Selection of informative monitoring techniques for bridge-performance evaluations

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ABSTRACT: Decisions regarding the management of civil infrastructure are becoming more crucial as a large share of bridges is presently approaching what is often considered to be the end of their theoretical service duration. Evaluating existing structures using a data-driven approach rather than subjective visual inspections, conservative modeling assumptions and unrealistic re-calculations can avoid replacing existing infrastructure prematurely. Structural performance monitoring uses field measurements to provide more accurate evaluations of bridge behavior. As the goal of this monitoring method is to verify bridge safety at a given time, it should be differentiated from structural health monitoring, which aims at detecting structural damage. Possible techniques for structural performance monitoring include non-destructive testing, bridge load testing, and continuous monitoring of structural behavior, load levels, and environmental conditions. Nonetheless, selecting the optimal combination of monitoring techniques is challenging due to the difficulty in predicting their unique information gain and the redundancy in this information. Moreover, information collected on bridge parameters may have various influences on structural verifications, especially because different limit states are usually considered. The value of information must be evaluated before monitoring to ensure that collected data can impact engineering decisions regarding structural safety. This study proposes a method to assess the value of information from multiple bridge monitoring techniques. A riveted steel railway bridge from 1897 in Switzerland is taken as an example. The optimal monitoring technique is defined based on the effects of uncertainty reductions on structural verifications and monitoring costs. Field measurements collected through bridge load testing and continuous monitoring validate results in terms of value-of-information predictions.

1. INTRODUCTION

The collection of field measurements provides information on structural behavior that can either be used to detect structural damage or evaluate structural performance. Structural performance monitoring (SPM) enables the re-evaluation of safety assessments based on the latest sensor data (Feng et al. 2004). This process often helps unlock untapped reserve capacity in existing structures (Pai and Smith 2022). Then, this information can be leveraged to extend bridge service duration, avoid unnecessary structural strengthening and focus future rehabilitation and inspection (Frangopol et al. 2008; Smith 2016).

SPM can be performed using several monitoring techniques. SPM techniques include non-destructive testing (NDT) (Helal et al. 2015), bridge load testing (Lantsoght et al. 2017), bridge weight-in-motion (Hekič et al. 2023), and continuous monitoring of structural behavior (Sawicki and Brühwiler 2022), which can all be referred to as non-destructive evaluation (NDE) methods . Each NDE technique provides data on particular aspects of bridge behavior. However, the potential information collected is limited (Bertola et al. 2023). Selecting the appropriate combination of monitoring techniques is thus crucial. The value of information (VoI) helps define which information can impact decisions regarding bridge safety (Bertola et al. 2020; Straub et al. 2017; Zhang et al. 2021; Zonta et al. 2014).

Before assessing the information-gain potential of monitoring techniques, the first step is to define the metric for structural evaluations. Several metrics have been proposed (Ghosn et al. 2016b; a). In Switzerland, structural safety is evaluated based on the degree of compliance n (Eq. 1), where a value larger than 1.0 means that structural safety is ensured (Brühwiler et al. 2012). The advantage of this metric is that it is generic and can be applied to any structural verifications for serviceability limit states (SLS, ultimate limit states (ULS) and fatigue limit states (FLS), or service limit states (SLS). Analytical or numerical models, such as finite element models, are required to evaluate structural capacity and calculate load effects. Several structural verifications are usually made for each limit state for a given case study.

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

This paper proposes a methodology to evaluate the VoI for SPM. This methodology involves a stepwise process that first identifies structural deficiencies based on Swiss standards for existing structures. Then, the optimal combination of monitoring is selected based on the maximization of the VoI for the structural deficiencies observed in the case study. The method is applied to a steel-riveted bridge case study in Switzerland. Monitoring data during 400 days confirms the prediction that continuous monitoring can reveal additional reserve capacity for FLS deficiencies.

2. VALUE OF INFORMATION OF BRIDGE-MONITORING SYSTEMS

SPM can be used for all types of structural verifications as it can influence both demand (load level) and structural capacity. It has thus a lot of use cases in practice when structural deficiencies are initially predicted. The following procedure is recommended for structural performance monitoring:

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

The aim of this paper is to propose a method to select the appropriate monitoring system that will maximize the VoI (step 3 of the SPM process). Maximizing the VoI of monitoring systems involves defining which data collected is the most likely to affect decision-makers' actions with the smallest monitoring costs.

In SPM, decisions are related to structural-safety assessments, and actions involve strengthening interventions. Monitoring activities are valuable if the data collected can impact the decision regarding bridge safety for structural verifications that initially showed deficiencies. Field measurements may lead to an increase of degrees of compliance (Eq. 1) by reducing uncertainties on three main aspects: material properties (i.e., elastic modulus), load levels (i.e., maximum stress difference due to operating traffic), and structural modeling (i.e., boundary conditions). Each monitoring technique provides a reduction of a subset of these uncertainties that may influence the structural safety assessments (Figure 1).

This reduction of uncertainty can be quantified using either Bayesian decision analysis (Zhang et al. 2021) or pre-posterior analysis (Konakli and Faber 2014). In the present study, pre-posterior analyses are used for the quantification of the VoI.

In this paper, it is assumed that measurements may only lead to an increase in the degrees of compliance as initial evaluations are made using the most conservative values in plausible ranges. In practice, it may arise that measurements will decrease the degrees of compliance. This situation means that errors were made in the initial models, either in the loading or structural properties in the estimates of conservative values. This situation was not accounted for in this paper.

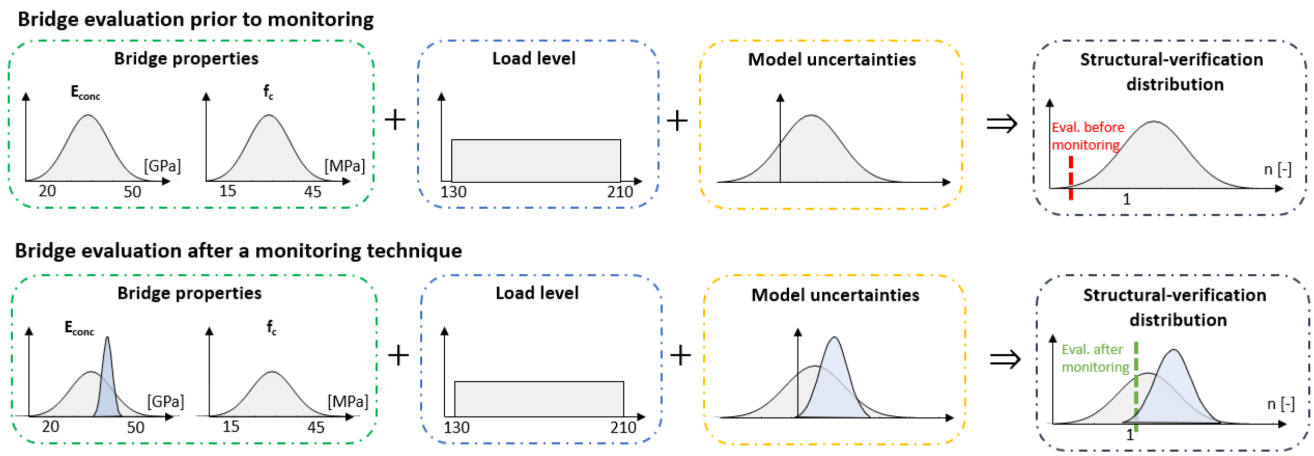

Figure 1 Definition of the bridge evaluation processes prior to and after monitoring.

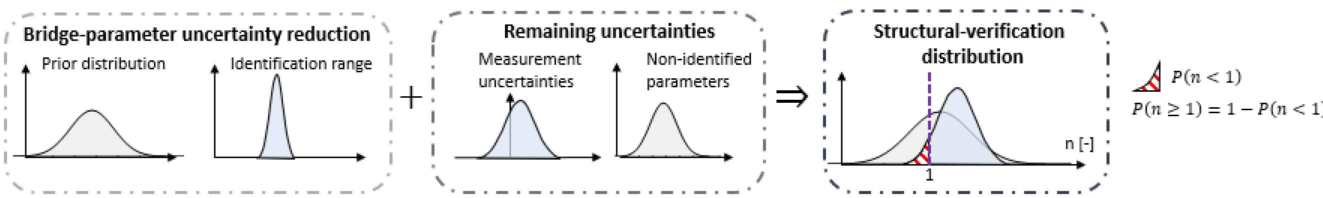

Figure 2 Evaluation of the probability that monitoring data can improve the degree of compliance of a structural verification with a value larger than 1.0.

The VoI of a monitoring technique (or combination of techniques) is quantified using Eq. (2), where the C_{int} is the cost of interventions, C_{mon} the monitoring costs, and $P(n \geq 1)$ is the probability that the degree of compliance will be higher than 1.0 after monitoring. In this study, C_{int} is assumed to be a constant and independent of the monitoring campaign outcomes.

$$VoI_{SPM} = C_{int} * P(n \geq 1) - C_{mon} \quad (2)$$

Selecting the appropriate combination of monitoring techniques that maximize $P(n \geq 1)$ with a minimal C_{mon}. The bridge may present several structural verifications with deficiencies that are uncorrelated, and therefore $P(n \geq 1)$ may be multi-dimensional. Moreover, several bridge parameters affect each dimension of $P(n \geq 1)$, such as material properties (i.e., structural rigidity) and real load level (i.e., frequent and maximum axle loads).

The main difficulty of the VoI estimation lies in the evaluation of $P(n \geq 1)$ with respect to the parameters that can be identified during monitoring, identification range, and remaining uncertainties (Figure 2). Quantification of the identification range depends if the monitoring provides information on the bridge parameters directly or indirectly. When direct measurements (i.e., using strain gauges at fatigue location), this identification range is very precise and straightforward to define. For indirect measurements (i.e., through an inverse analysis after bridge load testing), sensor-placement methodologies can provide a distribution of the potential identification precision (Bertola et al. 2017, 2020). Then, the remaining uncertainties that should account for the measurement uncertainties as well as unidentified parameters are estimated. Next, the posterior distribution of the structural verification is computed using a Monte-Carlo Sampling of all distributions. Finally, $P(n \geq 1)$ is evaluated based on this posterior distribution and verification criterion.

A quantitative evaluation of $P(n \geq 1)$ requires complex analyses of the potential information gain of monitoring systems and the impacts of this monitoring activity on structural verifications, especially when multiple dimensions of structural verifications and several monitoring techniques are involved. As each monitoring technique provides information on a subset of bridge parameters, a sensitivity analysis may allow discarding some monitoring techniques if they do not provide significant improvement of degrees of compliance or if they are clearly suboptimal compared to another monitoring technique.

3. CASE STUDY

3.1. Bridge description

In this Section, the methodology to evaluate the VoI of monitoring systems is applied to a bridge case study in Switzerland. The bridge involves a railway structure from 1897 with a span of 19.6 m (Figure 3). The steel-riveted truss has a height of 2.5 m and supports a steel-concrete through and the ballasted track. The bridge is in good condition with no apparent damage that could significantly affect performance evaluations.

3.2. Evaluation of bridge safety before monitoring

In the first stage, the bridge is evaluated based on Swiss standards for existing structures (Swiss Society of Engineers and Architects 2011) without accounting for monitoring information at this stage. A structural analysis has been performed for the bridge (Schiltz and Brühwiler 2021). The bridge only presents potential fatigue issues on some critical structural elements, while ULS verifications have degrees of compliance larger than 1.0.

For the FLS verifications, the following parameters are mostly affecting the evaluations of structural safety (from the most to the least important uncertainty source):

- The load level on the bridge could be significantly lower than in code requirements (load-level uncertainty) – U1
- The load repartition between the two trusses, currently assumed at 60/40 (model uncertainty) – U2
- The support conditions, currently modelled as a perfect pin (parameter uncertainty) – U3
- The steel elastic modulus (parameter uncertainty) – U4

3.3. Optimal monitoring system

Each monitoring technique provides information only on a subset of these parameters. Four potential monitoring techniques are involved in this study (Table 1). Continuous monitoring involves placing sensors directly in critical areas for fatigue. As this monitoring system involves only simple devices (strain gauges) and a few sensors placed at critical locations, the associated costs of monitoring remain minimal, following the concept of “pocket monitoring” (Brühwiler 2017). Thus, a qualitative analysis shows that this monitoring technique is likely to have the largest potential information gain among all techniques. B-WIM (monitoring the traffic loading) and NDT provide information on a single uncertainty source for monitoring costs similar to other techniques. Therefore, they are suboptimal compared to bridge load testing and continuous monitoring and are not investigated with further details.

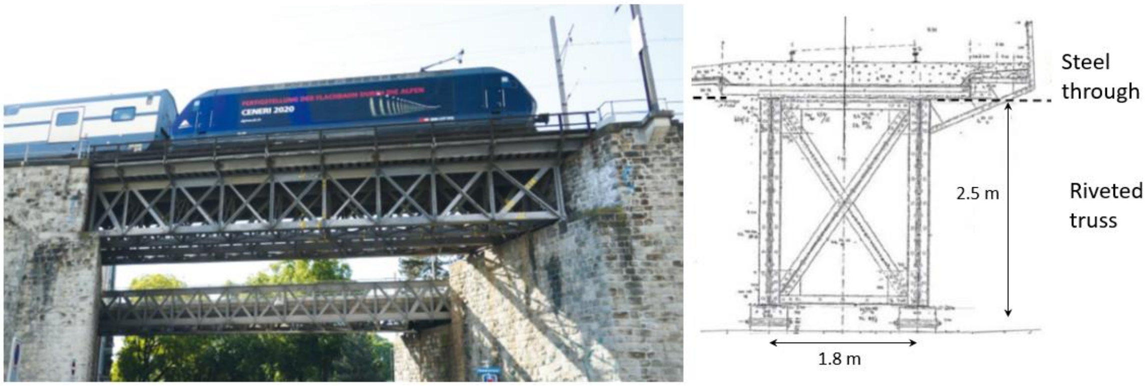

Figure 3 Presentation of the steel-riveted railway bridge and its main sectional hypotheses.

Table 1 Potential information gain for each monitoring technique.

Monitoring technique	*Information uncertainty source*	*Costs*	*Qualitative Info. gain evaluation*
Continuous monitoring	*U1; U2; U3*	*Low*	*Very high*
Bridge load testing	*U2; U3; U4*	*Low*	*High*
BWIM	*U1*	*Low*	*Medium*
NDT	*U4*	*Very low*	*Medium*

Figure 4 shows the prediction of the posterior distribution of the structural verification using continuous monitoring. First, the prior distribution that will be identified using this direct monitoring technique is calculated by combining prior distributions of U1, U2, and U3. As this technique involves direct monitoring, the identification range is very narrow and is estimated to be equal to 1.0 MPa. Then, the remaining uncertainty distribution is estimated using the combination of measurement uncertainty and U4 distributions. By combining these two distributions using Monte Carlo Sampling, a posterior distribution of the degree of compliance is obtained, and $P(n \geq 1)$ can be evaluated. $P(n \geq 1)$ is equal to 0.85, which means that we have an 85 % chance that the degree of compliance is larger than 1.0 after monitoring, meaning that the FLS structural safety is verified. As the costs of this pocket monitoring are significantly smaller than intervention costs, the VoI is largely positive (Eq. 2), and the monitoring should be performed.

Bridge load testing provides information on model and parameter uncertainties. Nonetheless, the biggest uncertainty source, which is the actual load level, is not reduced using this monitoring technique. A quantitative evaluation of the VoI is thus of particular interest. Moreover, this technique involves an inverse analysis based on field measurements during load testing. Predicting the information gain is thus non-trivial and depends on the sensor network installed. In this study, it is assumed that only strain gauges could be installed and dynamic excitations involved by the train passing through the bridge are implicitly considered in the data interpretation. Following studies on sensor placement using entropy-based metrics, the identification range for each parameter can be identified (Bertola et al. 2020; Bertola and Smith 2019).

Figure 5 shows the identification range (based on sensor configuration and parameter identification), the remaining uncertainty distribution involving both U1 and measurement uncertainties, and the posterior distribution of the degree of compliance. For this monitoring technique, $P(n \geq 1)$ is equal to 0.63, showing that this monitoring technique has a significant chance to provide information that can change the decision regarding bridge safety.

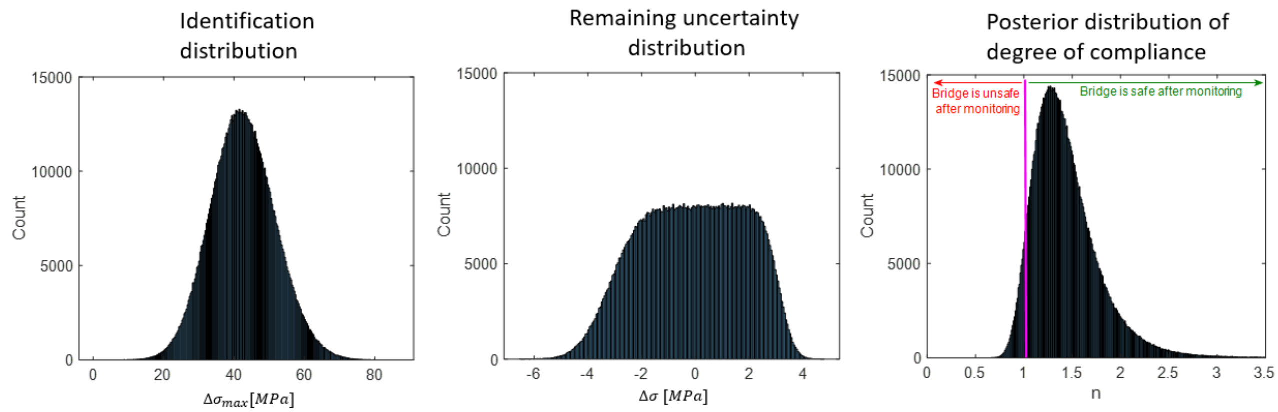

Figure 4 Evaluation of the identification distribution (from initial parameter distribution), remaining uncertainty distribution, and posterior distribution of the critical FLS structural verification after continuous monitoring.

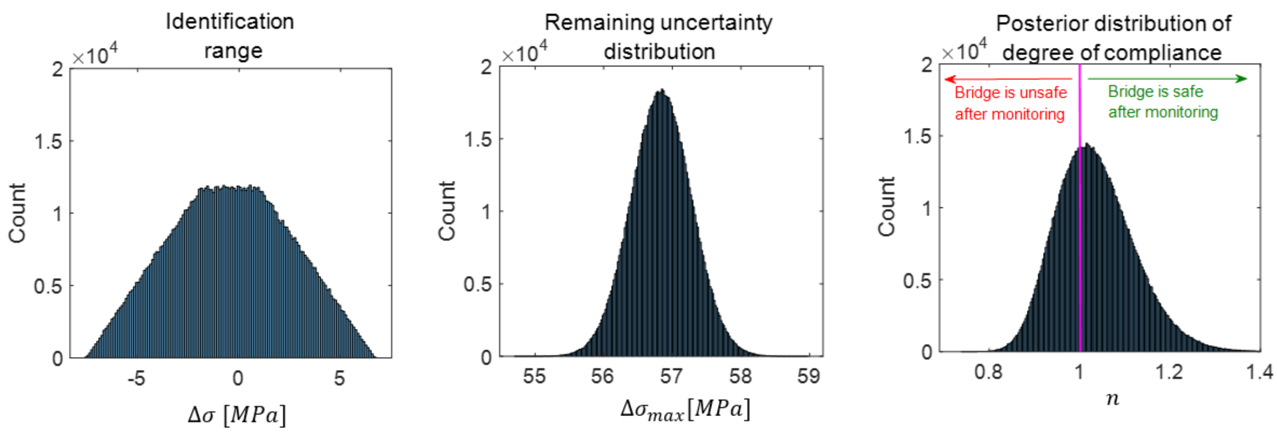

Figure 5 Evaluation of the identification range, remaining uncertainty distribution, and posterior distribution of the critical FLS structural verification after bridge load testing.

VoI of monitoring techniques are compared in Table 2. It is assumed that the C_{mon} of both bridge load testing and continuous monitoring are the same as they involve the same sensor type, with a C_{mon} equal to X. Moreover, performing both techniques is assumed to cost 1.5X. The VoI is maximized when only the continuous-monitoring technique is performed. The pocket monitoring is thus recommended in the present case study.

Table 2 Value of information of monitoring techniques.

Monitoring technique	$P(n \geq 1)$	*Costs*	*VoI > 0 if*
Continuous monitoring	*0.83*	*X*	$X/C_{int} > 0.83$
Bridge load testing	*0.63*	*X*	$X/C_{int} > 0.63$
Combination	*0.85*	*1.5X*	$X/C_{int} > 0.57$

3.4. Result corroboration

For the riveted steel railway bridge, nine strain gauges were installed at critical locations, and the bridge was monitored for 400 days between 2018 and 2019. Additional details on this monitoring campaign can be found in (Schiltz and Brühwiler 2021). The histogram of stress difference is shown in Figure 6. The maximum stress difference obtained during this monitoring is 40 MPa and is associated with a degree of compliance n equal to 1.45. Thanks to the monitoring data, the structural system is now verified, and the bridge does not require strengthening. Moreover, this degree of compliance validates the prediction prior to monitoring based on the proposed methodology

(Figure 4). The value obtained is close to the predicted most likely output, showing that field measurements validate the predictions in terms of information gain.

4. CONCLUSIONS

In this study, a method is proposed to quantify the value of information of monitoring techniques for the purpose of structural performance monitoring. This method supports engineers in selecting the best combination of monitoring techniques (i.e., load testing, continuous monitoring, and non-destructive tests) to improve the structural-verification metric with a minimum monitoring cost. The case study has shown that the optimal monitoring technique may vary significantly with the types of bridges and associated uncertainties. Monitoring data have confirmed the predictions in terms of expected information gain and shows that bridge monitoring has the potential to modify and improve bridge performance evaluation and the decision regarding interventions.

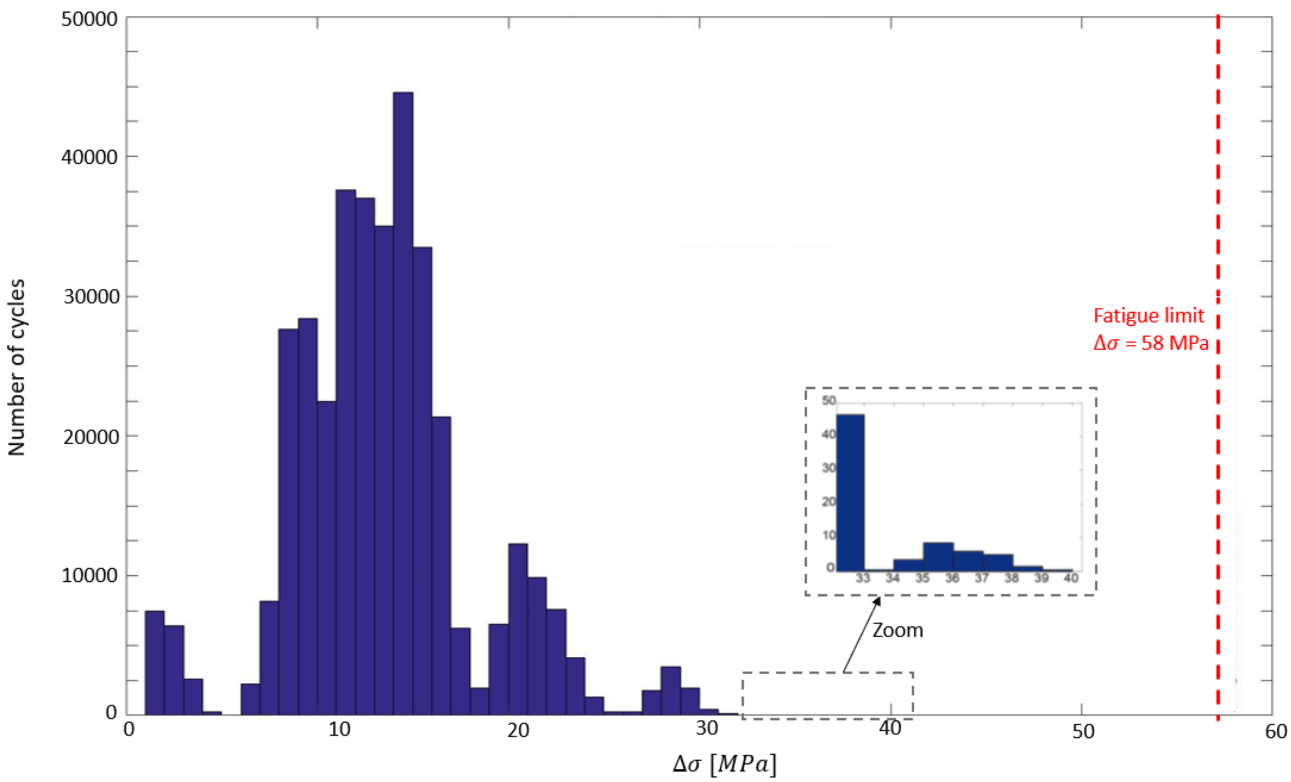

Figure 6 Histogram of stress difference using strain-gauge monitoring at the critical element for 400 days and 50572 trains.

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