fourth span in 2016 using a truck of 40 tons passing over the bridge at 10 km/h. Deflections and strains in the concrete deck were measured, and the sensor network involves three LVDTs, four strain gauges on the concrete deck, and one strain gauge and two LVDTs on the bottom of the steel girder at mid-span (Figure 5c and d). Strain gauges are glued to the rebars on the bottom layer of the steel reinforcement in the concrete deck in longitudinal and transverse directions (Figure 5e).

The third MT involves continuous strain monitoring using conventional gauges and thermocouples to evaluate traffic effects and temperature variations for three years continuously for a predefined period of three years. Additionally, weight-in-motion (WIM) station (fourth MT) was installed prior to the bridge to estimate axle-load distribution to re-evaluate ULS load model for three years (fourth MT). Table 1 provides a summary of the MTs implemented and their expected information gain on bridge parameters. These techniques have been selected as they provide information on different properties of the structural system, and they are thus complementary.

The bridge superstructure is modelled using the finite-element software SCIA (Khemlani, 2010) (Figure 6). The model involves 1D and 2D elements. Although most activities were performed on the same span, the entire bridge is modelled to improve the accuracy of the predictions. For the same reason, piers are included in the numerical model. The complex geometry of the RC deck is precisely modelled to predict the transverse deformation accurately. The mesh size has been defined as 400 mm, except for the span that has been monitored, where it is reduced to 100 mm, improving the precision of the predictions. This mesh size has been determined based on engineering experience and the sensitivity of the numerical model predictions at sensor locations. Predictions of this model are used for the structural verifications of all limit states.

3.2. Initial bridge examination without monitoring data

The bridge examination is performed without including monitoring data in the verifications (the first step of the SPM procedure). For this case study, this examination involves in total 25 verifications: 13 for the ultimate limit state (ULS), 10 for the fatigue limit state (FLS), and 2 for the serviceability limit state (SLS). These verifications involve structural capacity for ULS, fatigue capacity for FLS, and bridge deflections for SLS based on the requirements of the Swiss standards (SIA 269). ULS verifications involve comparing shear and bending actions to structural

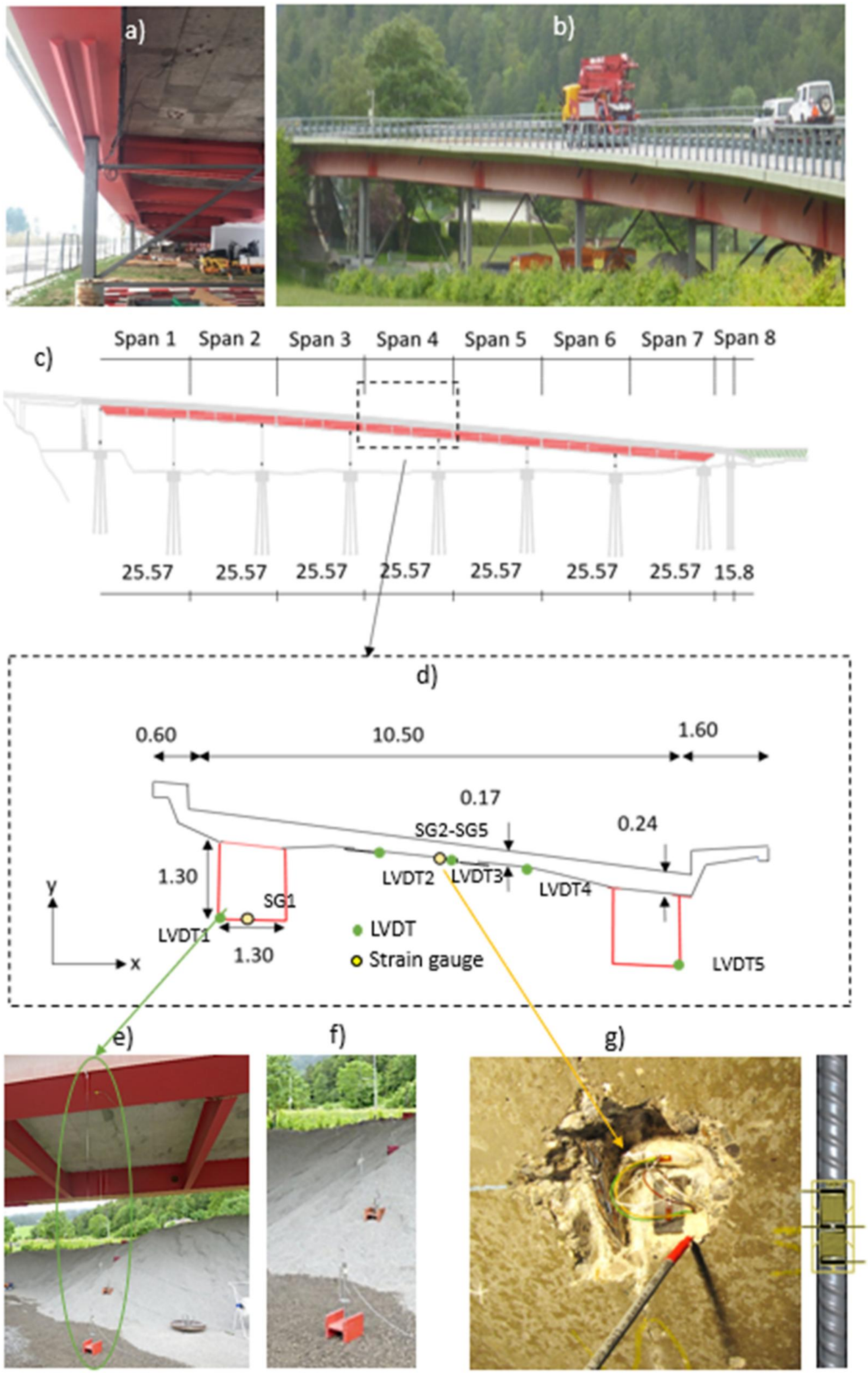

Figure 5. Bridge presentation. a; b) Bridge photographs; c) evaluation of the bridge; d) monitoring installed on the fourth span of the bridge; e,f) LVDT measurements; g) strain gauge glued on the longitudinal rebar at midspan.

resistances at multiple locations on steel girders, secondary steel beams, and the concrete deck. FLS verifications include comparing the maximum stress difference in the steel girders, secondary steel beams, and rebar in the concrete deck to acceptable values in the standards for the selected details. SLS verifications involve computing the short and long-term deflections of the bridge and comparing these predictions to the respective maximum requirement in the standards.

For each verification, the degree of compliance (Equation (7)) is calculated using predictions in terms of structural

Table 1. Summary of the monitoring technique performed on the bridge and their expected information gain on bridge parameters.

Name	Monitoring technique	Bridge parameters updated	Influence of structural verifications
MT1	Non-destructive tests	Material strength	Ultimate limit states (Verifications 1 to 13)
MT2	Load testing	Structural rigidity, Boundary condition	Serviceability limit states (Verifications 24 to 25)
MT3	Continuous monitoring	Traffic effects on rebar stress differences	Fatigue limit states (Verifications 14 to 23)
MT4	Weigh-in-motion	Axle-load distribution	Ultimate limit states (Verifications 1 to 13)

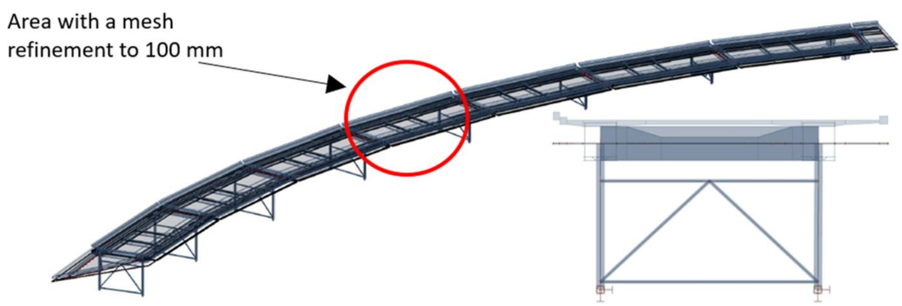

Figure 6. Bridge numerical model.

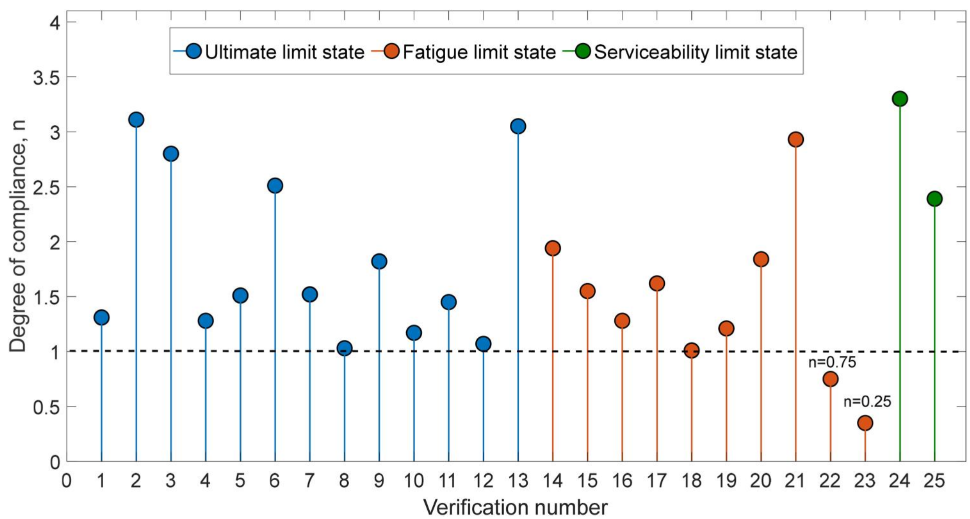

Figure 7. Degree of compliance for each structural verification.

capacity and load effects of the finite-element model. 2 out of the 25 structural verifications present a degree of compliance smaller than 1.0 (Figure 7). These verifications correspond to a fatigue deficiency due to important stress differences in the longitudinal and transverse rebars on the bottom of the RC deck. The bridge has a reserve capacity for ULS thanks to the intervention in 2002.

3.3. VoI evaluation

In this section, the VoI is evaluated for each combination of MTs. More specifically, a combination of MTs involves combining the monitoring outputs (in terms of bridge-parameter posterior distributions) from one or multiple techniques linearly. Five MT combinations are used in this study: the four MTs (Table 1) and their linear combinations. The VoI is independently calculated for the two structural verifications presenting deficiencies (N°22 et N°23) for the fatigue limit state (Figure 7), as it is conservatively assumed that these two verifications are independent.

The evaluation of the VoI of each combination of MTs is based on the decision tree shown in Figure 8. The decision tree shows the potential outcomes regarding bridge safety assessment of the four MTs (Table 1) and the linear combination of their outcomes. Based on this decision tree, the VoI of each combination of MTs is evaluated. The optimal combination of MTs is then defined using the solution with the largest positive VoI value compared to the solution without monitoring (NM). Four MTs (bridge load testing, continuous monitoring, WIM, NDT) are performed on the bridge (Section 3.2). Each MT will enable the update (using pre-posterior analysis) of various bridge parameters. These bridge parameters have a significant influence on a subset of structural verifications, and these relations are summarized in Table 1.

The VoI of each MT is first evaluated individually (Table 2). For the two structural verification (Structural Verifications 22 and 23) showing deficiencies ($n < 1$, Figure 7), the probability that structural safety will be ensured after monitoring $P(n \geq 1)$ is calculated for each MT. Results are detailed in the sequence. The NDTs enable

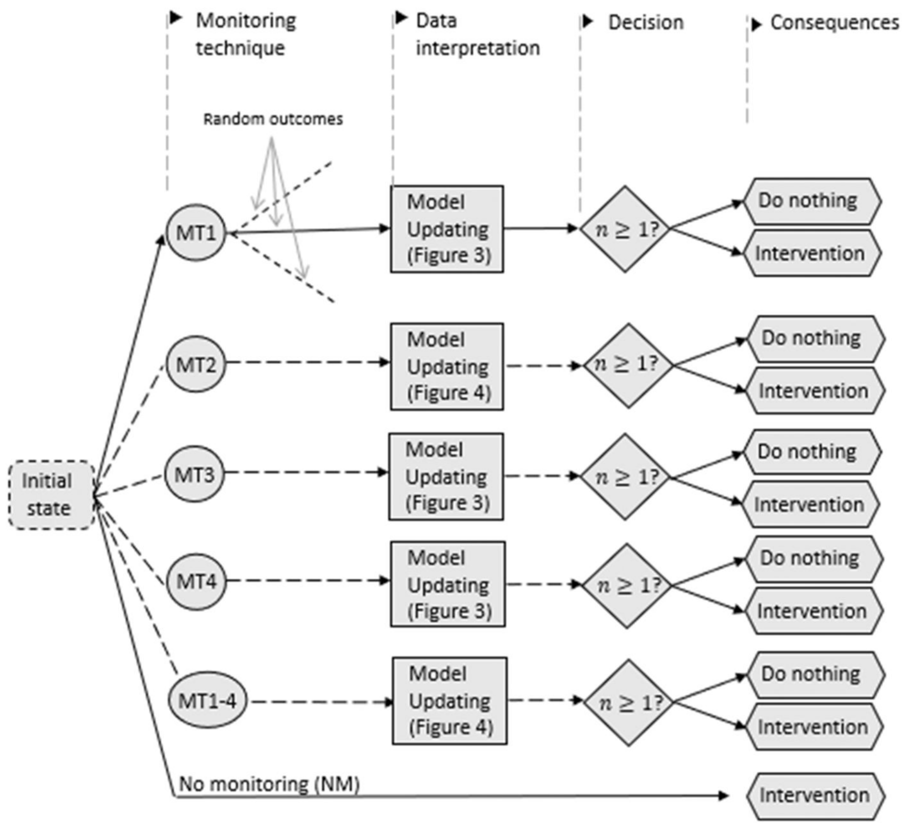

Figure 8. Decision tree for the VoI-based design of the optimal set of monitoring techniques for the present case study based on the four monitoring techniques and the linear combination of their outcomes.

Table 2. Probability that the monitoring-technique outcome will lead to a degree of compliance larger than 1.0 after monitoring for the two insufficient structural verifications.

Structural verification	Verification number	Degree of compliance before monitoring	Probability that the degree of compliance will be higher than 1.0 after monitoring $P(n \geq 1)$				
			NDT	*Load testing*	*Cont. Monitoring*	*WIM*	*Combined*
Fatigue long.	22	0.75	0	0	0.92	0	0.92
Fatigue trans.	23	0.34	0	0	0.25	0	0.25

the precise identification of the compressive strength of concrete, but this information does not influence the FLS verifications on the RC-deck rebars, $P(n \geq 1)$ of this MT is thus equal to zero. WIM data near the bridge provides information on the ULS load level, and this technique also has $P(n \geq 1)$ equal to zero. Both the continuous monitoring and the load testing may have a $P(n \geq 1)$ larger than 0, and their evaluations are detailed below.

The continuous measurements during the three years were implemented on the rebars subject to potential fatigue problems, providing direct monitoring of the strain in these rebars. These measurements are then transformed into stress difference by multiplying them with the steel elastic modulus estimated to 205 GPa. The prior distribution of the maximum stress difference is defined using a normal distribution with a mean value of 85 MPa and a standard deviation of 20 MPa. This distribution has been estimated based on sensitivity analysis of the numerical model, WIM data in Switzerland, and engineering judgment. Due to the large data sample, the posterior parameter distribution is taken as quasi-equal to the prior distribution with an identification range of 1 MPa (Figure 9). This identification value is based on the sensor precision and measurement repeatability (reproducibility) of the instrument.

The total uncertainty distribution is calculated as the combination of distributions of sensor precision and steel elastic modulus variability (Figure 9b). The predictive distribution of the degree of compliance is calculated using Monte-Carlo Sampling (1'000'000 simulations) by combining both the posterior parameter (stress-difference) distributions and the total uncertainty (discrepancy distribution). Then this distribution is divided by the steel fatigue capacity is equal to $\Delta\sigma_{Rd} = 80\ MPa$ to obtain the predictive distribution of the degree of compliance. Figure 9c shows the predictive distribution of the degree of compliance for the longitudinal rebar (Structural Verification 22). Given this predictive distribution, $P_{CM,22}(n \geq 1)$ is equal to 0.92, showing that the probability that the degree of compliance is larger than 1.0 after monitoring, is significant using this MT. In other words, it means that the safety for Structural Verification 22 is ensured with a probability of 92% after performing the continuous-monitoring technique. Therefore, there is only an 8% probability that structural safety will not be ensured for Structural Verification 22

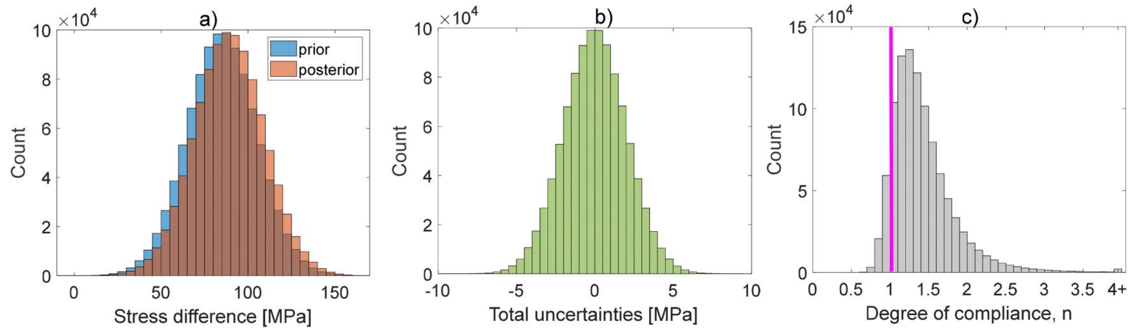

Figure 9. Evaluation of the value of information of the continuous monitoring technique for Verification 22. a) Prior-posterior distributions of stress difference; b) evaluation of total uncertainties in the stress difference (discrepancy distribution); c) estimation of the predictive distribution of the degree of compliance obtained after monitoring.

once data from the continuous-monitoring technique is collected.

The static load testing on the bridge provides indirect information on structural properties, as deflection and strain are measured rather than the structural stiffnesses and boundary conditions. Details on the sensor network and the three selected model parameters are presented in Section 3.4. Three parameters have been identified using sensitivity analysis for the given load test (see details in Section 3.4). In this 3-parameter space, 806 model instances are generated using a grid-space sampling technique (J.-A. Goulet, Kripakaran, & Smith, 2010). These models represent the initial model class that will be used in the data interpretation in the next section.

The hierarchical algorithm (Section 2.1.2) is used to predict the information gain (Figure 10a), given this model-instance set, sensor network, and total uncertainties (Figure 10c). Results show that more than 30 model-instance subsets are predicted by the algorithm (Figure 10b). Each subset represents a possible monitoring outcome (or scenario) obtained by the algorithm. Each outcome has an assigned probability depending on the number of model instances in the subset (Section 2.1.2). For each subset, a mean value for each parameter is taken as the critical structural verifications involved FLS limit states. The posterior parameter distributions are then calculated (Figure 10d). If ULS verifications are critical, conservative parameter values are taken from the subset parameter ranges to evaluate the predictive distributions of structural verifications to ensure structural safety. Based on these expected posterior parameter distributions, the predictive distributions of the degree of compliance are evaluated (Figure 10e and f), where Structural Verifications 22 and 25 are taken as examples.

For Structural Verification 22, the degree-of-compliance predictive distribution is significantly lower than 1.0, showing that this monitoring technique does not provide significant information for this structural verification. This result is explained because the parameters identified during the static load testing (structural stiffnesses and boundary conditions), do not significantly influence the FLS verifications that mainly depend on the action effects of the traffic loading.

Although load testing provides information on the structural stiffness and boundary condition, this monitoring technique is not recommended as it cannot significantly influence the decision regarding FLS bridge safety. Therefore, continuous monitoring is recommended based on the VoI of each monitoring technique as long as the VoI is larger than 0 (Equation (8)) using the minimum value of $P(n \geq 1)$ found in Table 2. For Structural Verification 22, $P(n \geq 1)$ is equal to 0.25 which means that there is a probability of 25% that the structural safety will be ensured after monitoring. The costs of monitoring and the costs of intervention should then be compared (Equation (9)) in order to take the decision whether the monitoring technique should be performed or not. In practice, it is very likely that C_{mon} will be significantly lower than the C_{int}, and consequently the monitoring is recommended:

$$VoI_{SPM} = C_{int} * P(n \geq 1) - C_{mon} \tag{8}$$

$$\frac{C_{mon}}{P(n \geq 1)} = \frac{C_{mon}}{0.25} \leq C_{int} \tag{9}$$

3.4. Data collection and interpretation

In this section, the data collection and data interpretation of the four MTs are summarized. Detailed analyses are presented in Bertola et al. (2023, 2022). The first MT involves NDTs (rebound hammer and sound velocity measurements). These tests were performed on the concrete deck on the four spans at several locations. Thanks to this monitoring, an update of the concrete compressive strength, initially assessed at 30 MPa, to f_{ck} (characteristic value) equal to 38 MPa was possible. This result slightly influences evaluations of the structural capacity for ULS verifications.

The second technique involves long-term monitoring of longitudinal and transverse rebars in the concrete deck, showing potential fatigue deficiencies. Based on the measurements, stress histograms are created (Figure 11a and b), and are compared to the fatigue endurance limit of 80 MPa for straight ribbed steel rebar fatigue detail in Swiss standards (Swiss Society of Engineers & Architects, 2011). The measured stress levels are significantly lower than predicted using code-based load levels without monitoring information. One reason for this large difference is that the actual traffic on the bridge produces significantly lower action effects than code load models. This information is only used for these two FLS verifications.

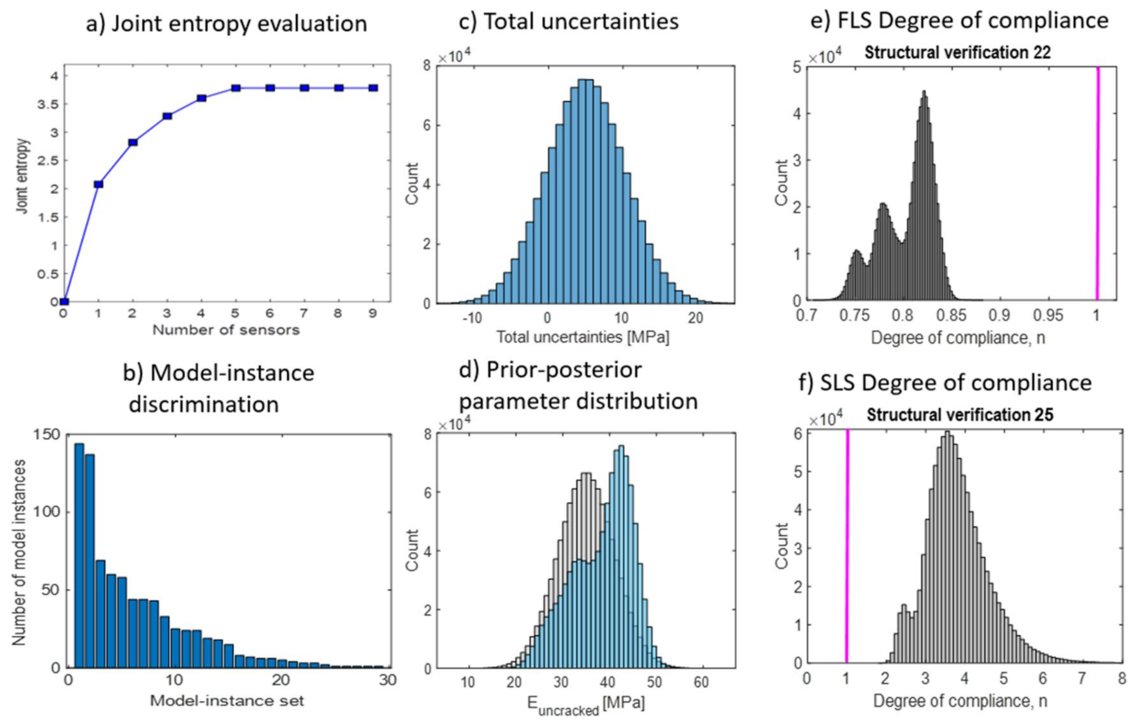

Figure 10. Evaluation of the value of information of the load-testing technique for several structural verifications. a) Joint-entropy results obtained with the hierarchical algorithm; b) discrimination of the model-instance set; c) evaluation of total uncertainties for the $E_{uncracked}$ parameter (discrepancy distribution); d) estimation of the pre-posterior parameter distribution for the $E_{uncracked}$ will be obtained after monitoring. e, f) Estimation of the predictive distribution of the degree of compliance that will be obtained after monitoring for structural verifications 22 (FLS) and 25 (SLS), respectively.

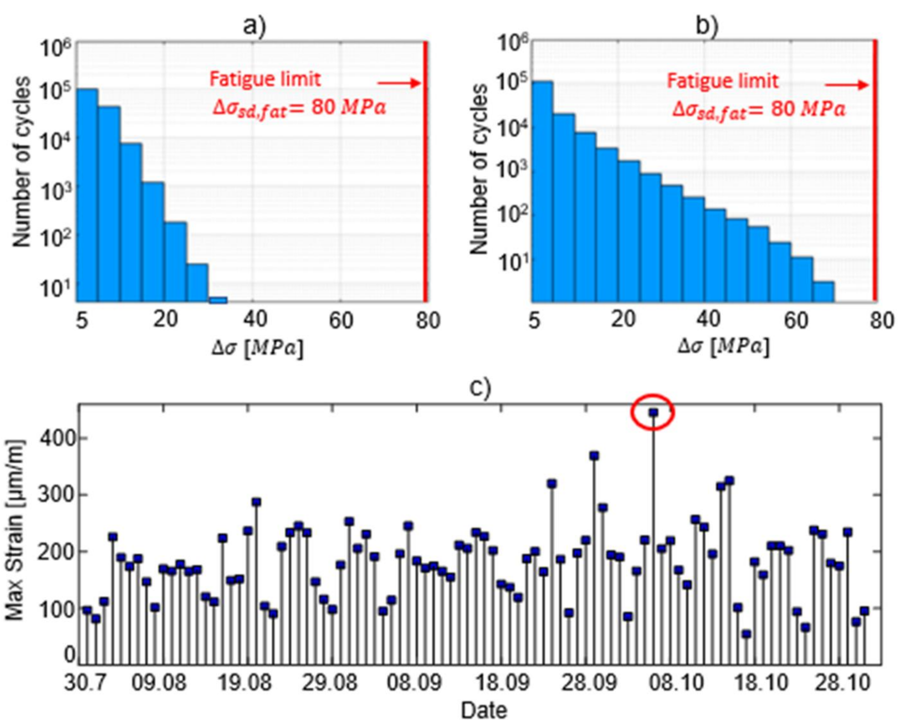

Figure 11. Results of the data collection. a), b) histogram of stress difference measured during three years in the transverse and longitudinal rebar subjected to potential fatigue insufficiency; C) daily maximum strain measured when the unauthorized crane passed through the bridge.

The third MT involves a WIM station near the bridge to determine axle-load distribution. The monitoring was made over three years between 2016 and 2019, and detail of this monitoring can be found Bayane, Mankar, Brühwiler, and Sørensen (2019). On the 6th of October 2016, an unauthorized crane of 60 tons passed over the bridge. The continuous monitoring shows that this crane produces a much larger recorded stress level. The load level associated with this crane is twice as large as the average value and 25% larger than the second-largest measurement of usual traffic (Figure 11c). This load level has a probability of occurrence smaller than 10^{-6}/year (Bayane et al., 2019). Further to this, the ULS load level is updated, and this crane is considered as exceptional traffic loading, and placed at the locations that maximize action effects on the bridge. The structural safety of the ULS can then be re-evaluated.

The fourth MT involved bridge load testing in 2016. The measurements from the static load test are then used to update the FE model. Three model parameters are selected based on a sensitivity analysis and model-class selection process. The first two parameters: cracked and uncracked rigidity of the deck. Based on the traffic on the bridge, it was concluded that the bridge deck should be cracked in the middle portion, reducing its rigidity. This rigidity variation is simplified as a variation of concrete modulus of elasticity. Smaller values are considered in the central part of the slab due to the expected cracking. The third parameter involves the rotational stiffness between the elements at the Gerber joints due to steel connectors. Uncertainty levels associated with the measurements and the modelling have been estimated based on sensor-supplier information, literature review, repeatability during load testing, and engineering judgment. Larger model uncertainties are considered for concrete measurements due to the higher variability of material properties and difficulties in predicting cracking behaviour.

The initial parameter ranges are presented in Table 3. Ranges of equivalent moduli of elasticity for both cracked E_{cr} and uncracked E_{nc} sections are considered following SIA 269 (Swiss Society of Engineers & Architects, 2011). Ranges are defined with the minimum and maximum bounds, and these values are evaluated based on these Swiss standards and engineering experience. The value range models the connection from a perfect hinge to a fixed joint. A set of 806 model instances, with a unique combination of parameter values, has been generated using the finite-element model. The data interpretation is made using EDMF (Section 2.1.1).

The results of the identification are also shown in Table 3. From the initial 806 model instances, only 11 are candidates, meaning that the falsification process allowed the rejection of 795 models with large discrepancies between their predictions and measurements. A precise identification has been obtained for the cracked stiffness of the deck and rotational stiffness at the support, but little information has been collected on the uncracked stiffness of the deck. Based on the update of these structural properties, the structural verifications can be re-evaluated. Updated properties of this MT mainly influence SLS and FLS verifications.

3.5. VoI results validation using field measurements

In this section, VoI estimations based on the proposed methodology are compared to observations after the performance of the MTs. In Section 3.3, it was concluded that the continuous monitoring would provide significant information gain for the two deficient structural verifications (Verifications 22 and 23), while the bridge load testing will not provide information enabling a degree of compliance larger than 1.0. Predictive distributions of the degrees of compliance were obtained and will be compared to the true value after monitoring. The predictive distribution is computed by combining the prior distributions and the discrepancy function, following methodologies shown in Figure 3 or Figure 4. The shape of the predictive distribution mostly depends on the MT implemented that leads to different parameter posterior distributions.

Figure 12 depicts the degree-of-compliance predictive distributions of both deficient structural verifications based on expected information collected with the continuous-monitoring technique. The predictive distribution of the degree of compliance is compared with the observed value after monitoring ($n_{i,meas}$). The degree of compliance without monitoring ($n_{i,NM}$, obtained deterministically) is provided as a benchmark. Mean values of the predictive distribution (n_{mean}) are significantly larger than the values obtained without monitoring information (n_{MN}). Moreover, the observed values after monitoring (n_{meas}) are within the predictive distributions, showing that the methodology was able to accurately predict the information gain of the continuous-monitoring technique. Monitoring results also show that the observed degrees of compliance are larger than code requirements ($n_{required}$), meaning that the bridge safety is verified, and structural strengthening is not needed (do-nothing action).

The predictive distributions of the degrees of compliance of both deficient structural verifications based on the expected results of the bridge load testing are shown in Figure 13. The predictive distribution of the degree of compliance is compared with the observed value after monitoring ($n_{i,meas}$). The degree of compliance without monitoring ($n_{i,NM}$, obtained deterministically) is provided as a benchmark. As predicted by the VoI framework, the results of the revaluation of the degrees of compliance for both structural verifications show that this MT cannot improve the degrees of compliance above the code requirements ($n_{required}$). Moreover, n_{meas} values are within the predictive distributions obtained with the proposed methodology, showing that the methodology also accurately predicts the expected information gain for this MT.

Although VoI is negative, the framework also enables the evaluation of the information gain after monitoring for structural verifications with an initial degree of compliance larger than 1.0 (Figure 14). The predictive distribution of the degree of compliance is compared with the observed value after monitoring ($n_{i,meas}$). The degree of compliance

Table 3. Results of parameter identification based on the static load tests and data interpretation using EDMF.

Parameters	Unit	Prior to load testing	After load testing
Number of plausible model instances	[-]	806	11
P1 - Cracked stiffness of the deck ($E_{cracked}$) range	[GPa]	3–20	11.5–12.5
P2 - Uncracked stiffness of the deck ($E_{uncracked}$) range	[GPa]	20–50	24–42
P3 - Rotational stiffness at the support (K_{rot}) range	[MNm/rad]	0–400	49–55

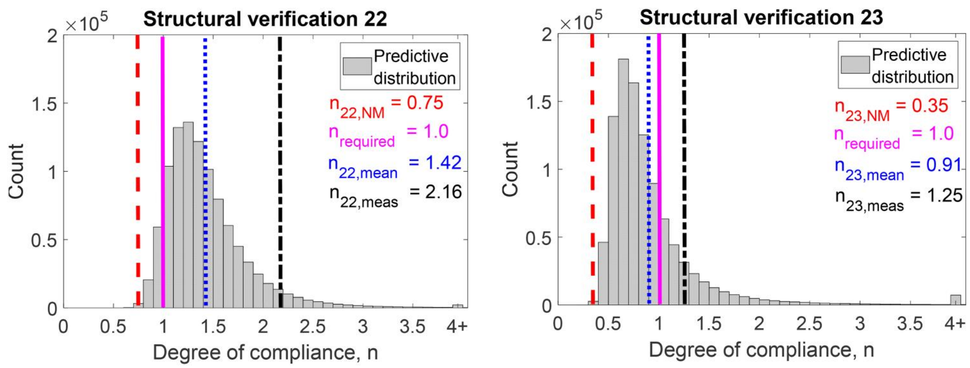

Figure 12. Validation of VoI estimation of the observed degree of compliance of both insufficient structural verifications using the continuous monitoring technique.

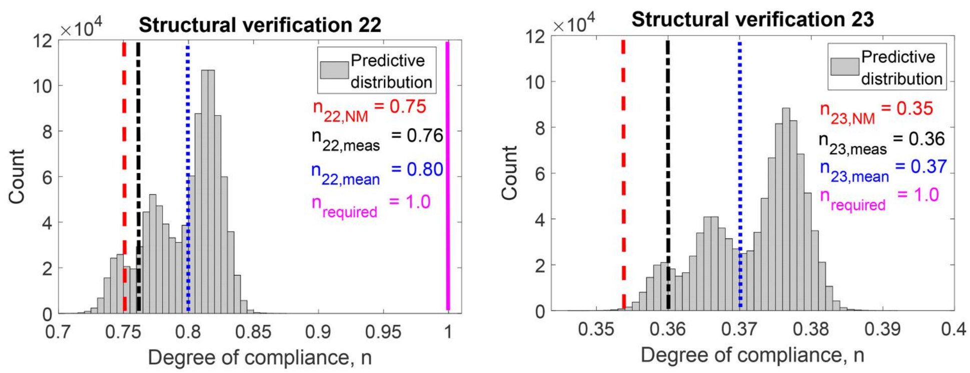

Figure 13. Validation of VoI estimation using the observed degree of compliance both insufficient structural verifications using bridge load testing.

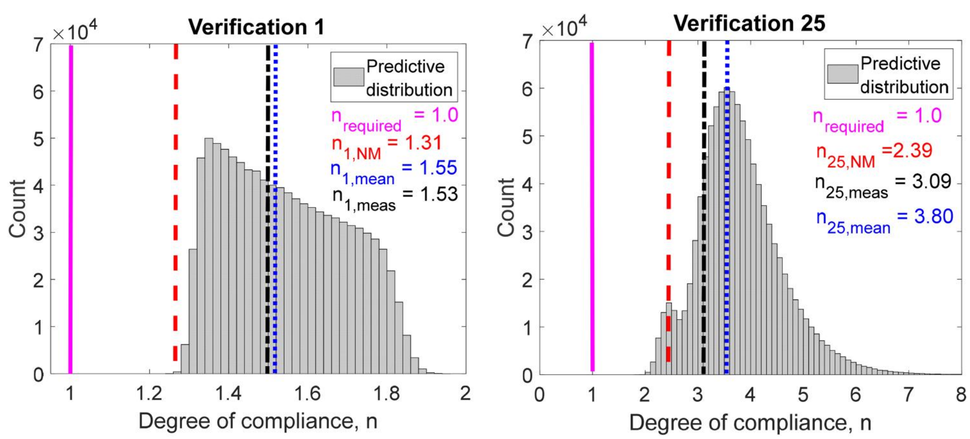

Figure 14. Validation of information-gain prediction using the observed degree of compliance after monitoring for two structural verifications for ULS (left) and WIM monitoring and SLS (right) with bridge load testing.

without monitoring ($n_{i,NM}$, obtained deterministically) is provided as a benchmark. This evaluation provides information on whether a MT is useful to increase the degree of compliance, which could be helpful if modifications are made to the bridge (i.e., widening) in the future. The WIM MT enables an information gain for the ULS verifications, such as Verification 1, while the bridge load testing provides significant information for the SLS verification (i.e., Verification 25). The observed values (n_{prior}) are close to the mean values of the predictive distributions (n_{mean}), showing that the VoI framework accurately predicts information gain for SPM for all types of structural verifications and MTs.

4. Discussion

In this study, a framework has been introduced to evaluate the value of information (VoI) of MTs for SPM. The framework was applied to a composite bridge in Switzerland that has been extensively monitored between 2016 and 2019. Results show that only continuous monitoring has a positive VoI. The VoI is a strict metric that only provides useful information when it can change the decision, in the present case regarding bridge fatigue-safety assessment. This definition implies that a MT that improves a degree of compliance larger than 1.0 without monitoring information, is not recommended.

Table 4. Expected influence of monitoring information on structural verifications.

Structural verification	Mean degrees of compliance before monitoring	Expected mean degrees of compliance after monitoring				
		NDT (MT1)	Load testing (MT2)	Cont. Monitoring (MT3)	WIM (MT4)	Combined (MT5)
SLS	2.84	2.91 (+3%)	3.23 (+14%)	2.84 (+0%)	2.84 (+0%)	3.23 (+14%)
FLS	1.45	1.45 (+0%)	1.45 (+0%)	1.76 (+25%)	1.45 (+0%)	1.76 (+25%)
ULS	1.82	1.88 (+2%)	1.82 (+0%)	1.82 (+0%)	2.12 (17%)	2.15 (+18%)
All (average)	1.75	1.79 (+2%)	1.79 (+2%)	1.80 (+3%)	1.91 (+9%)	2.08 (+19%)

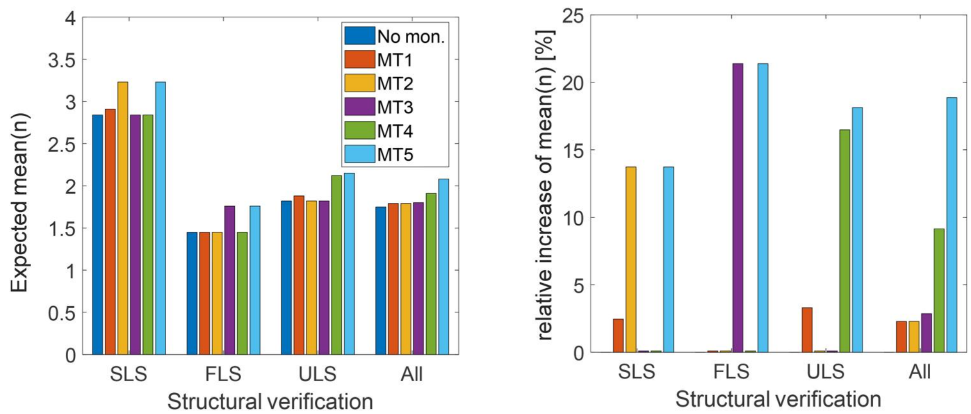

Figure 15. Expected mean degree of compliance for each combination of monitoring technique (left). Relative increase of the mean degree of compliance compared to the no-monitoring scenario (right).

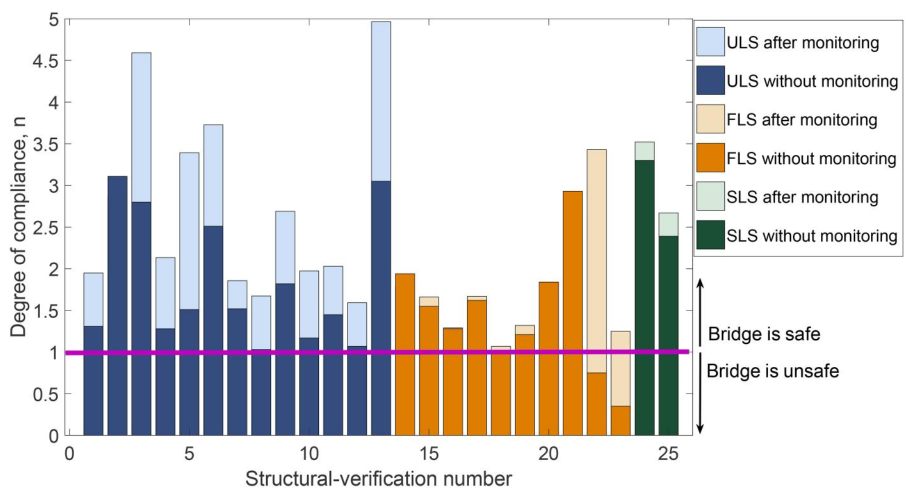

Figure 16. Degrees of compliance for all structural verifications before and after monitoring.

A less-strict definition of the information gain (i.e., the average increase of degrees of compliance) would have led to a different conclusion regarding recommended MTs. Table 4 shows the expected information gain for each monitoring and structural verification, using the mean value of the predictive distributions of the degrees of compliance (n_{meas}). Results are also presented as a bar plot in Figure 15. Except for the NDTs, all MTs provide information that significantly improves the degrees of compliance of structural verifications. Nonetheless, only load testing provides useful information for SLS verifications, while FLS verifications are mostly influenced by continuous monitoring and ULS verifications by the WIM data. Combining all MTs leads to an average expected increase of degrees of compliance of 19% over the 25 structural verifications, showing that monitoring can provide significant information for bridge performance evaluation. This expected increase in degrees of compliance is calculated as the average value of mean values of predictive distributions from all structural verifications (SLS, FLS, ULS) that are calculated independently.

Figure 16 presents the degrees of compliance, including and without monitoring information for all structural verifications. All MTs are used to re-evaluate the degree-of-compliance values. Most structural verifications have a significant increase of degree-of-compliance values, with an average increase of 36%. This result shows that monitoring information has an important potential to improve evaluations of the structural performance of bridges. Additionally, all structural verifications have a degree of compliance larger than 1.0 after monitoring, meaning that the bridge is safe and no structural strengthening is needed.

The following limitations of the framework are recognized. The framework predictions involving predictive distributions of degrees of compliance are significantly influenced by the initial prior distributions of bridge parameters. Although prior distributions for material properties or boundary conditions are well documented, it may be challenging to define load levels accurately if reliable WIM data are unavailable near the bridge.

The predictions of the structural capacity depend on the quality of the numerical model provided. A numerical model is required to accurately predict the predictive distribution of the degrees of compliance that match the observed values. It has been seen that sometimes the monitoring results lead to a modification of the physics-based model, as shown for steel bridge case studies where boundary conditions have been modified in an iterative process (Pasquier & Smith, 2016; Proverbio, Favre, et al., 2018), meaning that initial model predictions were inaccurate. For the present case study, a simpler numerical model (for instance, without properly modelling the complex geometry of the deck), would have led to the entire falsification of the 806 model instances, leading to refining the model simplification.

In such situations, the initial evaluation of the VoI may also be inaccurate. Nonetheless, the monitoring information leads to an iterative process where the numerical model is updated and then updated based on the data collected. If monitoring data enables an improvement of the numerical model, which leads to more accurate predictions of structural capacity, the benefit of the monitoring is already significant. Nonetheless, this information gain is difficult to be quantified. For the present case study, using a simpler numerical model would have led to inaccurate VoI estimations, but monitoring data would trigger a refinement of the numerical model, providing crucial information for decision-making. In case of uncertainties in the model class, multiple scenarios of structural models could be incorporated in the VoI evaluations, following recommendations for optimal sensor placement in such situations (Bertola, Pai, & Smith, 2021). Future work will consist in quantifying the impact of multiple models on the VoI estimations.

The proposed framework requires evaluating the degrees of compliance for a significant number of simulations. Evaluating structural capacity may require significant computational time, especially when using non-linear numerical models. In such situations, building surrogate models of structural verifications is recommended to overcome the computational costs (Cheng & Lu, 2020; Pai & Smith, 2022).

5. Conclusions

In this paper, a framework is introduced to quantify the value of information of MTs for structural performance monitoring. A combination of four MTs is evaluated mainly: non-destructive tests, bridge-load testing, continuous monitoring of stress due to traffic loading, and weight-in-motion. These evaluations account for the monitoring costs and the probability that structural interventions will be avoided after monitoring. The methodology has been applied to a composite steel-concrete bridge in Switzerland, and monitoring results have corroborated the prediction in terms of expected information gain (i.e., increase of degrees of compliance) from multiple MTs. The expected average increase of degrees of compliance of 19% is estimated using the proposed framework, which is consistent with the 36% average compliance increase observed after monitoring. In this context, the following general conclusions are drawn:

- Performing a monitoring campaign can effectively update the assessment regarding bridge fatigue and structural safety as well as serviceability, as monitoring often leads to accurate rather than conservative bridge-property values.
- Each monitoring technique provides unique but also redundant information about the bridge properties. Therefore, their optimal combination should be carefully evaluated.
- The proposed framework can support engineers in the selection of the optimal monitoring techniques for structural performance monitoring when multiple techniques are possible. The framework enables maximizing the value of monitoring information when multiple monitoring techniques are possible.

Considering the assumptions used in the present work, future research consists of including the expected impacts of monitoring information on the design of the interventions and refining the proposed methodology for the inclusion of the cost of intervention as a variable. Another research topic will be the extension of the proposed methodology to include the possibility that monitoring information will lead to significant modifications of the bridge behavior models.

Disclosure statement

No potential conflict of interest was reported by the authors.

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