NDT-CE 2022 - The International Symposium
on Nondestructive Testing in Civil Engineering
Zurich, Switzerland, August 16-18, 2022

Engineering of Existing Structures: The Need and Place for Non-destructive Evaluation

Numa BERTOLA[1]*, Guillaume HENRIQUES[1], Thomas SCHUMACHER[1,2], Eugen BRÜHWILER[1]

[1] Laboratory for Maintenance and Safety of Structures, Ecole Polytechnique Fédérale de Lausanne (EPFL), Station 18, 1015 Lausanne, Switzerland
[2] Civil and Environmental Engineering, Portland State University; Portland, OR, USA
*Corresponding author, e-mail address: *[numa.bertola@epfl.ch]*

Abstract

Structural engineers today are still educated mainly to design new structures. This ignores the fact that most structures already exist and need to be maintained. Students are thus often ill-equipped to deal with maintenance and preservation of existing structures. As an example, when a structural analysis model of an existing structure such as a bridge is built to predict its response, it is often done using ideal boundary conditions and hypothetical design properties rather than actual behavior or measured properties - this would require the engineer to have skills and knowledge in the examination of existing structures. As a result, these models are often inaccurate, which can lead to unnecessary strengthening or even replacement of structures. This is not only costly, but it also significantly impacts the environment. In this paper, we argue that new educational programs that specifically address this need should be developed that revolve around the idea of "engineering of existing structures". Such programs would still include certain traditional structural engineering courses but also discuss structural behavior and materials properties, and how these can be determined by means of non-destructive testing (NDT) and structural health monitoring (SHM), in sum referred to as non-destructive evaluation (NDE). Because these tools are not traditionally included in the structural engineering curriculum, a new set of basic interdisciplinary skills from the domains of mechanical and electrical engineering, as well as computer science (data analysis, signal processing, etc.), need to be acquired by the students. This paper makes a case for the need for training in engineering of existing structures. A case study of a bridge in Switzerland shows that monitoring information and knowledge about engineering of existing structures can provide more accurate predictions of bridge structural capacity, leading to more sustainable and cost-effective infrastructure asset management.

Keywords: Existing Structures; Non-destructive Evaluation; Structural Health Monitoring; Bridge Load Testing; Structural Behavior; Asset Management; Preservation

1 Introduction

Current structural engineering is predominately driven by the philosophy of designing new structures. The structural engineer's vocation is to build structures, and this approach prevails even when dealing with existing structures. For many structural engineers, an existing structure has a finite service life of 80 to 100 years, after which it should be replaced by a new structure. While this philosophy was perhaps rational 50 years ago, it is nowadays far away from the demands of modern society in terms of sustainability [1]. Existing structures represent tremendous assets and wealth to a society that must be preserved. Additionally, some structures are of such technical or cultural significance that replacement is simply not an option (e.g., Brooklyn Bridge). Structural engineers are thus increasingly called upon to maintain and preserve the existing infrastructure, as replacement is often neither sustainable nor cost-effective.

Assessing existing structures is typically performed using construction drawings, recorded information on the materials used, and visual inspection. While a broad range of sensing and monitoring technologies have been developed over the last decades, non-destructive evaluation

(NDE) is still rarely used for the condition survey of existing bridges [2]. NDE techniques include both non-destructive testing (NDT), bridge load testing and structural health monitoring (SHM). In NDT, instruments and sensors are deployed temporarily to measure the response due to a known stimulus to determine structural (e.g., location of reinforcing bars, thickness of a member, etc.) and material properties (e.g., modulus of elasticity). Techniques include ground penetrating radar (GPR), ultrasonic testing (UST), and rebound ("Schmidt") hammer testing [3].

Bridge load testing with controlled static and dynamic excitations is used to characterize the structural and material properties, including the boundary conditions of an existing structure [2] through model updating. Field measurements collected through bridge load testing often provide information on current bridge behavior. These data are typically used to update a numerical model, improving the predictions of current structural capacity. As the data-interpretation is not trivial [6], advanced methodologies for model updating are recommended [7].

SHM entails the use of sensors that are installed to measure (short- or long-term) the response of a structure due to typically unknown stimuli such as vehicle loading, wind, and temperature variation [4]. In SHM, changes of structural and material properties are inferred from the measurements (e.g., strain monitoring of a reinforcing bar to determine fatigue [5]).

No matter what technique or approach is utilized, sensors and measurement systems must be carefully selected and configured [8], and the value of information should be estimated by comparing the expected benefits against the costs of monitoring [9].

To conclude, performing NDE work is an important part of examining an existing structure. It requires a broad skillset that is not part of a typical structural engineering curriculum. This has been recognized recently, and concerted efforts are ongoing to promote the inclusion of NDE courses in current civil engineering curricula [10]. In this paper, we demonstrate the value and place of NDE, specifically bridge load testing, in the examination of existing structures in the form of a case study.

2 Examination of existing structures

While obvious, it is still worth stating: An existing structure exists! The verification of structural safety must thus be based on in-situ measurements of actual structural behavior, rather than theoretical design-based engineering values. Several ways to measure, monitor, and analyze structural behavior are possible and should be carefully selected based on the objective of monitoring, case study, sensor availability, and training of engineers.

Some NDT techniques provide information about material properties and geometry of the structure at the time of the measurement. Nonetheless, most sensor data such as deformations, strains, and accelerations in bridge load testing are indirect measures of structural properties (material properties, boundary conditions). Therefore, data interpretation is necessary. In such cases, field measurements must be complemented by advanced structural analysis. Calibrated finite-element (FE) models are needed to provide accurate estimations of structural capacity. SHM data are useful to detect condition changes and monitor degradation processes, but do not provide any information on the current state of the structure.

Although NDE information may lead to more sustainable and cost-effective management of existing infrastructure, it requires additional training for structural engineers that are often not included in current curricula (Figure 1). While most structural engineering courses focus on designing new structures, data-driven investigations of existing assets require multidisciplinary training that is missing at most technical universities. Greater emphasis is needed on principles comprising the essentials of all construction materials in both existing and new structures. Moreover, it is essential to include courses on the history of construction for better and more respectful intervention on existing structures.

Measurement-informed approaches for structural analysis require training beyond traditional structural engineering backgrounds. Engineers must understand the requirements of these sensor devices in terms of data collection and signal processing. Moreover, model updating requires building refined FE models to accurately predict structural behavior under real-world conditions. These FE models are typically much more complex than the ones used for designing new structures. When long-term monitoring measurements are available, engineers have to deal with potentially very large data sets, which requires special training. Statistical and data science tools, such as machine learning, must be appropriately used to differentiate signal from noise.

In the next section, this argumentation is developed using a bridge case study in Switzerland. The structure is examined based on a stepwise procedure with increasing refinement that differ from the data included and engineer training.

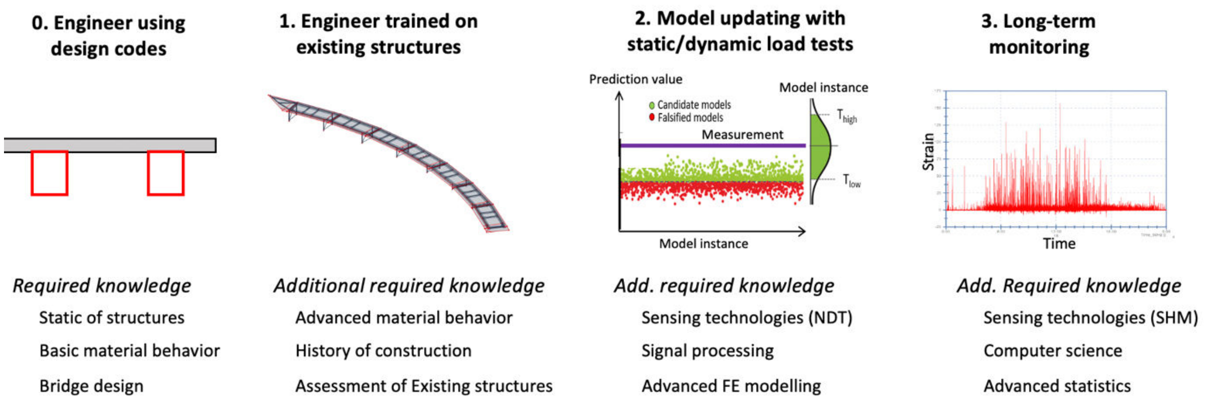

Figure 1: Stepwise procedure with increasing refinement, from Step 0 to 3, for the examination of existing structures with the associated training required.

3 Case study

3.1 Description of the bridge

In this section, the methodology proposed in Section 2 is implemented using a case study of an in-service bridge. This bridge, built in 1959, is an eight-span viaduct located in Switzerland (Figure 2). It is one of the first steel-concrete composite bridges built in Switzerland and is thus significant from a historical perspective. The superstructure consists of a reinforced concrete (RC) slab fixed to two steel box girders. The spans vary between 12 and 25.6 m, and the bridge width is 12.7 m. The RC slab has a thickness between 0.17 and 0.24 m, while the two steel girders have a height of 1.30 m. The structure was subject to an intervention in 2002 to add longitudinal stiffeners on the steel girders, as well as bolts at the Gerber joints between the spans.

This bridge was monitored between 2016 and 2019. Strain gauges and thermocouples were installed to monitor traffic effects and temperature variations. A static load test was performed on the fourth span in 2016. To measure deflections and strains during the test, five LVDTs at mid-span and five strain gauges both in the transverse and longitudinal directions near midspan were mounted [5]. Transverse and longitudinal strains were measured using four strain gauges at the mid-span of Slabs 2 and 4. Additionally, one strain gauge was installed at the bottom of the steel girder at the mid-span of Slab 4.

A numerical model was built using SCIA software [11] (Figure 3). The model involves 2D and 1D elements. Although all measurements were made on the same span of the structure, the entire bridge is modeled to improve the accuracy of the predictions. The bridge deck geometry is modeled accurately, representing the complex shape of the real deck. Bridge piers are also included in the model. The size of the elements is set to 400 mm, except for the monitored slab where it is reduced to 100 mm to improve the quality of the predictions. This model is used for all structural safety calculations described in this paper based on the stepwise procedure of refinement based on additional engineer training and available monitoring data.

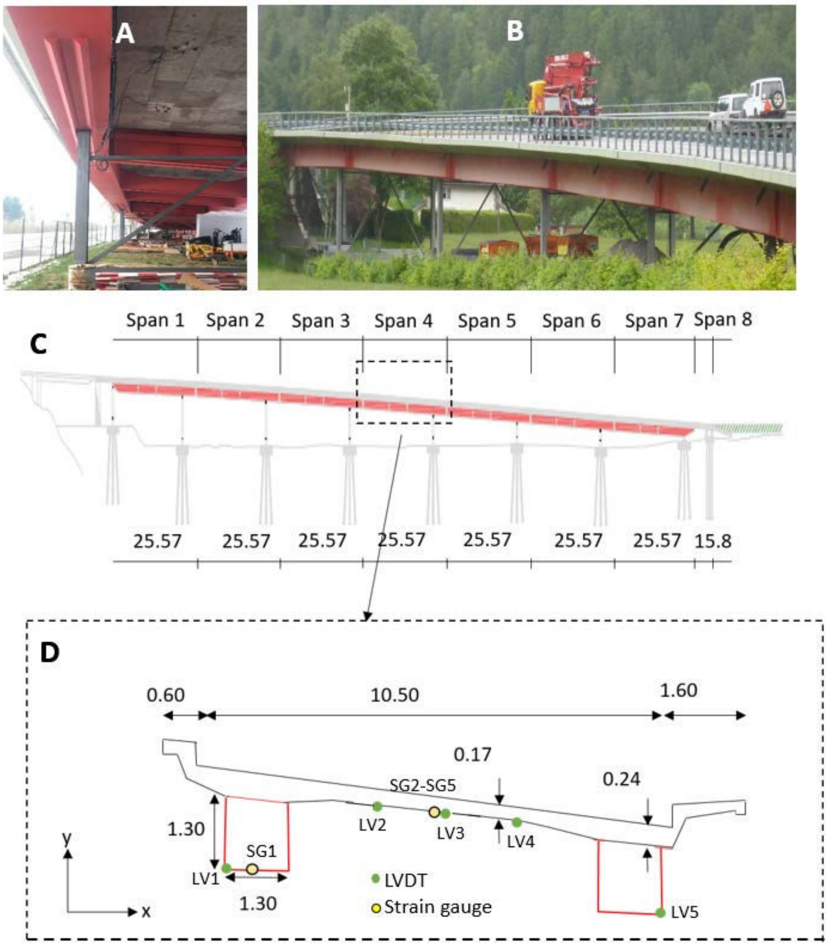

Figure 2: Overview of the case study bridge. A; B) Photographs (taken by authors); C) Elevation view; D) Cross-section showing instrumentation of Span 4.

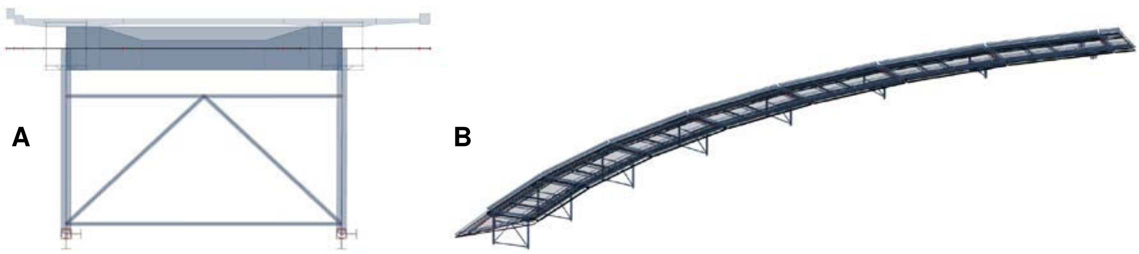

Figure 3: FE model of the bridge using SCIA. A) Cross-section and B) 3-D view of entire model.

3.2 Examinations of bridge structural capacity

3.2.1 Stepwise procedure of refinement

The structural capacity of the bridge is examined using a stepwise procedure depending on the information used and level of engineering training. The first two steps (0 and 1) do not involve considering any monitoring information in the structural safety evaluations, while static load testing and long-term monitoring information are included in the next two steps (3 and 4). Three structural capacity evaluations are considered for each step: the displacement at mid-span (Serviceability Limit State (SLS)), the stress variation in a longitudinal rebar on the concrete deck (Fatigue Limit State (FLS)), and the maximum stress in the steel box girder (Ultimate Limit State (ULS)). For these structural evaluations, the same numerical model is used (Figure 3). For all verifications, results are presented in terms of the degree of compliance, n (Equation 1), where a value larger than 1.0 means that structural safety is ensured:

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

3.2.2 Assessments without monitoring information

In the first two steps, only information from the construction of the bridge and standards are used. Depending on their training, engineers may use either design codes or, if available, codes for existing structures [12]. The main differences in the structural-capacity assessments between these two types of codes are summarized in Table 1. Assessment based on design codes is a wrong approach and would typically lead to very conservative results. Using the code for existing structures, an updated more accurate concrete resistance and updated load levels are used for the structural evaluations, but it requires engineering training on material behavior, load modeling, as well as safety and reliability of existing structures. Additionally, it requires knowledge and understanding of the history of construction and a visual inspection of the structure.

Table 1: Material properties and characteristic values of road traffic loads according to the first two steps of refinement (Steps 0 and 1).

Stepwise procedure of refinement	**Concrete**	**Steel**	**Characteristic value of road traffic load (Lane 1) Q_k [kN] / q_k [kN/m^2]**
Step 0 – Engineer using design codes SIA 260-263	C25/30	S355	270 / 8.1
Step 1 – Engineer with skills on existing structures using SIA 269	C55/60	S355	210 / 3.6

3.2.3 Data-driven model updating

In this section, the measurements from the static load test are used to update the FE model (Step 2). This calibration is made using displacement and strain measurements collected in 2016.

Based on a sensitivity analysis and model-class selection process, three model parameters are selected because their parameter values significantly influence model predictions at the sensor locations for the given excitation. The initial parameter ranges are presented in Table 2. The first two parameters involve the rigidity of the concrete 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 variation of rigidity is simplified as a variation of concrete modulus of elasticity,

E_c. Therefore, smaller values are accounted for in the central part of the slab due to the expected cracking. This hypothesis is verified by the model-updating process. Ranges of equivalent moduli of elasticity for both cracked and uncracked concrete are considered following [12]. The third parameter involves the rotational stiffness between the elements at the Gerber joints, as steel connectors were added during the intervention in 2002. The value range models the connection from a perfect hinge to a fixed joint.
Uncertainty levels associated with the measurements and the modeling are presented in Table 3. These uncertainties are estimated based on sensor-supplier information, a literature review [5, 13], repeatability during load testing, and engineering judgment. Larger model uncertainties are accounted for in the measurements on concrete due to the higher variability of material properties and difficulties in predicting the cracking.

Table 2: Initial parameter ranges and ranges identified from model updating.

Parameter	Description and unit	Initial range	Identified range
Cracked stiffness of the deck, E_{cr}	Equivalent concrete modulus of elasticity [GPa]	3 – 20	11.5 – 12.5
Uncracked stiffness of the deck, E_{nc}	Equivalent concrete modulus of elasticity [GPa]	20 – 50	24 – 42
Rotational stiffness at the support, K_{rot}	Discrete rotational spring [MNm/rad]	0 – 400	49 – 55

Table 3: 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

Error-domain model falsification (EDMF) is a methodology for structural identification introduced in 2013 [7]. This method aims to accurately identify plausible parameter values based on field measurements and prescribed uncertainty levels. Model instances are generated with a unique combination of parameter values. Then, their predictions are compared with the field measurements. Models for which predictions exceed measurements and uncertainty levels are falsified and discarded. Information on structural behavior is gained by reducing initial model parameter ranges through falsifying model instances.
For each location $i \in \{1, \dots, n_y\}$ with n_y the number of measurement locations, R_i denotes the true structural response (unknown in practice). The sensor data, y_i is compared to model-instance predictions, $g_i(\boldsymbol{\theta})$. As both predictions, g_i and sensor data, y_i are imperfect,

uncertainties on model predictions, $U_{i,g}$ and measurements, $U_{i,y}$ should be considered in the analysis. The relation between R_i, y_i, and $g_i(\boldsymbol{\theta})$ is presented in Equation (2):

$$g_i(\boldsymbol{\theta}) + U_{i,g} = R_i = y_i + U_{i,y} \; \forall i \in \{1, \ldots, n_y\} \quad (2)$$

by rearranging the terms in Equation (1) and merging the two sources of uncertainty, $U_{i,g}$ and $U_{i,y}$ in a combined uncertainty, $U_{i,c}$, Equation (3) is obtained. The left-hand side of (3) expresses the discrepancy between the model instance prediction and the sensor data at location, i and is called the residual, r_i.

$$g_i(\boldsymbol{\theta}) - y_i = U_{i,c} = r_i \; \forall i \in \{1, \ldots, n_y\} \quad (3)$$

At each sensor location, falsification thresholds are defined using a level of confidence on the combined uncertainty distribution, typically set at 95% [7]. If the residual of a model instance exceeds the thresholds at one sensor location, this model instance is falsified, meaning that the associated combination of model parameter values is discarded. Model instances for which residuals are within threshold bounds at all sensor locations are included in the candidate model set (CMS), meaning their model parameter values are deemed plausible. Using the CMS, parameter value ranges are thus updated by removing falsified model parameter combinations.

EDMF is applied in this case study based on data of the static load testing. 983 model instances are generated using a grid-based sampling method. Each model has a unique combination of parameter values within the ranges presented in Table 2. Predictions and measurements of model instances are presented in Figure 4. Each line represents a model instance (parameter values and prediction at sensor locations). Candidate models are shown in green. Only six model instances are not falsified, meaning that significant information gain is attained through static load testing. Identified parameter ranges are presented in Table 2. A precise identification is obtained for two parameters: cracked rigidity and rotational stiffness at the Gerber joints.

This data-driven model updating improves the accuracy of predictions of the FE model. Updating rigidity of the structure and boundary conditions can be expected to mostly influence structural capacity values in conjunction with the SLS and FLS limit states.

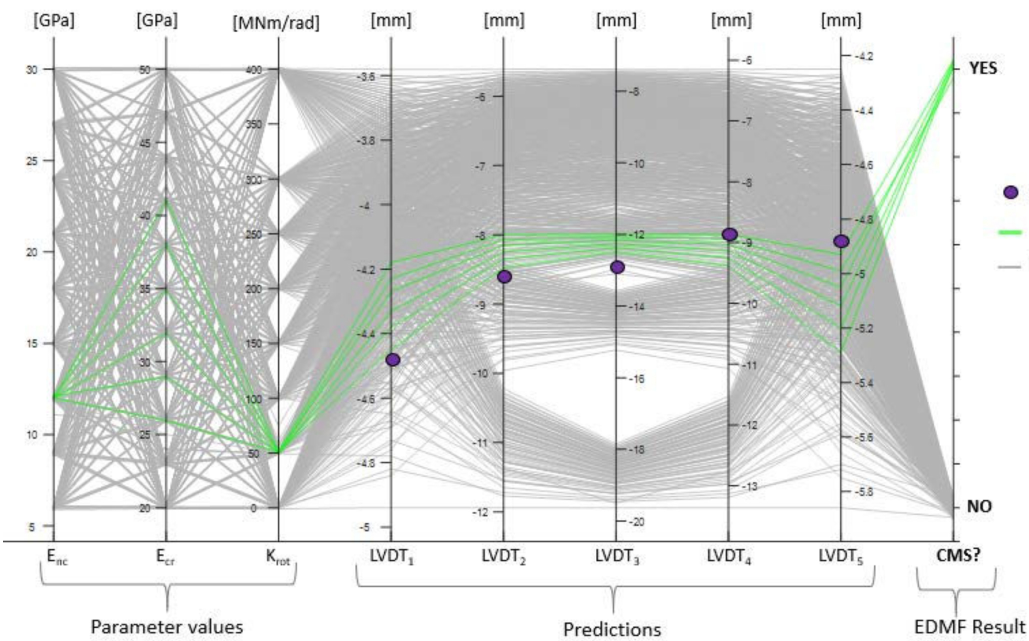

Figure 4: Results of the model updating process (EDMF).

3.2.4 Inclusion of long-term monitoring

This section describes how the long-term monitoring information is used to determine the bridge structural capacity (Step 3). The monitoring occurred over a period of three years using strain gauges. To improve fatigue limit state (FLS) predictions, in-situ monitoring of rebar strains in the concrete deck that were expected to have high-stress variations was implemented. Based on the measurements, stress histograms are created (Figure 5). The measured stress levels are found to be much lower than predicted in the previous code-based levels without monitoring information. This difference is explained by the actual traffic on the bridge, which produces a much lower traffic action effect compared to code load models. This information can be used for the predictions of structural capacity for the FLS.

A strain gauge was installed on the steel girder at mid-span, which is representative of the global structural response. The highest daily strains recorded are presented in Figure 6. On the 6th of October 2016, a much larger stress level was recorded, twice as large as the average value and 25 % larger than the second-largest measurement. Results of the three years of monitoring show that this load level has a probability of occurrence smaller than 10^{-5}/year [14]. This measurement could be associated with the crossing of a large crane of 60 tons. As this vehicle was not authorized to pass over the bridge, this load level is significantly higher than loading due to usual traffic. To approximate a ULS load level, this crane is considered with a safety factor of 1.3 and placed at the most unconservative locations. The structural safety for the ULS can be re-evaluated using this crane as the new maximum demand level for the bridge.

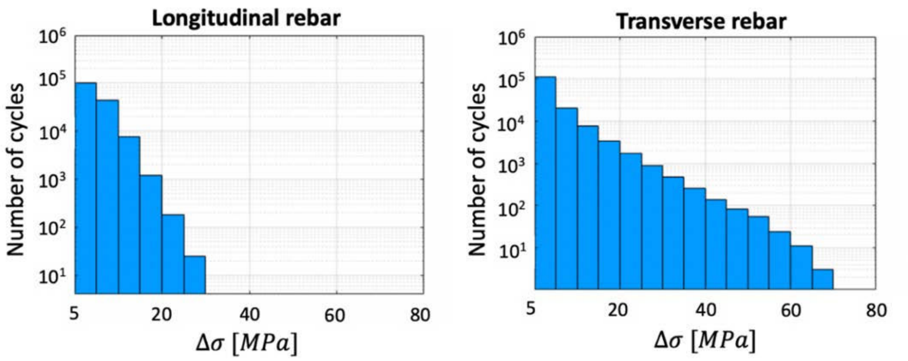

Figure 5: Annual histograms of stress ranges in rebars in the concrete slab.

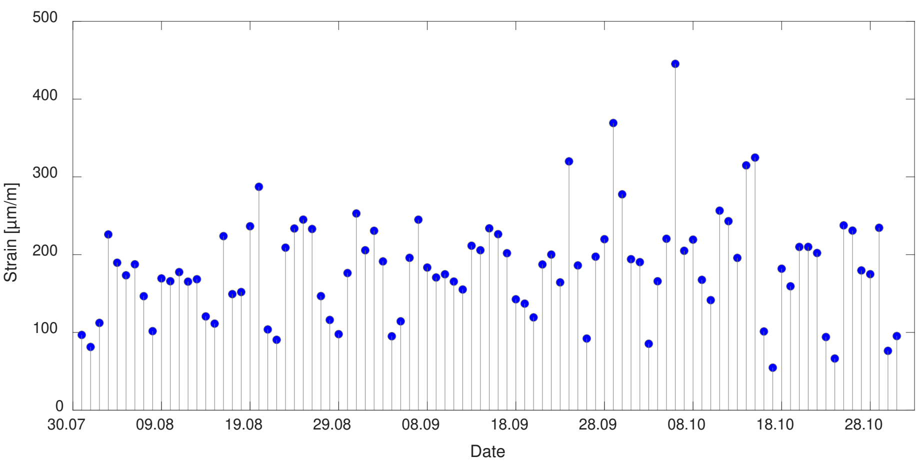

Figure 6: Maximum daily strain recorded.

3.3 Structural examinations based on the stepwise procedure of refinement

In this section, structural safety examinations are discussed for the three limit states according to the levels of information included in the analysis. With the increasing level of information in the stepwise procedure of refinement, the accuracy and reliability of structural evaluations are significantly increased (Table 4).

This refinement based on Steps 3 and 4 helps to avoid over-conservative assumptions as it leads to more accurate evaluations of bridge safety. These results show that with advanced knowledge and data measured at the structure, the safety of a bridge can be verified. Assumptions in Steps 0 and 1 would have likely led to an unnecessary bridge intervention (or even bridge replacement) as the fatigue limit state has a degree of compliance less than 1.0.

Data-driven examinations significantly improve the predictions for all limit states. Model updating based on static load testing (Step 2) provides additional information on structural capacity, for all limit states. In the present study, the evaluations of degrees of compliance are little influenced (mean variation of 5%) due to the type of structure (steel-concrete composite bridge) and because updated bridge-parameter values are close to the initially assigned ones. For other case studies, this methodology has significantly influenced reserve-capacity estimations [15]. Long-term monitoring (Step 3) provides additional information on the demand level for the bridge. Including these data in the bridge examination leads to significantly higher degrees of compliance for both the FLS and ULS.

These results show the benefits of including monitoring information in the structural-capacity computations of bridges. Model updating and long-term monitoring strategies provide unique information on the capacity and demand, respectively (Equation 1). Therefore, these monitoring techniques are necessary complementary approaches rather than competing solutions.

Table 4: Degree of compliance as a function of the level of refinement.

Degree of compliance, *n* (Equation 1)	**Based on design codes (Step 0)**	**Based on standards for existing structures (Step 1)**	**Model updating (Step 2)**	**Long term monitoring (Step 3)**
In-situ data informed?	*No*	*Partly*	*Yes*	*Yes*
Serv. limit state (SLS)	1.78	3.30	3.52	3.52
Fatigue limit state (FLS)	0.42	0.75	0.71	3.43
Ultimate limit state (ULS)	1.05	1.31	1.35	1.95

4 Conclusions

In this paper, the importance and place of non-destructive evaluation (NDE), specifically structural health monitoring (SHM) in the form of bridge load testing, is demonstrated. Based on the example of a bridge case study in Switzerland, the benefits of employing monitoring information in bridge structural capacity computations are shown. For all limit states, data-driven evaluations are more accurate and lead to the conclusion that the bridge has significant reserve capacity. Therefore, NDE offers an important building block for more sustainable and cost-effective infrastructure asset management. However, these advanced examination methods require additional training for structural engineers that go beyond the traditional curriculum. Specifically, literacy in measurement, instrumentation, data analysis, statistics, and history of construction are required. Structural engineering programs at technical universities must thus develop the necessary multidisciplinary backgrounds to ensure that we can better address today's needs of society.

References

1. Brühwiler E (2017) Learning from the past to build the future, Editorial. Proceedings of the Institution of Civil Engineers - Engineering History and Heritage 170:163–165. https://doi.org/10.1680/jenhh.2017.170.4.163
2. Alampalli S, Frangopol DM, Grimson J, et al (2021) Bridge Load Testing: State-of-the-Practice. Journal of Bridge Engineering 26:03120002. https://doi.org/10.1061/(ASCE)BE.1943-5592.0001678
3. Lee S, Kalos N, Shin DH (2014) Non-destructive testing methods in the U.S. for bridge inspection and maintenance. KSCE J Civ Eng 18:1322–1331. https://doi.org/10.1007/s12205-014-0633-9
4. Farrar CR, Worden K (2010) An introduction to structural health monitoring. In: New Trends in Vibration Based Structural Health Monitoring. Springer, pp 1–17
5. Bayane I, Pai SGS, Smith IFC, Brühwiler E (2021) Model-Based Interpretation of Measurements for Fatigue Evaluation of Existing Reinforced Concrete Bridges. Journal of Bridge Engineering 26:04021054. https://doi.org/10.1061/(ASCE)BE.1943-5592.0001742
6. Smith IFC (2016) Studies of Sensor Data interpretation for Asset Management of the Built environment. Frontiers in Built Environment 2:2–8
7. Goulet J-A, Smith IFC (2013) Structural identification with systematic errors and unknown uncertainty dependencies. Computers & Structures 128:251–258
8. Bertola NJ, Papadopoulou M, Vernay D, Smith IFC (2017) Optimal multi-type sensor placement for structural identification by static-load testing. Sensors 17:2904
9. Bertola NJ, Proverbio M, Smith IFC (2020) Framework to Approximate the Value of Information of Bridge Load Testing for Reserve Capacity Assessment. Front Built Environ 6:. https://doi.org/10.3389/fbuil.2020.00065
10. Große CU, Arndt RW, Mähner D, et al (2019) Zerstörungsfreie Prüfung im Bauwesen: Memorandum zur Lehre an deutschsprachigen Hochschulen. Bautechnik 96:360–368. https://doi.org/10.1002/bate.201900008
11. Khemlani L (2010) Scia Engineer. AECbytes< http://www aecbytes com/review/2010/SciaEngineer html>(Oct 20, 2011)
12. Swiss Society of Engineers and Architects (2011) Existing structures, SIA 269, 269/1-269/7. Swiss Society of Engineers and Architects, Zurich, Switzerland
13. Pasquier R, Smith IFC (2015) Sources and forms of modelling uncertainties for structural identification. In: 7th International Conference on Structural Health Monitoring of Intelligent Infrastructure (SHMII)
14. Bayane I, Mankar A, Brühwiler E, Sørensen JD (2019) Quantification of traffic and temperature effects on the fatigue safety of a reinforced-concrete bridge deck based on monitoring data. Engineering Structures 196:109357. https://doi.org/10.1016/j.engstruct.2019.109357
15. Proverbio M, Vernay DG, Smith IFC (2018) Population-based structural identification for reserve-capacity assessment of existing bridges. Journal of Civil Structural Health Monitoring 1–20