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Assessment of the information gain of several monitoring techniques for bridge structural examination

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Abstract

The examination of existing civil structures must be differentiated from designing new structures. To have sustainable and circular asset management, the behavior of these existing structures must be better understood to avoid unnecessary maintenance and replacements. Monitoring data collected through bridge load testing, structural health monitoring, and non-destructive tests may provide useful information that could significantly influence their structural-safety evaluations. Nonetheless, these monitoring techniques are often elaborate, and the monitoring costs may not always justify the benefits of the information gained. Additionally, it is challenging to quantify the expected information gain before monitoring, especially when combining several techniques. This paper proposes several definitions and metrics to quantify the information gained from monitoring data to better evaluate the benefits of monitoring techniques. A full-scale bridge case study in Switzerland is used to illustrate the information gain from multiple monitoring techniques. On this structure, static load tests, three years of strain monitoring, weigh-in-motion measurements, and non-destructive tests were performed between 2016 and 2019. The influence on structural-safety examination is evaluated for each combination of monitoring techniques. Results show that each technique provides unique information and the optimal combination depends on the selected definition of information gain. When data from monitoring techniques are combined, significant reserve capacity of the bridge is determined.

Keywords Existing bridges · Non-destructive evaluation · Structural health monitoring · Bridge load testing · Bridge assessment

1 Introduction

Current structural-engineering research is predominately driven by the goal of improving the designs of new structures. The vocation of structural engineers still is mainly to build new structures rather than assess existing ones. For many structural engineers, an existing structure has a service duration of 80 to 100 years, after which a new structure should replace it. While this approach was perhaps rational 50 years ago, it is nowadays far away from the sustainability requirements of modern societies [1]. As existing structures represent tremendous assets and wealth, societies must preserve them as much as possible. Additionally, some structures are of such technical or cultural significance

that replacement is simply not acceptable, such as Golden Gate Bridge and Eiffel Tower. Structural engineers are thus increasingly called upon to maintain and preserve existing structures, as replacements are neither sustainable nor cost-effective [2].

In practice, the assessment of existing structures is typically made based on construction drawings, recorded information on the materials used, and visual inspection [3, 4]. Missing information, such as material properties or rebar layouts, is compensated by conservative assumptions by structural engineers following new-design principles. Nonetheless, existing structures are physical assets that can be monitored. Therefore, uncertainties related to existing structures can be drastically reduced [5], leading to more accurate estimations of structural safety [6]. Two main approaches of structural monitoring should be differentiated: the estimation of the structural capacity at a given time, called structural performance monitoring (SPM), and the evolution of the structural behavior over time, called structural health monitoring (SHM). Both monitoring techniques can be regrouped

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under the name of non-destructive evaluation (NDE) [7]. Although a broad range of sensing and monitoring technologies have been developed over the last decades, NDE is still rarely used in practice for the structural examination of existing bridges [8].

SHM uses sensor networks that monitor the structural response over time due to typically unknown stimuli such as vehicle loading, wind, and temperature variation [9, 10]. One key goal of SHM is to detect damages based on changes in structural behavior inferred from sensor data [11, 12]. Another goal of these monitoring systems is to evaluate the environmental effects of the bridge behavior [13, 14]. Sensor networks typically involve many sensors, including accelerometers, thermocouples, strain gauges, and tiltmeters, among others [15, 16]. Due to the large datasets, machine learning and big data tools are required [17, 18]. As they are typically model-free approaches [19], the information extracted from field measurements often cannot be used to assess the compliance of the structural behavior with code requirements [20].

SPM includes several monitoring techniques, including non-destructive tests (NDT), weight-in-motion (WIM), and bridge load testing. In NDT, instruments are locally deployed to temporarily measure the structural response under a known test setup [21, 22]. Structural properties (such as the location of steel reinforcement and concrete cover) and material properties (such as modulus of elasticity and concrete strength) are typically measured [23]. Techniques include ground penetrating radar [24], ultrasonic testing [25], and rebound hammer testing[26], among others.

WIM stations measure axle and gross vehicle weights as vehicles pass through the measurement site. The maximum traffic demand can be updated by extrapolating the measurements over a given period of time [27, 28]. Bridge weight in motion (BWIM) uses monitoring systems, such as strain gauges to infer actual traffic load based on sensor measurements [29, 30]. BWIM presents the advantage of being easier to install than WIM devices and simultaneously provides information on the structural systems. For instance, strain gauges installed on critical elements for fatigue limit states can measure actual stress differences on these elements [31, 32].

Bridge load testing with controlled static [33], dynamic [34], or both [35] excitations is used to characterize the structural and material properties, including the boundary conditions of an existing structure [36]. These data are typically used to update a numerical model, improving the predictions of current structural capacity [37, 38], and this process is called structural identification [39]. As the data interpretation is not trivial, advanced methodologies for model updating are recommended [2, 40]. Structural identification is often made using a residual-minimization approach due to its simple formulation [41, 42]. This methodology has

been shown to provide inaccurate and unsafe predictions, especially in extrapolation tasks [43, 44]. Researchers have developed a structural-identification framework based on Bayesian model updating [45, 46] and the model-falsification approach [6, 47].

No matter what monitoring technique is performed, sensors and measurement systems must be carefully selected to maximize the information gain during monitoring [48, 49]. Studies have developed strategies to predict information gain of monitoring systems, for instance, based on information entropy [50–52]. Nonetheless, in these studies, the information gain is evaluated based on uncertainty reduction rather than impacts on decision-making. Other researchers have evaluated the value of information by comparing the expected benefits against monitoring costs [53–55].

Although several monitoring techniques are used for SPM, they are barely combined. One reason is the large number of sensor devices and data-interpretation tools that are required to perform several monitoring campaigns on the same structure. Another reason is the lack of understanding and predictability of the complementary information gained by these monitoring technics. The comparison of the information gain from multiple monitoring techniques is difficult as these techniques provide data on different aspects of the structural behavior.

This paper presents metrics to evaluate the information gain from several monitoring technics. Rather than estimating the reduction of uncertainties, these metrics evaluate the influence on structural verifications for all limit states. Three information gain metrics are introduced. Results of a full-scale bridge case study that has been monitored using four techniques between 2016 and 2019 show that the useful monitoring data mainly depends on the definition of information gain.

The manuscript is organized as follows. Section 2 presents the metrics for the evaluation of information gain from monitoring techniques. In Sect. 3, the monitoring of the case study is shown, and the information gain from each technique for each metric is assessed. A discussion on the predictability of the monitoring-technique information gain is made in Sect. 4.

2 Evaluating information gain from monitoring techniques

2.1 Examination of existing structures

Current structural engineering is predominantly driven by the approach of designing new structures. Existing structures cannot be treated as new designs as the uncertainties differ significantly. This section introduces the approach to

examining the structural safety of existing structures and evaluating the information gain from monitoring techniques.

The main differences between examining existing structures and designing new structures are listed below. Existing structures are physical assets that can be inspected and monitored. Geometrical uncertainties, such as bridge-element dimensions, are thus small. As they were often built decades ago, available information from the construction may be limited; for instance, reinforcement drawings are sometimes missing. Material properties can have large uncertainties due to the historical construction techniques and industrial processes. Additionally, deterioration processes may impact the structural behavior and reduce the structural-element capacity.

In Switzerland, the Swiss Standards for Existing Structures (SIA 269) was introduced in 2011 [56]. In this standard, the notion of degree of compliance, n (Eq. 1), is introduced for the verification of structural safety. Each element is evaluated for each structural verification of serviceability, fatigue, and ultimate limit states. A value of n larger than 1.0 means that structural safety is ensured for a given structural verification. Using this metric, the reserve capacity (or the structural deficiency) is quantified.

$$n = Capacity/Demand \tag{1}$$

2.2 Metrics to quantify information gain from monitoring

Monitoring activities can reduce the uncertainties on the structural behavior of existing structures. Field measurements, collected using sensor devices, provide information on the structural behavior under given load conditions. The measurements are then interpreted, the structural capacity is re-examined, and degrees of compliance are updated.

The quantification of the information gain from monitoring is of particular interest as several monitoring techniques exist, and they provide different measurements of the structural behavior. For instance, bridge load testing may provide information on the structural rigidity, while SHM is monitoring the changes in structural and material properties over time. To select the most appropriate technique (or combination of techniques), metrics must be evaluated prior to the monitoring.

The conventional approach is to quantify the uncertainty reduction using, for instance, information entropy [51, 57]. Nonetheless, the reduction of plausible initial ranges of bridge parameters (such as material properties) does not mean that degrees of compliance will be significantly affected. Utility theory has been used to quantify the value of information (VoI) [58]. In other words, the information gain from monitoring systems can be estimated by the influence

of collected data on the degrees of compliance. One of the limitations of these methodologies lies in the required computational time to evaluate the influence on structural-capacity evaluations of each possible monitoring output.

Another aspect is that a bridge is typically examined through the evaluation of several degrees of compliance. Therefore, the assessment of the information gain should be multidimensional, and several approaches are possible. These information gain metrics are introduced below. These metrics involve absolute variation of the degrees of compliance to account for both potential increase or decrease of the degrees of compliance.

The first definition of information gain involves only degrees of compliance smaller than 1.0. This strict definition is based on the utility theory that is used in VoI frameworks. Decisions on asset management are mainly based on these degrees of compliance as it influences the assessment of whether the bridge is safe or not. This first definition of information gain IG_1, called the utility metric. This metric is evaluated using Eq. (2), with k the number or degrees of compliance initially evaluated smaller than 1.0. $n_{i,0}$ and $n_{i,1}$ are the degree of compliance prior to and after monitoring respectively.

$$IG_1 = \frac{1}{k} \sum_{i}^{k} abs\left(\frac{n_{i,1} - n_{i,0}}{n_{i,0}}\right) \tag{2}$$

The second definition of information gain includes only the most critical degree of compliance. Engineers often make this action as a simplification of the bridge-examination process. The critical-verification metric IG_2 is evaluated using Eq. (3). This metric could also be evaluated for each limit state (serviceability, fatigue, and ultimate) using its respective critical degree of compliance.

$$IG_2 = abs\frac{n_1 - n_0}{n_{,0}} \tag{3}$$

The third information gain definition is the average influence of the monitoring data on the degrees of compliance. This broader definition is evaluated using Eq. (4) and is called the broad-definition metric IG_3.

$$IG_3 = \frac{1}{m} \sum_{i}^{m} abs\left(\frac{n_{i,1} - n_{i,0}}{n_{i,0}}\right) \tag{4}$$

These definitions are all possible and depend on the choice of engineers and discussions with asset managers. This study involves a comparison of monitoring techniques based on these definitions. The choice of the best information gain metric also depends on the time horizon of the analysis. Utility and critical-verification metrics are related to current demand and capacity levels that may change in the future. Optimal monitoring techniques selected using

these metrics may be suboptimal in the future if load models in the standards are modified. Conversely, a comprehensive evaluation of the information gain is obtained using the broad-definition metric. This definition thus ensures that the monitoring information will be also useful after future modifications of structural verifications.

3 Case study

3.1 Presentation

In this section, the bridge used as a case study is presented. Built in 1959, this bridge is a viaduct located in Switzerland (Fig. 1). It is one of the first steel–concrete composite bridges in the country and has an important historical perspective.

The superstructure involves a reinforced-concrete (RC) slab fixed to two steel box girders. A monolithic behavior is expected in this composite structure. The bridge consists of eight spans between 15.8 and 25.6 m. The RC slab width is 12.7 m and has a thickness between 17 and 24 cm. The two steel girders have a square section of 1.30 m. In 2002, longitudinal stiffeners were added to the steel box girders, and the Gerber's joints between the spans were fixed using steel connectors.

The bridge was monitored between 2016 and 2019 using several monitoring techniques. Strain gauges and thermocouples were installed to monitor traffic effects and temperature variations continuously during these three years. Additionally, a weight-in-motion (WIM) station was installed prior to the bridge to measure the traffic axle load. A quasi-static

Fig. 1 Bridge presentation. (**a**, **b**) Bridge photographs; (**c**) Evaluation of the bridge; (**d**) monitoring installed on the fourth span of the bridge
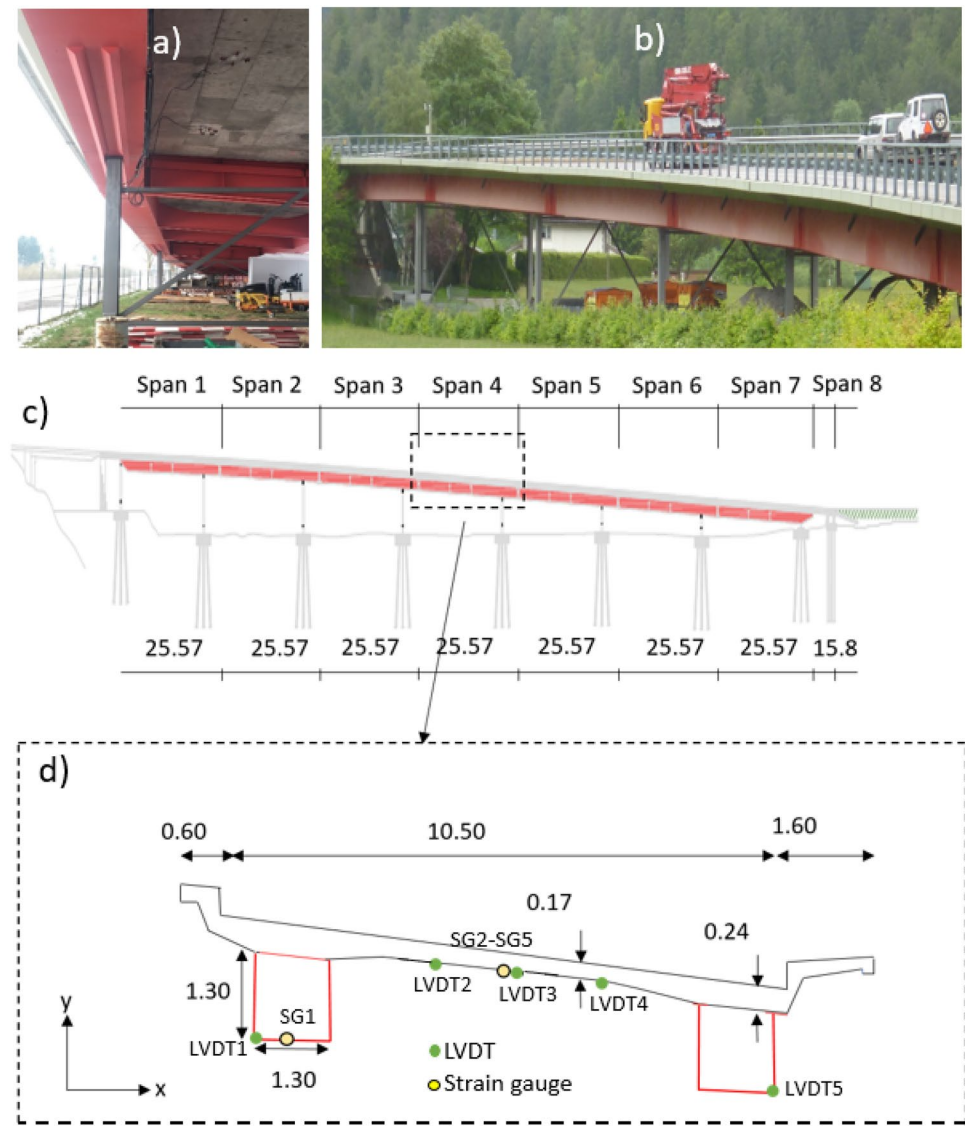
load test was performed on the fourth span in 2016 using a truck of 40 tons passing through the bridge at 10 km/h. To measure deflections and strains in the concrete deck, three LVDTs, and four strain gauges, both in the transverse and longitudinal directions, were mounted near mid-span [32]. Stain gauges are glued to the rebars on the bottom layer of the steel reinforcement in the concrete deck. Additionally, one strain gauge and two LVDTs were installed at the bottom of the steel girder at mid-span (Fig. 1C, D).

A numerical model of the entire bridge was built using SCIA software [59] (Fig. 2). The model involves 2D and 1D elements. Although all monitoring activities were performed on the same span, the entire bridge is modeled to improve the accuracy of the predictions. The complex RC deck geometry is precisely modeled to predict the transverse deformation of the slab accurately. Bridge piers are also included in the model. The mesh size is set to 400 mm, except for the monitored span, where it is reduced to 100 mm to improve the precision of the predictions. 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 first performed without considering monitoring data. This examination involves several structural verifications for the ultimate limit state (ULS), the fatigue limit state (FLS), and the serviceability limit state (SLS). These verifications involve structural capacity for ULS, fatigue capacity for FLS, and bridge deflection for SLS based on the requirements of the SIA 269.

For each verification, the degree of compliance (Eq. 1) is calculated using predictions of the numerical model. On the 27 structural verifications, two of them present a degree of compliance smaller than 1.0 (Fig. 3). These verifications correspond to the stress difference in the longitudinal and transverse rebars on the bottom of the concrete deck. These steel reinforcements are the ones that have been monitored (Fig. 1). Concerning the ULS, the bridge has a reserve of capacity thanks to the intervention in 2002.

Based on the monitoring data, these structural verifications are re-evaluated. Four different monitoring techniques are compared in terms of information gain that they provide: the bridge static load test (C1), the long-term strain monitoring in the bottom-layer rebars of the concrete deck

Fig. 2 Finite-element model of the bridge. (**a**) Overiew of the model; (**b**) cross-section

Fig. 3 Degree of compliance for each structural verification
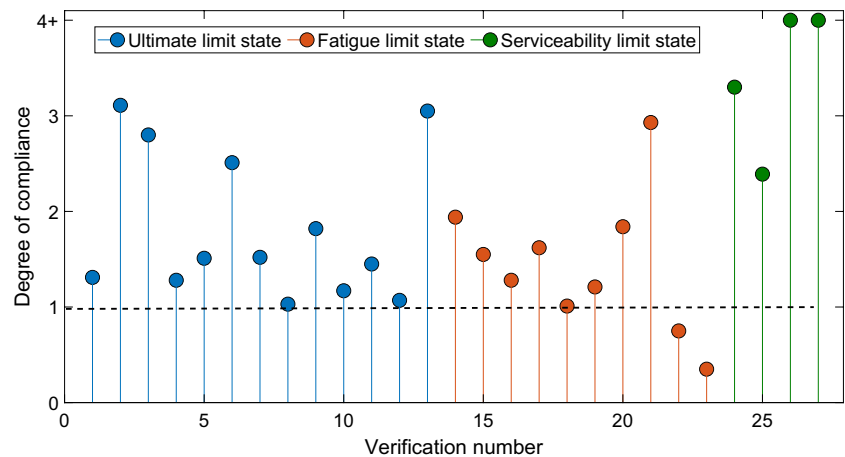
(transversally and longitudinally) (C2), the WIM data (C3) and non-destructive tests (C4) performed using a rebound hammer and sound-velocity measurements. The data collection and, when necessary, the data interpretation is presented in Sect. 3.3. Then, all possible combinations of monitoring-technique data are generated. Eleven combinations (C5–C14) are made, including two and three monitoring techniques. The last case (C15) combined all the available monitoring techniques. Results of structural verifications for each combination are presented in Appendix. Next, the information gain of each combination is assessed (Sect. 3.4) using the three metrics proposed in Sect. 2.

3.3 Data collection and interpretation

3.3.1 Static load testing

The first data collected is the quasi-static bridge load test performed in 2016. This load test involves a truck of 40 tons (5 axles with known load) going through the bridge in the middle of the lanes at the speed of 10 km/h. The test has been repeated to evaluate the reproducibility of the results. Deflections and strain measurements have been recorded using the ten sensors (5 strain gauges and five LVDTs) shown in Fig. 1D. This load test is used to update parameter values of the numerical model using a population-based data-interpretation method.

Three model parameters are selected based on a sensitivity analysis and model-class selection processes [32, 60]. These parameters are the ones that affect most the model predictions at the sensor locations for the given load test. The initial parameter ranges are presented in Table 1 and are selected based on engineering judgment.

The first two parameters involve the rigidity of the concrete deck. Based on the recorded traffic on the bridge and the small thickness of the slab, it has been concluded that the bridge deck is cracked in the middle portion, reducing its rigidity. This rigidity reduction is simplified by reducing the concrete elastic modulus E_c, leading to an equivalent rigidity. Therefore, smaller elastic-modulus values are accounted for in the central part of the slab due to the cracked concrete E_{cr} compared to near the steel box girder, where it is expected that the concrete is mostly uncracked E_{nc}. Based

on an sensitivity analysis of the actual traffic effects on the bridge, the slab area with the smaller rigidity is taken to the slab area the minimal thickness of 17 cm (Fig. 1).

Ranges of equivalent elasticity moduli for cracked and uncracked concrete are considered, following [60]. The third parameter involves the stiffness of rotational spring between the elements at the Gerber joints as steel bolts were added in 2002 between steel box girders. The value range models the spring from a perfect hinge to a fixed joint. Ranges of parameter values are taken explicitly wide to ensure an identification within range extrema.

Estimations of the uncertainty magnitudes and distributions associated with the measurements and the modeling are presented in Table 2. These uncertainties are estimated based on the sensor-supplier information, the literature review [32, 61], measurement repeatability during load testing, and engineering judgment. Larger model uncertainties are considered for measurements on concrete due to the higher variability of material properties and difficulties in predicting the cracking behavior.

Error-domain model falsification (EDMF) is a methodology for structural identification from bridge load testing introduced in 2013 [47]. This methodology aims to accurately identify plausible bridge-parameter values based on field measurements and prescribed uncertainty levels. A population of model instances is generated where each instance has a unique combination of parameter values. Then, their model predictions are compared with the sensor data collected during static and dynamic load testing.

Table 2 Uncertainties considered in the model-updating process

Source	Min	Max	Distribution
Model (steel) [%]	−5	2.5	Uniform
Model (Concrete) [%]	−10	5	Uniform
Load position [%]	−5	5	Uniform
FE size [%]	−1	1	Uniform
Secondary parameters [%]	−2	2	Uniform
LVDT precision [mm]	−0.1	0.1	Uniform
Strain-gauge precision [μm/m]	−1	1	Uniform
Strain-gauge orientation [%]	−5	0	Uniform
Strain-gauge variability (concrete) [%]	0	10	Normal

Table 1 Initial parameter ranges and identification ranges after model updating

Parameter	Unit	Initial range	Identified range
Cracked stiffness of the deck—E_{cr}	Equivalent concrete Young's modulus [GPa]	6–20	11.5–12.5
Uncracked stiffness of the deck—E_{nc}	Equivalent concrete Young's modulus [GPa]	20–50	24–42
Rotational stiffness at the support—K_{rot}	[MNm/rad]	0–400	49–55

Model instances where the difference between predictions and measurements exceeds thresholds defined based on uncertainty levels are falsified. Updated bridge-parameter ranges are obtained by discarding parameter-value combinations from falsified model instances.

The true structural response (unknown in practice) is denoted as R_i where $i \in \{1, \dots, n_y\}$ is the sensor location and n_y is the number of measurement locations. The sensor data, denoted y_i, is compared to model-instance predictions denoted $g_i(\theta)$. As both predictions and sensor data, are imperfect, uncertainties in model predictions (denoted $U_{i,g}$ and measurements denoted $U_{i,y}$) should be considered in the analysis. The relation between R_i, y_i, and $g_i(\theta)$ is presented in Eq. (5).

$$g_i(\theta) + U_{i,g} = R_i = y_i + U_{i,y} \forall i \in \{1, \dots, n_y\} \tag{5}$$

By merging the model $U_{i,g}$ and measurement $U_{i,y}$ uncertainties in a global uncertainty distribution $U_{i,c}$, The terms in Eq. (5) are rearranged in Eq. (6) [62]. The discrepancy between the model instance prediction and the field measurement at a sensor location is called the residual r_i.

$$g_i(\theta) - y_i = U_{i,c} = r_i \forall i \in \{1, \dots, n_y\} \tag{6}$$

At each sensor location, falsification thresholds are defined using a level of confidence on the combined uncertainty distribution, and they are typically set at 95% [47]. When multiple sensor data are included, the level of confidence is adjusted using the Šidák correction [63]. If the residual of a model instance exceeds the thresholds at one sensor location, this model instance is falsified. The associated combination of model parameter values is discarded, reducing initial bridge-parameter ranges. If a model instance has residuals within threshold bounds at all sensor locations, this instance is included in the candidate-model set. It means that the associated parameter values of this model instance are plausible. After data interpretation, updated parameter ranges are obtained with instances in the candidate model set [43].

EDMF is applied for the present case study using data from static load testing. 983 model instances are generated using a grid-based sampling method [64, 65]. Each instance has a unique combination of bridge-parameter values within the initial ranges presented in Table 1. Results of the model-falsification procedure are presented in Fig. 4. Each line shows a model instance, first its parameter values and then its predictions at LVDTs locations. Strain-gauges data have also been used for the model-falsification procedure, but they are not shown in Fig. 4 to improve the figure readability. Candidate models are highlighted in blue. Only 13 model instances are not falsified, showing a reduction from the initial set of 98.6%. Identified parameter ranges are shown in Table 1. A precise identification is obtained for two parameters: cracked rigidity and rotational stiffness at the Gerber joints.
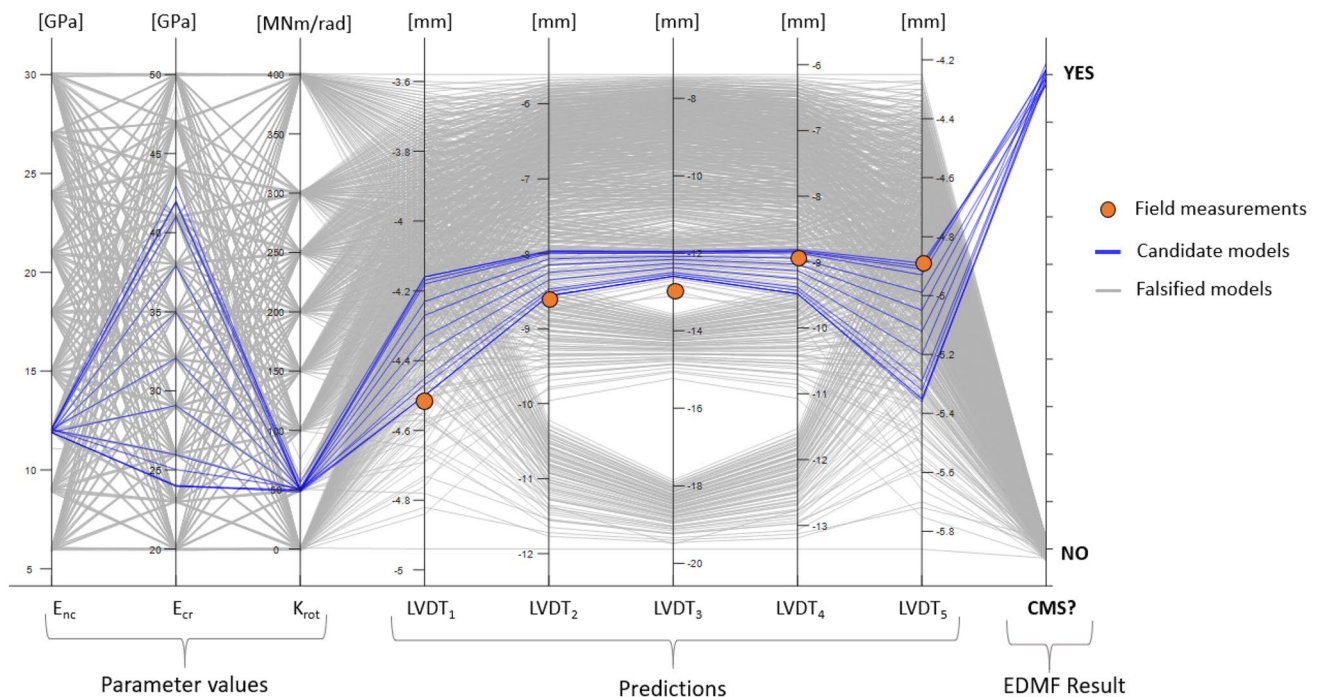

Fig. 4 Results of the model updating process (EDMF), strain data, and predictions are not shown in this figure

This model updating from the static load test helps provide more accurate numerical model predictions. The 27 degrees of compliance are thus re-evaluated with the updated model, and details of the influence of this model updating on bridge-safety examination are shown in the Appendix. As the rigidity of the bridge is mostly updated, the structural evaluations related to SLS are significantly influenced. For FLS and ULS, the influence is smaller but non-negligible. A small decrease in some degrees of compliance has been observed for some FLS verifications (i.e., Verifications 22 and 23, Fig. 3) due to the increase of the deck rigidity, leading to an increase in the efforts in both longitudinal and transverse rebars. The average influence on the degrees of compliance is 6.1%.

3.3.2 Long-term strain monitoring

The second monitoring technique involves the measurements of the strain of the bottom-layer rebars in the concrete deck. Both longitudinal and transverse steel reinforcement have been monitored for three years between 2016 and 2019. These rebars correspond to the most critical bars in fatigue loading. Implemented strain gauges on these rebars are the same device used for bridge load testing (Fig. 1D). Moreover, temperature data have also been recorded, but.

Annual histograms of the stress differences in the longitudinal and transverse rebars are presented in Fig. 5. For each element, the maximum value recorded with at least 10^2 cycles per year is taken as a conservative estimate of the stress level for FLSs. Thanks to the monitoring, FLS verifications 22 and 23 can be updated. Thanks to the low monitored stresses, the degrees of compliance after including these data are significantly increased, with an average increase value by 250% for these two verifications. These results are primarily due to the conservative axle load and load disposition and distribution of load models in the standards for existing bridges. For these two verifications, the large difference with the initial stress-difference evaluation of the SIA 269 FLS model is thus more related to the actual traffic (i.e., axle load, load position, and distance between axles) than the influence on the slab structural-rigidity values. Action effects of the actual traffic on the bridge are significantly lower than assumed in the SIA 269 for FLS verifications.

These data involve strain measurements on rebars in the deck. As these measurements have only been used to update the FLS verifications directly associated with these structural elements, measurements did not require to be corrected to account for the effects of the temperature. Although this monitoring is useful for FLS, these measurements are not used to assess the bridge ULSs and SLSs. Therefore, this monitoring campaign only provides updating of two structural verifications.

3.3.2.1 Weight inmotion The third monitoring technique involves measuring the traffic levels on the bridge using a weight-in-motion (WIM) station. This station has been installed just before the bridge to reduce the uncertainties of the traffic on the bridge as much as possible. Results of these traffic analyses can be found in [31].

On the 6th of October 2016, a much larger load level was recorded, twice as large as the average value and 20% larger than the second-largest measurement in terms of strain in the bridge (Fig. 6). The previous WIM monitoring study shows that this load level has a probability of occurrence smaller than 10^{-5}/year. This measurement is associated with the crossing of a large crane of 60 tons that is not authorized on this bridge. This crane of 15 m long and has five axles. The stress level induced by the crane is significantly higher than based on the actual traffic on the bridge. To approximate a novel ULS load model, the axle-load distribution of this crane is considered with a safety factor of 1.3 and placed at the most critical locations. The ULS structural verifications are then re-evaluated using this crane as the new maximum demand level for the bridge.

3.3.3 Non-destructive tests

The last monitoring technique used for this case study is the performance of non-destructive tests using rebound

Fig. 5 Annual histogram of stress ranges in rebars in the concrete slab. (**a**) longitudinal rebar; (**b**) transverse rebar
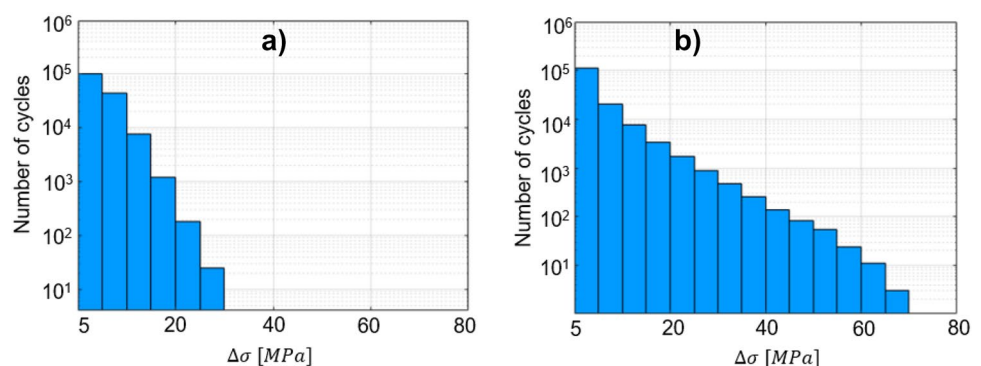
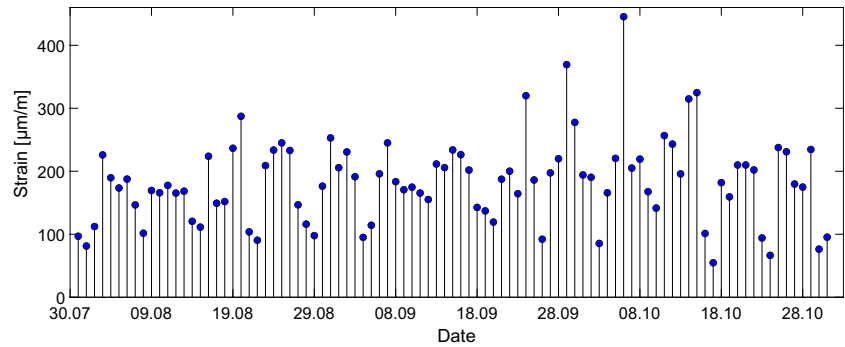**Fig. 6** Maximum daily strain recorded between three months in 2016

Table 3 Identification ranges using non-destructive tests

Parameter	Unit	Range of measurements
Concrete compressive strength f_{ck}	[MPa]	46–48
Uncracked stiffness of the deck—E_{nc}	Equivalent concrete elastic modulus [GPa]	24–35

hammers and sound-velocity measurements. Both techniques were used to evaluate concrete properties. These tests were performed multiple times at several locations on the same span that has been monitored for static load testing. These measurements were made on the areas where the concrete is supposed to be uncracked.

Results of the non-destructive tests are shown in Table 3. Both methods provide consistent results. Parameter ranges are based on the repeatability of measurements and the intersection of results from both tests. These measured values are closed to the initial evaluations of concrete properties based on SIA 269.

3.3.4 Influence on structural verifications

These monitoring techniques help identify some structural properties and load-level demand for the examination of these existing bridges. These identifications are summarized in Table 4. Each monitoring technique provides complementary information on bridge properties and load levels. Information on the deck rigidity and static system is provided by

the static load test. The long-term strain monitoring helps identify the accurate stress differences due to the true traffic load, while information from the WIM station leads to a new load model that has replaced the SIA 269 model for ULS verifications. NDTs provide information on the concrete properties, which coincide with the initial value of the concrete compressive strength based on the SIA 269. All these data lead to updating the degrees of compliance of all structural verifications. The influence of each combination of monitoring-technique data on the degrees of compliance is then evaluated. Detailed results are presented in the Appendix.

The distributions of the degrees of compliance for the 27 structural verifications are shown in Fig. 7. Compared to the initial distribution, each monitoring technique enables updating structural verifications. When all monitoring techniques are combined, all structural verifications have degrees of compliance larger than 1.0, showing that the bridge has reserve capacity. Thanks to the complementary information on monitoring techniques, the evaluation regarding bridge safety has changed. An intervention on the bridge is no longer necessary.

The influence of each monitoring technique is shown in Table 5. The mean variation of the degrees of compliance is between 0.6% (NDT) and 25% (WIM). This result shows that information gain differs for each monitoring technique. These results are case-study dependent and should not be generalized. Moreover, they also depend on the initial properties considered for the bridge examination prior to monitoring.

Table 4 Identification of bridge unknown parameters depending on the monitoring technique

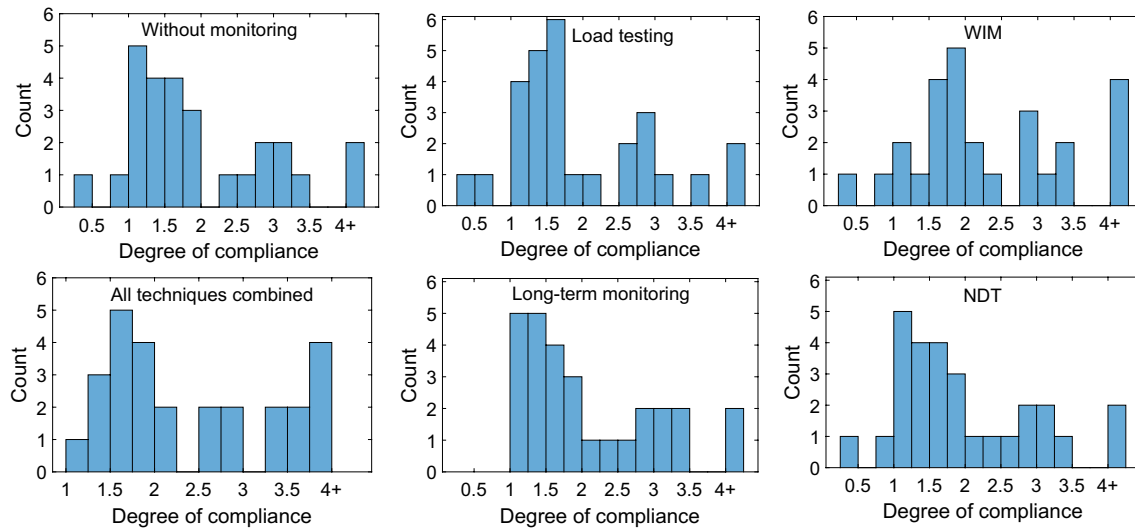| Parameter	Initial value	Load testing	Long-term strain	WIM	NDT
Load level (ULS)	SIA 269	–	–	New model	–
Load level (FLS)	SIA 269	–	Direct monitoring	–	–
F_{ck} [MPa]	47	–	–	–	47
$E_{c,uncracked}$ [GPa]	30	24–42	–	–	25–35
$E_{c,cracked}$ [GPa]	6	11.5–12.5	–	–	–
K_{rot} [MNm/m]	0	45–55	–	–	–

Fig. 7 Distribution of degrees of compliance after including monitoring-technique data in structural verification

Table 5 Influence of monitoring data on structural verifications

Monitoring technique	Combination name	Mean variation of the degree of compliance [%]	Influenced degree of compliance (var. > 5%)
Load testing	C1	6.74	17/27
Long-term monitoring	C2	23.1	3/27
Weight in motion	C3	25.0	13/27
Non-destructive tests	C4	0.6	0/27
All-technique combined	C16	51.9	24/27

When all monitoring techniques are combined, the influence on degrees of compliance has a mean value of 51.9%, with almost all degrees of compliance being influenced (24/27). The information gain is then quantified for each metric proposed in Sect. 2.2.

The combination of the monitoring-technique results has been done using the following procedure. First, the results of the load testing and non-destructive tests have enabled the updae of the properties of the numerical model (i.e., structural rigidity, boundary conditions, and concrete strength). Then, the ULS load model was updated using the WIM data, leading to the re-evaluations of structural verifications for ULS. Finally, Structural verifications 22 and 23 (Fig. 3) have been updated based on the stress-difference histograms derived from the 3-year continuous monitoring.

3.4 Information-gain evaluation

3.4.1 Utility function

The first evaluation of the information gain from each monitoring technique is based on the utility metric. This metric involves looking at only structural verifications initially assessed with a degree of compliance smaller than 1.0. According to this metric, only the long-term strain monitoring (C2) provides information (Fig. 8). Initial evaluations of the degree of compliance are shown as a benchmark (C0). Only two FLS verifications were initially estimated as insufficient, and both are updated only using this monitoring technique. According to this metric, only long-term strain monitoring provides useful information.

3.4.2 Critical verifications

The second metric involves assessing the influence of monitoring techniques on the degree of compliance of the critical structural verification. Figure 9 shows the variations of the critical verifications for the ULS (verification 8), FLS (verification 23), and SLS (verification 25). Initial evaluations of the degree of compliance are shown as a benchmark (C0). For each structural verification, only one monitoring technique provides information gain. Nonetheless, the useful monitoring technique differs for the considered structural verification. This result shows that all monitoring techniques

Fig. 8 Influence of the monitoring data on the structural verifications with a degree of compliance initially evaluated at smaller than 1.0. (**a**) Fatigue of longitudinal rebars in concrete (Verification 22); (**b**) Fatigue of transverse rebars in concrete (Verification 23)
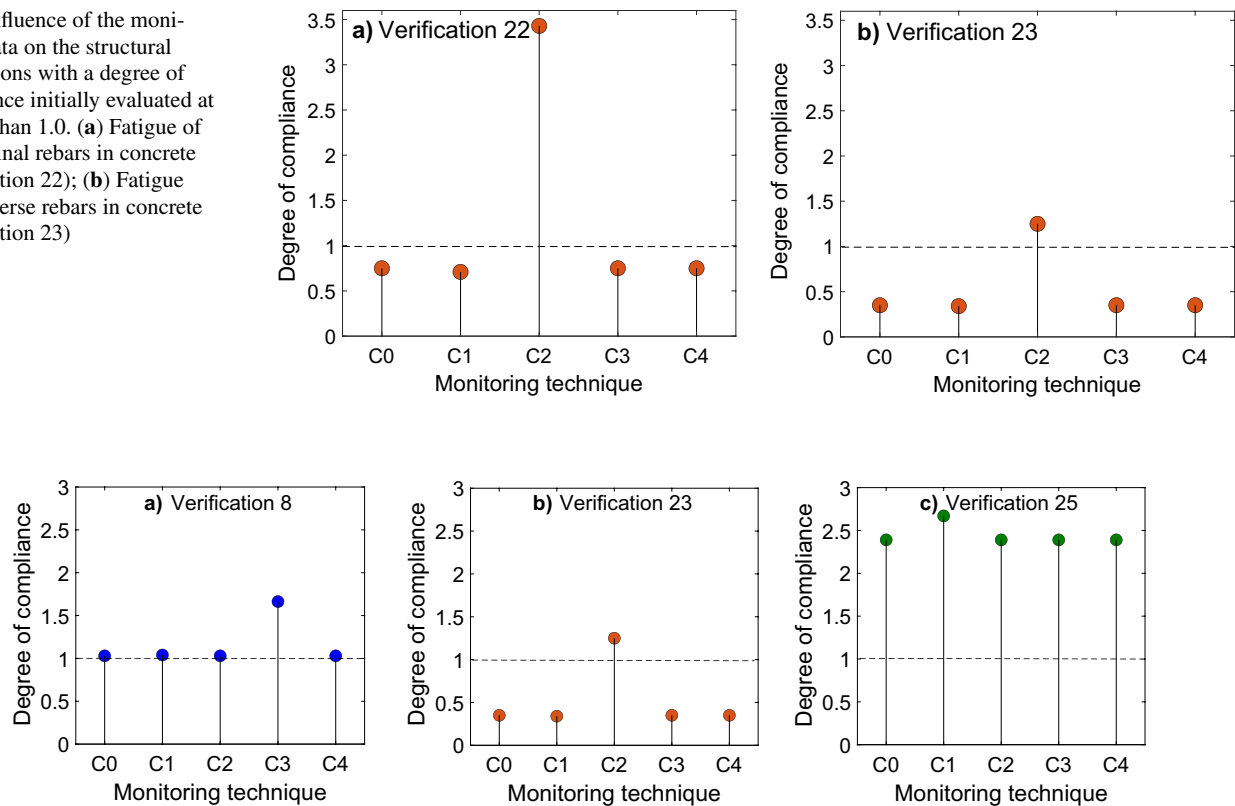

Fig. 9 Influence of the monitoring data on the critical structural verifications. (**a**) Flexural strength at the support (Verification 8—ULS); (**b**) Fatigue of transverse rebars in concrete (Verification 23—FLS). (**c**) Slab displacement (Verification 25—SLS)

provide useful information, but this information only influences a limited number of degrees of compliance.

3.4.3 Broad information gain

The next metric involves evaluating the mean influence of the monitoring data on the degrees of compliance of all structural verifications. Distributions of the variation are shown in Fig. 10. Load-test data have a small variation on almost all structural verifications. The WIM data have significant variations on all ULS verifications. For most ULS structural verifications, this modification enables a reduction of the load demand on the bridge, except for the slight increase of bending moment in the main girder on the supports. The long-term strain monitoring significantly influences only two verifications for FLS (Verifications 22 and 23). Due to the small difference between initial and updated concrete properties, NDTs have little effect on degrees of compliance.

The broad information gain metric is evaluated with respect to the number of monitoring-technique data (Fig. 11). For a given number of monitoring techniques, only the best combination is shown. When looking at all structural verifications combined, the maximum value of

the metric is obtained when the four monitoring techniques are included. When the same analysis is performed for all structural verifications of each limit state independently (Fig. 11B), the maximum value is always reached using two monitoring techniques.

Using this information gain metric, the conclusion on the optimal number of monitoring techniques differs from using other metrics. Based on the broad-definition metric, all monitoring techniques provide useful information. This result shows the monitoring techniques provide unique information gain. These techniques should thus be seen as complementary rather than competing solutions.

4 Summary

Results of the evaluations of information gain according to the three metrics are summarized in Table 6. For the utility metric, only the long-term strain monitoring provides information. For the critical-verification metric, the load test, long-term strain monitoring, and WIM are the only useful metric for the SLS, FLS, and ULS, respectively. Nonetheless, using the broad-definition metric, each monitoring

Fig. 10 Distribution of influence of monitoring data on the structural verifications. (**a**) Bridge load testing; (**b**) Long-term strain monitoring; (**c**) Weight in motion measurement; (**d**) Non-destructive tests
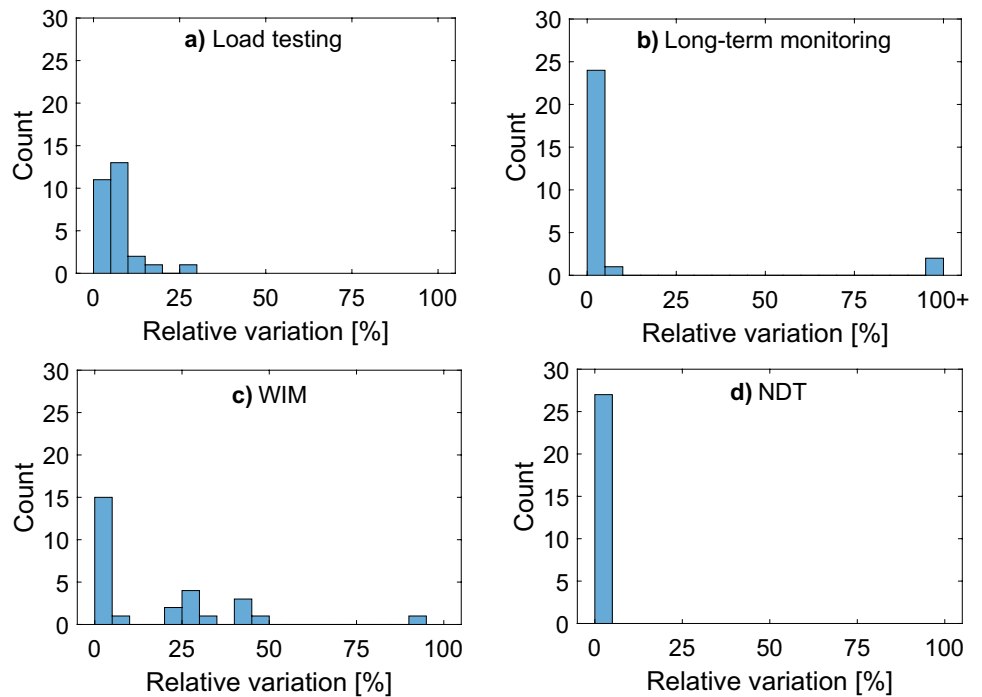

Fig. 11 Average influence of the structural verifications with respect to the number of monitoring-technique data. (**a**) All structural verifications; (**b**) Separation by types of verifications
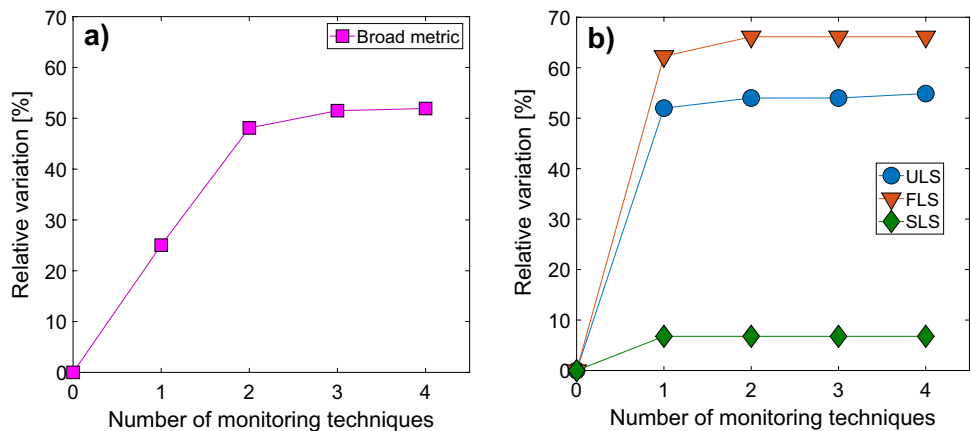

Table 6 Evaluation of monitoring-technique information gain

Method	Utility metric	Crit.-verif. metric	Crit.-verif. metric	Crit.-verif. metric	Broad-def. metric IG3
	IG_1	$IG_{2\text{-SLS}}$	$IG_{2\text{-FLS}}$	$IG_{2\text{-ULS}}$	IG_3
Load testing	0.041	0.117	0.029	0.010	0.067
Long-term strain monitoring	3.113	0	2.600	0	0.234
Weight in motion	0	0	0	0.615	0.250
Non-destructive tests	0.007	0.033	0	0.00	0.006
All techniques combined	3.072	0.117	2.571	0.624	0.519

technique provides additional information, and their combination is recommended.

The selection of the optimal monitoring technique thus depends on the used definition of information gain. Each method provides unique information on the structural

Table 7 Qualitative evaluation of the accuracy of the value of information of monitoring activities

Method	Predictability of results	Monitoring costs estimation	Accuracy of value of information estimation
Load testing	Possible	Very precise	High
Non-destructive test	Possible	Very precise	High
Long-term monitoring (demand)	Difficult	Precise	Medium
Long-term monitoring (SHM)	Very difficult	Medium	Low

behavior, but not all of them are useful from a short-term decision-making perspective.

Using the information of all monitoring-technique combined, the mean variation of the degrees of compliance is equal to 50%. When using the best individual method (WIM), the mean variation of degrees of compliance is around 25%. Selecting the appropriate information gain metric is thus a crucial step in the non-destructive evaluation of a structure, and this choice must be discussed with asset managers.

This study also highlights the importance of the initial evaluation of bridge structural safety. Information gain is a relative metric compared to the initial evaluations before monitoring. The monitoring information gain is significantly higher if conservative estimates are initially made. For instance, in the present case study, the SIA 269 allows an update of the concrete grade from C25/30 to C45/55 for the initial examination of the bridge (Sect. 3.2). This update prior to monitoring significantly improves the predictions of the numerical models. NDTs have only confirmed this update, showing little information gain according to the metrics. If more conservative estimates of concrete grade had been initially made, the information gain from this monitoring technique would have been significant.

Prior to establishing a monitoring campaign, the bridge must be examined. Structural models (either numerical or analytical) must be built using all the available information. These initial structural verifications will help define the goals of the monitoring. Without this initial examination, the usefulness of monitoring techniques based on the

information gain metrics cannot be estimated. Selecting monitoring techniques before this examination will necessarily lead to suboptimal choices, increasing monitoring costs and reducing the benefits in terms of information gain from the monitoring campaign.

It may happen that the monitoring data are inconsistent with the model predictions. This inconsistency leads to the correction of the finite-element model following an iterative process [65]. In such cases, evaluations of the information gain using the proposed methodology may be inaccurate. Nonetheless, in such cases, the information gain is already significant as monitoring data led to an update of the initial numerical model.

5 Predictability of monitoring information

The next step involves evaluating the expected benefits of these monitoring techniques prior to data collection to estimate their value of information. These assessments require evaluating both the predictability of monitoring data and the monitoring costs.

In this study, only qualitative estimations of the accuracies of the VoI are proposed (Table 7). The qualitative assessment shows that the accuracy of the VoI predictions significantly varies with the monitoring techniques. Data from load testing and non-destructive tests are used to update the properties of structural materials and boundary conditions, and their costs are well-known. For these bridge

Fig. 12 Predicted and measured information gain for the bridge load testing. (**a**) joint entropy with respect to the number of sensors; (**b**) joint entropy with respect to the number of sensors
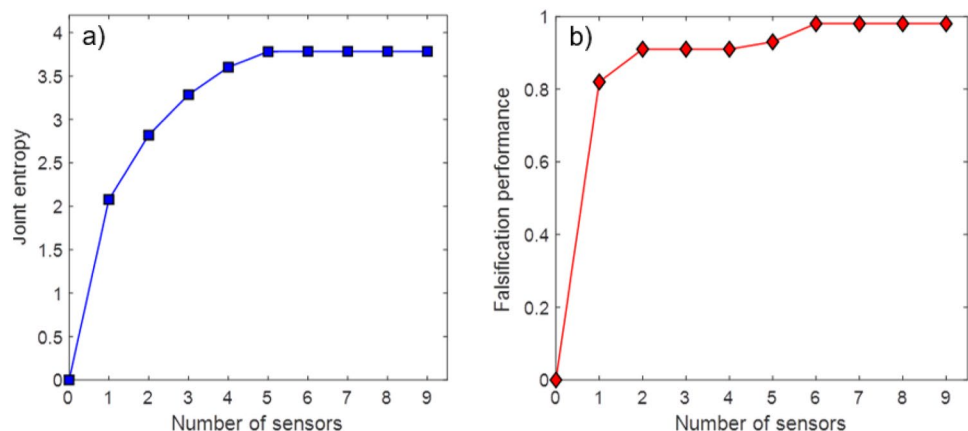
parameters, initial distributions can be evaluated. Therefore, potential information gain can be estimated precisely. A quantitative VoI framework has already been developed [66]. Long-term strain monitoring and weigh-in-motion are used to update the demand level (load models) for the structure. Although their costs are usually known precisely (fixed duration of monitoring), evaluations before monitoring the demand levels are difficult. These evaluations require an understanding of traffic flows in the geographic area of the bridge. SHM is the most difficult method to predict the VoI because of the unknown duration of monitoring, challenging predictions of future structural degradations and if the sensor network will detect them.

Figure 12 shows the predicted and observed information gain from bridge load testing. Following [51], the joint entropy of the bridge load testing is evaluated based on the model-instance predictions with respect to the number of sensors. This metric evaluates whether the data collected during load testing will provide precise information on the model parameters. The results are similar to the observed information gain (Fig. 12B). The predictability of information gain from bridge load testing is thus high. This type of information gain predictability must be generalized for all monitoring techniques. Quantitative evaluations will be provided in future works.

6 Conclusions

In this study, multiple metrics are introduced to evaluate the information gain from several bridge monitoring techniques. Static load testing, long-term strain monitoring, weigh-in-motion measurements, and non-destructive tests were performed on a composite steel–concrete bridge in Switzerland between 2016 and 2019. The following conclusions are drawn:

- Monitoring of bridges leads to more accurate structural verifications that can potentially change decisions on whether the bridge is safe or not. Each monitoring technique provides unique information on the bridge.
- The introduction of several metrics to measure information gain from monitoring supports asset managers in evaluating monitoring-technique performance.
- Selecting the optimal monitoring techniques depends on the information gain metric selected and the time horizon of the analysis. The decision on the goal of monitoring should be discussed with asset managers.

Appendix

In this section, the results of the degrees of compliance for each structural verification is provided depending on the monitoring-data included in the analyses. Table 8 shows the results of the initial assessment prior to monitoring (C0) and results for each monitoring technique included (C1 to C4). Table 9 presents the structural-verification results for combination of two to monitoring techniques (C5 to C10), while combinations of three and four combinations (C11 to C15) of techniques are shown in Table 10.

Table 8 Evaluation of degrees of compliance for each structural verification according to the initial evaluation prior to monitoring and after inclusion of information from one monitoring technique

| Structural verification | C0 | C1 | C2 | C3 | C4 |
Data used	None	Load testing	Long-term	WIM	NDTs
Ultimate limit state					
Main girder (M$^+$)	1.31	1.35	1.31	1.91	1.31
Main girder (M$^-$)	3.11	3.12	3.11	2.85	3.11
Main girder (V$^-$)	2.8	2.99	2.8	4.40	2.8
Secondary beam (span)	1.28	1.65	1.28	1.76	1.28
Secondary beam (support)	1.51	1.66	1.51	3.24	1.51
Piles	2.51	2.92	2.51	3.32	2.51
Trans. Rebar in concrete deck (top)	1.52	1.38	1.52	2.00	1.52
Long. Rebar in concrete deck (top)	1.03	1.04	1.03	1.66	1.03
Trans. Rebar in concrete deck (bot)	1.82	1.64	1.82	2.87	1.82
Long. Rebar in concrete deck (bot)	1.17	1.11	1.17	2.03	1.17
Concrete slab–middle (V)	1.45	1.42	1.45	2.06	1.45
Concrete slab–cantilever (V)	1.07	1.05	1.07	1.61	1.07
Concrete slab (N)	3.05	2.7	3.05	4.97	3.05
Fatigue limit state					
Main girder	1.94	1.98	1.78	1.94	1.94
Piles (vertical element)	1.55	1.66	1.55	1.55	1.55
Piles (diagonal)	1.28	1.29	1.28	1.28	1.28
Piles (welding)	1.62	1.67	1.62	1.62	1.62
Secondary beam (span)	1.01	1.07	1.01	1.01	1.01
Secondary beam (support)	1.21	1.32	1.21	1.21	1.21
Trans. Rebar in concrete deck (top)	1.84	1.72	1.84	1.84	1.84
Long. Rebar in concrete deck (top)	2.93	2.75	2.93	2.93	2.93
Trans. Rebar (bottom)	0.75	0.71	3.43	0.75	0.75
Long. Rebar (bottom)	0.35	0.34	1.25	0.35	0.35
Serviceability limit state					
Vertical displacement (traffic)	3.3	3.52	3.3	3.3	3.3
Vertical displacement (quasi perm)	2.39	2.67	2.39	2.39	2.39
Crack opening	6.25	6.25	6.25	6.25	6.25
Rebar yielding	9.18	8.38	9.18	9.18	9.18
Deformation capacity of the slab	3.3	3.52	3.3	3.3	3.3

Table 9 Evaluation of degrees of compliance for each structural verification according to the inclusion of information from of a combination of two monitoring techniques

| Verification | C5 | C6 | C7 | C8 | C9 | C10 |
Data used	C1 + C2	C1 + C3	C1 + C4	C2 + C3	C2 + C4	C3 + C4
Ultimate limit state						
Main girder (M^+)	1.35	1.95	1.35	1.91	1.31	1.95
Main girder (M^-)	3.12	2.86	3.12	2.85	3.11	2.86
Main girder (V^-)	2.99	4.59	2.99	4.40	2.8	4.59
Secondary beam (span)	1.65	2.13	1.65	1.76	1.28	2.13
Secondary beam (support)	1.66	3.39	1.66	3.24	1.51	3.39
Piles	2.92	3.73	2.92	3.32	2.51	3.73
Trans. Rebar in concrete deck (top)	1.38	1.86	1.38	2.00	1.52	1.86
Long. Rebar in concrete deck (top)	1.04	1.67	1.04	1.66	1.03	1.67
Trans. Rebar in concrete deck (bot)	1.64	2.69	1.64	2.87	1.82	2.69
Long. Rebar in concrete deck (bot)	1.11	1.97	1.11	2.03	1.17	1.97
Concrete slab–middle (V)	1.42	2.03	1.42	2.06	1.42	2.03
Concrete slab–cantilever (V)	1.05	1.59	1.05	1.61	1.05	1.59
Concrete slab (N)	2.7	4.62	2.99	4.97	2.99	4.62
Fatigue limit state						
Main girder	1.78	1.98	1.98	1.78	1.78	1.94
Piles (vertical element)	1.66	1.66	1.66	1.55	1.55	1.55
Piles (diagonal)	1.29	1.29	1.29	1.28	1.28	1.28
Piles (welding)	1.67	1.67	1.67	1.62	1.62	1.62
Secondary beam (span)	1.07	1.07	1.07	1.01	1.01	1.01
Secondary beam (support)	1.32	1.32	1.32	1.21	1.21	1.21
Trans. Rebar in concrete deck (top)	1.72	1.72	1.72	1.84	1.84	1.86
Long. Rebar in concrete deck (top)	2.75	2.75	2.75	2.93	2.93	2.98
Trans. Rebar (bottom)	3.43	0.71	0.71	3.43	3.43	0.76
Long. Rebar (bottom)	1.25	0.34	0.34	1.25	1.25	0.35
Serviceability limit state						
Vertical displacement (traffic)	3.52	3.52	3.52	3.3	3.3	3.3
Vertical displacement (quasi perm)	2.67	2.67	2.67	2.39	2.39	2.39
Crack opening	6.25	6.25	6.25	6.25	6.25	6.25
Rebar yielding	8.38	8.38	8.38	9.18	9.18	9.18
Deformation capacity of the slab	3.52	3.52	3.52	3.3	3.3	3.3

Table 10 Evaluation of degrees of compliance for each structural verification according to the inclusion of information from of a combination of several monitoring techniques

Verification	C11	C12	C13	C14	C15
Data used	C1+C2+C3	C1+C2+C4	C1+C3+C4	C2+C3+C4	C1+C2+C3+C4
Ultimate limit state					
Main girder (M^+)	1.35	1.95	1.91	1.95	1.95
Main girder (M^-)	3.12	2.86	2.85	2.86	2.86
Main girder (V^-)	2.99	4.59	4.40	4.59	4.59
Secondary beam (span)	1.65	2.13	1.76	2.13	2.13
Secondary beam (support)	1.66	3.39	3.24	3.39	3.39
Piles	2.92	3.73	3.32	3.73	3.73
Trans. Rebar in concrete deck (top)	1.38	1.86	2.00	1.86	1.86
Long. Rebar in concrete deck (top)	1.04	1.67	1.66	1.67	1.67
Trans. Rebar in concrete deck (bot)	1.64	2.69	2.87	2.69	2.69
Long. Rebar in concrete deck (bot)	1.11	1.97	2.03	1.97	1.97
Concrete slab–middle (V)	1.42	2.03	2.06	2.03	2.03
Concrete slab–cantele (V)	1.05	1.59	1.61	1.59	1.59
Concrete slab (N)	2.7	4.62	4.97	4.97	4.62
Fatigue limit state					
Main girder	1.78	1.98	1.78	1.78	1.78
Piles (vertical element)	1.66	1.66	1.66	1.66	1.66
Piles (diagonal)	1.29	1.29	1.29	1.29	1.29
Piles (welding)	1.67	1.67	1.67	1.67	1.67
Secondary beam (span)	1.07	1.07	1.07	1.07	1.07
Secondary beam (support)	1.32	1.32	1.32	1.32	1.32
Trans. Rebar in concrete deck (top)	1.72	1.72	1.72	1.72	1.72
Long. Rebar in concrete deck (top)	2.75	2.75	2.75	2.75	2.75
Trans. Rebar (bottom)	3.43	0.71	3.43	3.43	3.43
Long. Rebar (bottom)	1.25	0.34	1.25	1.25	1.25
Serviceability limit state					
Vertical displacement (traffic)	3.52	3.52	3.52	3.52	3.52
Vertical displacement (quasi perm)	2.67	2.67	2.67	2.67	2.67
Crack opening	6.25	6.25	6.25	6.25	6.25
Rebar yielding	8.38	8.38	8.38	8.38	8.38
Deformation capacity of the slab	3.52	3.52	3.52	3.52	3.52

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