AI Based Surrogate Model for Digital Twins in Structural Health Monitoring of Reinforced Concrete Structures

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Abstract:

Artificial Intelligence (AI), with particular emphasis on Artificial Neural Networks (ANNs), has become an integral component of contemporary scientific and engineering disciplines. An important emerging application is the use of real-time surrogate models within digital twin frameworks for structural health monitoring. In the methodology presented, ANNs serve two principal functions. First, during the calibration phase, they are employed to ensure that the digital twin accurately reproduces the mechanical response of the corresponding physical structure. Following calibration, the digital twin provides a platform for ANN training through physics-informed deep learning, drawing on data generated by sensitivity analyses conducted via nonlinear finite element simulations in ATENA software. In the subsequent stage, the trained ANN is deployed as a rapid-response surrogate model, delivering critical safety-related information to support the continuous monitoring of bridge structures. This study presents the development of a computationally efficient and accurate ANN-based surrogate model and highlights advances in physics-informed deep learning methodologies for structural analysis, reliability assessment, and life-cycle evaluation of critical infrastructure. The calibrated numerical model has been successfully applied to the durability assessment and life-cycle prediction of reinforced concrete bridges.

Keywords: artificial intelligence, deep machine learning, digital twin, reinforced concrete bridges, reinforced concrete modelling, nonlinear simulation, durability modelling, reinforcement corrosion.

1 Introduction

A resilient and efficient transport infrastructure is a cornerstone of economic productivity and social development in both industrialized and emerging economies. In the European Union, road and rail networks play a vital role in ensuring the mobility of goods, services, and people, directly supporting competitiveness and cohesion across member states. However, a substantial proportion of this infrastructure was constructed during the post-World War II economic expansion, which implies that many bridges, tunnels, and railway structures have now exceeded half a century of service. The ageing of these critical assets poses significant challenges, not only in terms of safety and reliability but also with respect to the escalating costs of maintenance and rehabilitation. Statistical evidence from 22 OECD countries [1] shows that between 1997 and 2016 the average annual expenditure on infrastructure maintenance increased by approximately 1.78 billion euros, underscoring the growing financial burden placed on public authorities and operators.

To address these challenges, innovative approaches are being explored to extend service life and optimize resource allocation. Among these, the concept of the digital twin has gained increasing prominence across engineering disciplines, including structural design and monitoring [2]. By creating a dynamic, data-driven virtual replica of a physical asset, digital twins offer the potential to improve predictive maintenance, enhance decision-making, and reduce lifecycle costs.

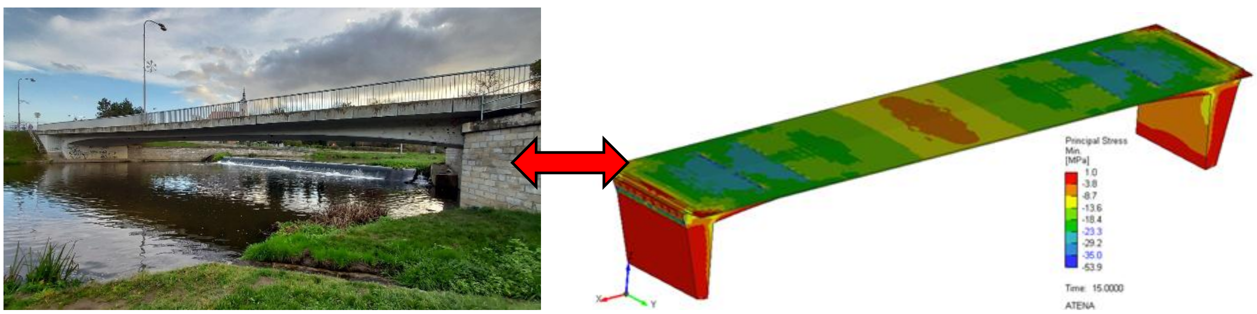


Fig. 1: Bridge digital Twin is typically a combination of monitoring of real structural response and a numerical model that exchange data to provide predictions and information on structural health and reliability.

The proposed methodology builds on the calibration of a computational model using data collected directly from the physical structure. This process ensures that the digital representation is not only geometrically accurate but also faithfully reproduces the essential mechanical and durability-related characteristics of its real-world counterpart. In structural engineering practice, such calibration involves simulating responses to both permanent (dead) and variable (live) loads, as well as capturing long-term phenomena that influence durability, including cracking, creep, shrinkage, and material degradation. A well-calibrated digital twin thus provides a robust platform for evaluating the present condition of a structure and for forecasting its future performance under evolving operational and environmental conditions. When complemented by systematic field inspections and monitoring campaigns, the digital twin becomes a strategic instrument for managing the ageing process of infrastructure assets and optimizing their maintenance schedules.

Artificial Intelligence (AI), particularly through the application of Artificial Neural Networks (ANNs), is increasingly reshaping industrial processes and engineering practices. One of its most promising roles in structural engineering is the development of real-time, rapid-response surrogate models embedded within digital twin frameworks. The digital twin paradigm refers to the creation of a dynamic, data-driven digital replica of a physical asset (see Fig. 2). This virtual counterpart is typically realized through advanced numerical models that remain in continuous interaction with the real structure via sensor data, measurements, and simulation updates. In the case of reinforced concrete structures, such twins are especially valuable for assessing safety margins, predicting durability, and evaluating reliability throughout the life cycle. A primary motivation for this approach is to overcome the limitations of current monitoring systems, where infrastructure owners and operators are often inundated with large and complex datasets that are difficult to interpret and transform into timely engineering or maintenance decisions.

Within this framework, ANNs assume two fundamental roles:

Calibration of the Digital Twin: During the calibration phase, ANNs are employed to refine the accuracy of the virtual model, ensuring that it replicates the actual behavior of the physical structure. This is achieved through physics-informed deep learning, in which the network is trained with data generated by systematic sensitivity analyses of the virtual model. These analyses are based on nonlinear finite element simulations conducted with the ATENA software [3], which captures complex material and structural responses. By integrating such simulated data into the training process, the ANN can learn meaningful structural relationships that extend beyond purely statistical correlations.

Real-Time Structural Health Monitoring: After training, the ANN is deployed as a rapid-response surrogate model capable of delivering near-instantaneous safety insights for continuous structural monitoring. This is particularly relevant for bridges and other critical transportation assets where timely decision-making can mitigate risks and prevent costly failures. By providing fast yet reliable assessments, this AI-driven strategy enhances the effectiveness of maintenance planning, supports risk-informed asset management, and strengthens the resilience of infrastructure systems.

The integration of AI with digital twin technology constitutes a substantial advancement in structural health monitoring. It enables infrastructure stakeholders to transition from reactive maintenance strategies to proactive, data-driven decision-making processes. Beyond efficiency gains, this synergy contributes to the long-term sustainability of critical assets by extending service life, reducing maintenance costs, and improving resilience against both everyday deterioration and extreme events. As such, the approach outlined here represents a significant step toward the realization of intelligent, adaptive infrastructure management systems.

2 ANN Model for model calibration

Ensuring the accuracy and reliability of a Digital Twin is of paramount importance, as the quality of its predictive capabilities depends directly on the fidelity of the underlying computational model. In the present study, this requirement is addressed by developing a detailed numerical model of a real-world bridge using the finite element simulation system ATENA [3]. This advanced software environment is particularly suited for modeling the nonlinear behavior of reinforced concrete structures. It is capable of simulating a wide range of critical mechanisms, including concrete cracking and crushing, reinforcement yielding, prestressing effects, and the bond interaction between concrete and steel reinforcement. Such comprehensive modeling capabilities are essential for reproducing the complex failure modes that typically govern the performance and durability of reinforced concrete bridges.

The constitutive material formulation employed is the fracture-plastic concrete model, which has been elaborated in detail in previous publications [4][5]. Its applicability to the simulation of common structural failure modes has been extensively validated in [6]. In that work, a systematic calibration of model uncertainty was carried out, resulting in a model uncertainty partial safety factor of 1.16. Furthermore, the statistical evaluation yielded a bias of of μ_θ=0.979 and a coefficient of variation V_θ = 0.081. These values define the level of confidence and accuracy required for parameter identification and provide a robust foundation for the application of Artificial Neural Networks (ANNs) in the present framework [7][8].

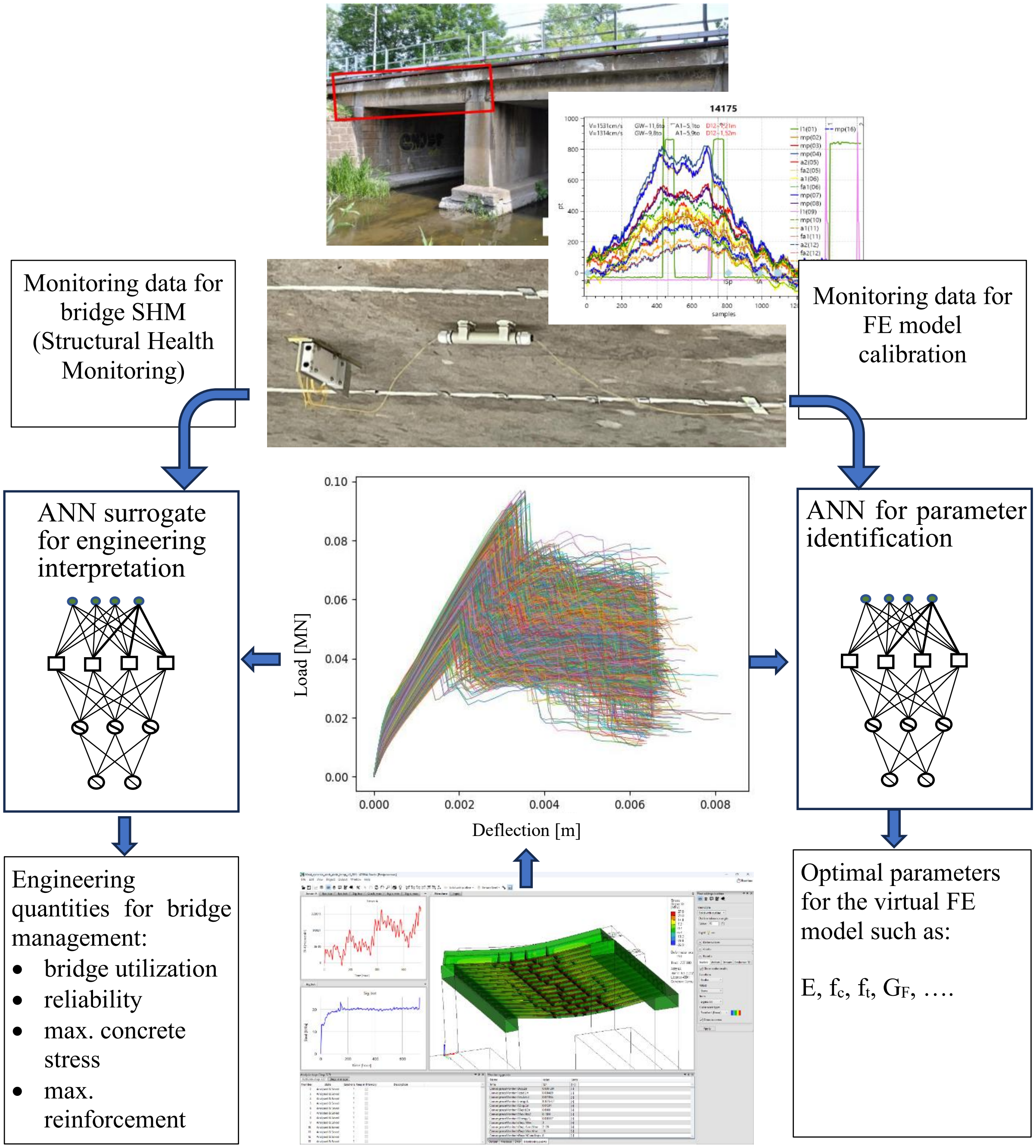


Fig. 2: Digital twin schema: ANN surrogate model is used for two purposes: ANN on the right for model calibration, i.e., parameter identification, and ANN on the left provides real-time engineering data for maintenance decisions.

To verify the feasibility of parameter identification with ANNs, a benchmark example was performed using a shear beam model (Fig. 3), which was based on the well-documented experimental campaign of Leonhardt [9]. The purpose of this verification was not to reproduce the experimental data exactly, but rather to test whether an ANN can reliably infer key input parameters of the material model from structural response data. Specifically, the parameters under investigation were the compressive strength (f_c), tensile strength (f_t), elastic modulus (E), and fracture energy (G_F). These parameters were chosen because they represent the most influential characteristics of concrete governing both stiffness and failure behavior.

For this purpose, a training dataset was generated consisting of up to 1000 precomputed load-displacement curves, each corresponding to a different combination of material parameters. Fig. 4 illustrates the scatter of these simulated responses, highlighting the variability introduced by changes in the selected input properties. The ANN was then trained to predict the most appropriate set of material parameters that could reproduce the experimentally obtained structural response (Fig. 5). The dataset was systematically partitioned, with 64% of samples used for training, 16% reserved for validation, and 20% allocated for independent testing. This division ensures both generalization and robustness of the trained network.

The results demonstrate that the ANN was able to achieve a high level of accuracy in predicting the target material parameters, as evidenced by the close agreement observed in the testing series (Fig. 6). This finding confirms that ANNs are capable of learning the nonlinear mapping between load-displacement responses and underlying material properties, providing a promising tool for automated parameter identification in digital twin applications. Importantly, this approach significantly reduces the need for labor-intensive trial-and-error calibration of finite element models, thereby accelerating the deployment of accurate digital twins for structural health monitoring and life-cycle assessment of reinforced concrete bridges.

Ensuring the accuracy of a Digital Twin is crucial. In the presented work, this means developing a numerical model of a real-world bridge, which was developed in the finite element simulation system ATENA [3]. The software can simulate the nonlinear behavior of reinforced concrete bridges, including cracking, crushing, reinforcement yielding, prestressing, and concrete-reinforcement bonding.

The fracture-plastic concrete material model was detailed in earlier studies [4][5], and its applicability for simulating typical failure modes was validated in [6]. There, the model uncertainty partial safety factor was calibrated, yielding a general value of 1.16, with a bias of μ_θ=0.979 and a coefficient of variation V_θ=0.081, defining the required accuracy for parameter identification.

The parameter identification process using ANN was verified using a shear beam example (Fig. 3), based on beams tested by Leonhardt [9]. The goal is not to match experimental data but to assess whether an ANN can accurately identify input parameters—compressive strength (f_c), tensile strength (f_t), elastic modulus (E), and fracture energy (G_F)—from a given load-displacement diagram (Fig. 4). The training dataset contained up to 1000 precomputed samples with varying material parameters. Fig. 4c illustrates the scatter of the calculated load-displacement diagrams. The neural network is then trained to predict the most suitable set of material parameters for predicting the experimentally obtained structural response indicated in Fig. 5. In each data set 64% samples are used for training, 16% for validation and 20% for testing. Fig. 6 demonstrates the accuracy of the predicted values for the selected material parameters from the testing series.

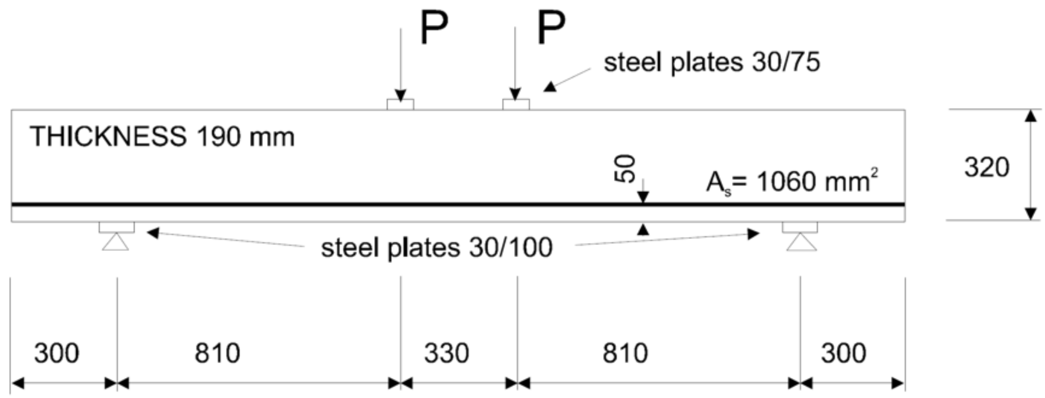
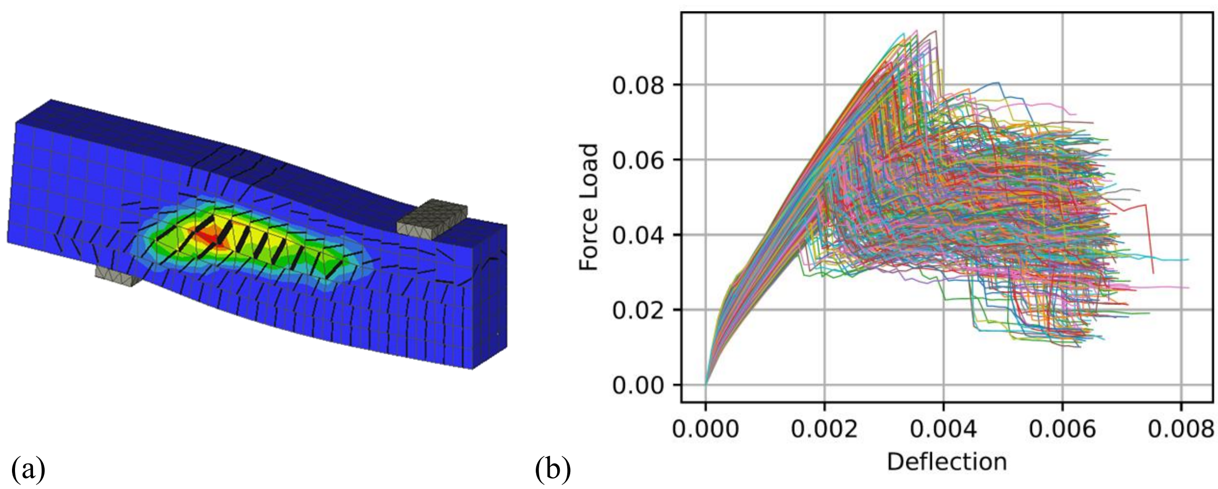


Fig. 3: The geometry of shear beam test [9] for the study of ANN accuracy for the model parameter identification and surrogate modelling. Units are in mm.



(a) (b)

Fig. 4: (a) Shear failure mode for the shear beam [9], (b) load-displacement diagrams of 1000 training and testing samples.

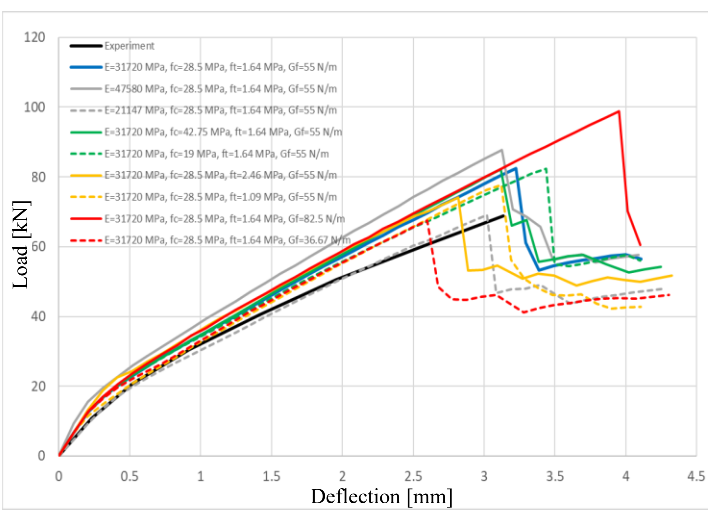


Fig. 5: Shear beam test experimental result with selected analyses with the closest match.

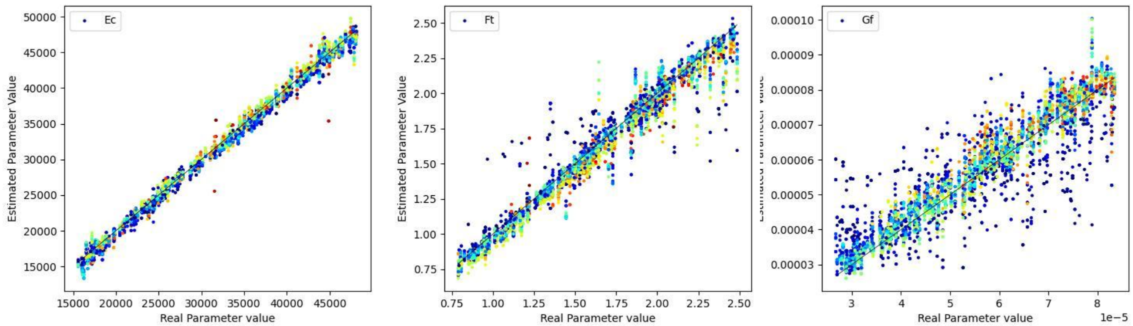


Fig. 6. ANN model accuracy for parameter identification of the critical material parameters for 1000 training dataset.

3 Rapid Response Surrogate Engineering Model

In conventional applications of bridge monitoring systems, vast quantities of data are continuously collected through networks of sensors strategically distributed across the structure. These sensors record real-time measurements of key physical quantities such as strain, displacement, acceleration, and temperature. In current practice, the monitoring strategy frequently relies on comparing these raw measurements against predefined threshold values. When a threshold is exceeded, the system issues warnings or alarms to alert operators of potential anomalies. Although this approach ensures a basic level of safety surveillance, it suffers from a significant drawback: the sensor readings themselves often lack direct interpretability and are not inherently linked to engineering-level indicators of structural performance. Consequently, operators are left with large datasets that may be difficult to interpret in terms of actual structural safety or serviceability.

For decision-makers and engineers, what is needed are higher-level performance indicators that can meaningfully capture the condition of the structure. Such engineering metrics include, for instance, the structural reliability index, the probability of failure or collapse, and the utilization ratio of specific structural components under applied loading. Unlike isolated sensor measurements, these indicators provide actionable insights into the safety margin of the bridge and its capacity to withstand current and future demands. The inability of conventional systems to directly provide this information underscores a critical gap between raw data collection and meaningful engineering assessment.

This gap can be addressed through the use of surrogate models, which serve as computationally efficient proxies that link raw sensor data with engineering-level quantities. A surrogate model essentially encapsulates the complex relationships derived from detailed numerical simulations or experimental data, enabling it to translate sensor inputs into interpretable metrics in near real time. In doing so, surrogate models not only reduce the computational burden associated with repeated nonlinear finite element analyses but also significantly enhance the responsiveness and utility of bridge monitoring systems. By delivering rapid estimations of performance indicators, they support informed decision-making regarding maintenance, operation, and risk management.

To demonstrate this concept, the previously introduced shear beam benchmark is revisited as a validation case. Here, a Dense Neural Network (Dense NN) architecture is employed to construct the surrogate model. The chosen network consists of four hidden layers, providing sufficient depth to capture the nonlinear relationships between inputs and outputs. The surrogate model in this context is designed to replicate the results of computationally demanding nonlinear simulations by learning a functional mapping, denoted as Φ_p. This mapping (1) estimates the applied load $\bar{F}_i$ based on a combination of deflection values D_i and material properties, including the elastic modulus (E), compressive strength (f_c), tensile strength (f_t), and fracture energy (G_F).

The advantage of this surrogate representation is twofold. First, it drastically reduces the time required to obtain load estimations compared to running full finite element analyses, enabling near real-time evaluation of structural behavior. Second, by embedding physics-informed training data, the surrogate model maintains a close correspondence with the underlying mechanics of reinforced concrete behavior. As a result, the model provides not only speed but also accuracy and interpretability, thereby enhancing the overall effectiveness of digital twin–based bridge monitoring systems. In practical terms, this allows engineers and operators to transition from being passive data collectors to proactive decision-makers equipped with reliable, timely, and actionable insights.

$$\bar{F}_i = \Phi_p(D_i, \mathrm{E_c}, \mathrm{f_c}, \mathrm{f_t}, \mathrm{G_F}) \tag{1}$$

Fig. 7 shows the training results of the surrogate model for the pilot case of the shear beam (see Fig. 3), evaluated for two different datasets, referred to as Dataset A and Dataset B. These datasets, containing 100 and 400 samples respectively, were generated through nonlinear finite element (FE) simulations. Each dataset captures the relationship between structural deflection and applied load across a range of varying material properties. The primary objective was to exploit these datasets to train an artificial neural network (ANN) capable of functioning as a computationally efficient surrogate, thereby replicating the results of full-scale FE simulations at a fraction of the computational cost.

The figure further illustrates the predictive performance of the surrogate model by comparing its outputs with the original FE simulations for previously unseen test data. These test samples were deliberately excluded from the training phase in order to provide an unbiased assessment of the generalization ability of the ANN. In the load–displacement diagrams presented, the solid curves correspond to the original FE responses, while the dotted curves depict the surrogate model predictions. Even in the case of Dataset A, with only 100 training samples, the ANN is able to approximate the FE responses with reasonable accuracy, capturing both the nonlinear behavior and the overall system trends. Minor discrepancies are visible, particularly in regions of high nonlinearity, yet the model consistently reproduces the essential features of the structural response. When trained with Dataset B (400 samples), the predictive quality improves markedly. The larger dataset provides the ANN with greater exposure to the variability of material parameters, enabling it to learn a more precise mapping between inputs and outputs. This results in a more robust model with reduced error and higher reliability in reproducing unseen responses.

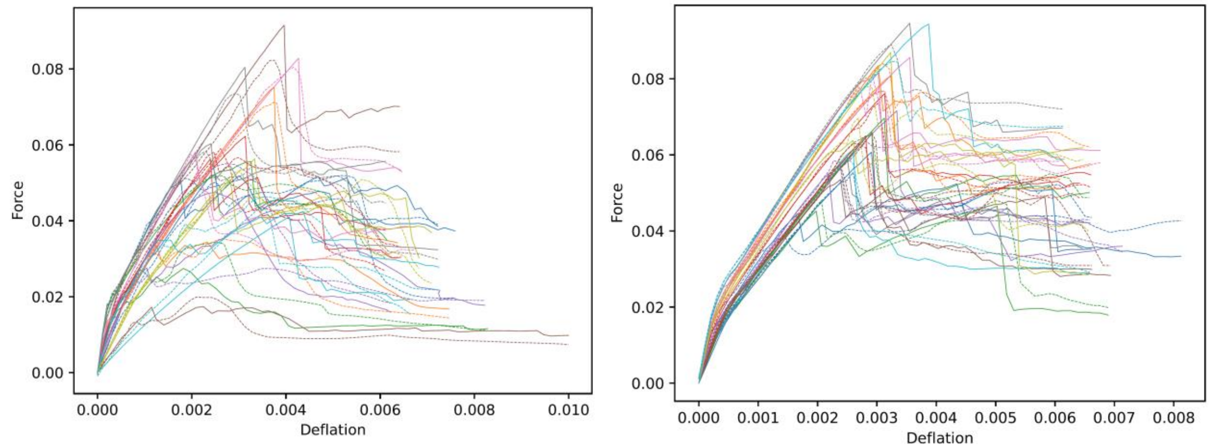


Fig. 7. Capability of the ANN surrogate model to predict the load-displacement curves of the shear beam model, (lef) Dataset A – 100 samples, (right) Dataset B – 400 samples.

The broader significance of this exercise extends beyond the pilot shear beam case. Within the framework of Digital Twin technology, ANN-based surrogate models such as the one demonstrated here can be deployed in near real time to evaluate structural condition and operational safety. A particularly valuable application lies in the estimation of utilization ratios, which quantify the proximity of a structure to its failure threshold under the prevailing load state. By providing this metric in real time, the surrogate model equips infrastructure managers with actionable insights that go far beyond raw sensor data. Such capabilities open the door to proactive maintenance strategies, early-warning systems for abnormal behavior, and optimization of load management. Ultimately, the integration of surrogate modeling into digital twins enhances not only the efficiency of monitoring but also the resilience and long-term sustainability of critical infrastructure systems.

4 Example of composite concrete steel railway bridge

This section introduces a pilot implementation of the proposed Digital Twin framework, integrating ANN-based surrogate modeling, applied to a real-world bridge structure. The case study focuses on a small railway bridge shown in Fig. 8, which is located near the village of Kostomlaty in the Czech Republic. The bridge, constructed in 1946, is a relatively modest two-span structure composed of four reinforced concrete slabs strengthened with embedded steel I-sections (see Fig. 9). After more than seven decades of service, the bridge exhibits pronounced signs of ageing and material deterioration. Most notably, longitudinal cracks have formed along the underside of the slabs, raising concerns regarding the structural integrity and long-term durability of the system.

Assessment of the bridge revealed that, while it narrowly satisfies the required load-bearing capacity under Ultimate Limit State (ULS) conditions, it performs poorly under Serviceability Limit State (SLS) checks. Excessive deflections and the extent of visible cracking indicate that the bridge does not meet current serviceability criteria, thereby limiting its reliability in day-to-day operation. Due to these issues, the structure was selected for continuous monitoring and designated as a pilot demonstrator within the ongoing Digital Twin research project. Its relatively simple geometry, coupled with its deteriorated condition, makes it an ideal candidate for testing and validating the practical integration of Digital Twin concepts with AI-driven surrogate models.

Within the proposed framework, the ANN model discussed in Section 2 is first used for system identification to find suitable material parameters as shown in Fig. 10. Then the ANN-based surrogate model developed in Section 3 is deployed to forecast the bridge's thermal response. The model, trained on a series of nonlinear FE simulations using the model shown in Fig. 11, is designed to estimate strain values resulting from time-varying ambient temperature conditions. Hourly temperature histories—such as the representative June profile used in this study—can be readily obtained from standard meteorological records. Structural response is tracked using fiber-optic sensors installed longitudinally along the underside of the bridge deck (Fig. 8 and Fig. 9). These sensors record strain at four distinct locations, with particular attention given here to the mid-span readings, where thermal effects are typically most pronounced.

Fig. 12 compares the FE-predicted strain responses at the sensor locations under the imposed temperature history. This simulated dataset provides the foundation for training the ANN-based surrogate model, enabling it to reproduce thermal strain behavior with high computational efficiency. Once trained, the ANN operates as a functional mapping that predicts thermal-induced strains directly from temperature input data, thus enabling real-time evaluation of structural response within the Digital Twin environment. This approach demonstrates how surrogate models can bridge the gap between computationally demanding nonlinear simulations and the need for rapid, continuous predictions required in practical monitoring applications. The ANN based surrogate model from Section 3 then represents a functional:

$$\bar{S}_{n,i} = \Phi_T\left[\boldsymbol{f_{Ti}}(t_{i-24}, t_i), T_{Avg}(t_{i-72}, t_{i-24})\ \right] \tag{2}$$

The ANN model estimates the strain value at sensor S_n at time step i, using the ambient temperature history over the preceding 24 hours and the current time i. Additionally, it incorporates the average temperature from the earlier 48-hour period (i.e., between $i-72$ and $i-24$) to account for long-term thermal effects.

The developed ANN model is designed to provide an estimate of the structural response recorded at a given sensor S_n at time step *i.* The prediction is based on two sources of thermal information: (i) the detailed temperature history over the preceding 24 hours, and (ii) the average temperature trend calculated over the two days prior to that interval, i.e., the range from *(i-72, i-24)* hours. This combination of short-term fluctuations and longer-term thermal trends allows the surrogate model to capture both immediate and cumulative temperature effects on the bridge structure.

The accuracy of the ANN surrogate in reproducing measured strain values is demonstrated in Fig. 12, where the predicted sensor outputs show strong agreement with the reference data. This validation highlights the capability of the surrogate model to replace computationally demanding finite element simulations with near real-time predictions. Importantly, the approach is not restricted to strain measurements alone. Once trained, the ANN surrogate can be configured to predict a broad range of engineering performance quantities that are directly relevant for structural assessment. For instance, it may be employed to estimate the maximum crack width in critical regions of the slab or to identify the peak compressive stress developing in the concrete (see Fig. 13). Such indicators are of far greater practical significance for engineers than raw strain values, as they directly relate to serviceability and safety criteria.

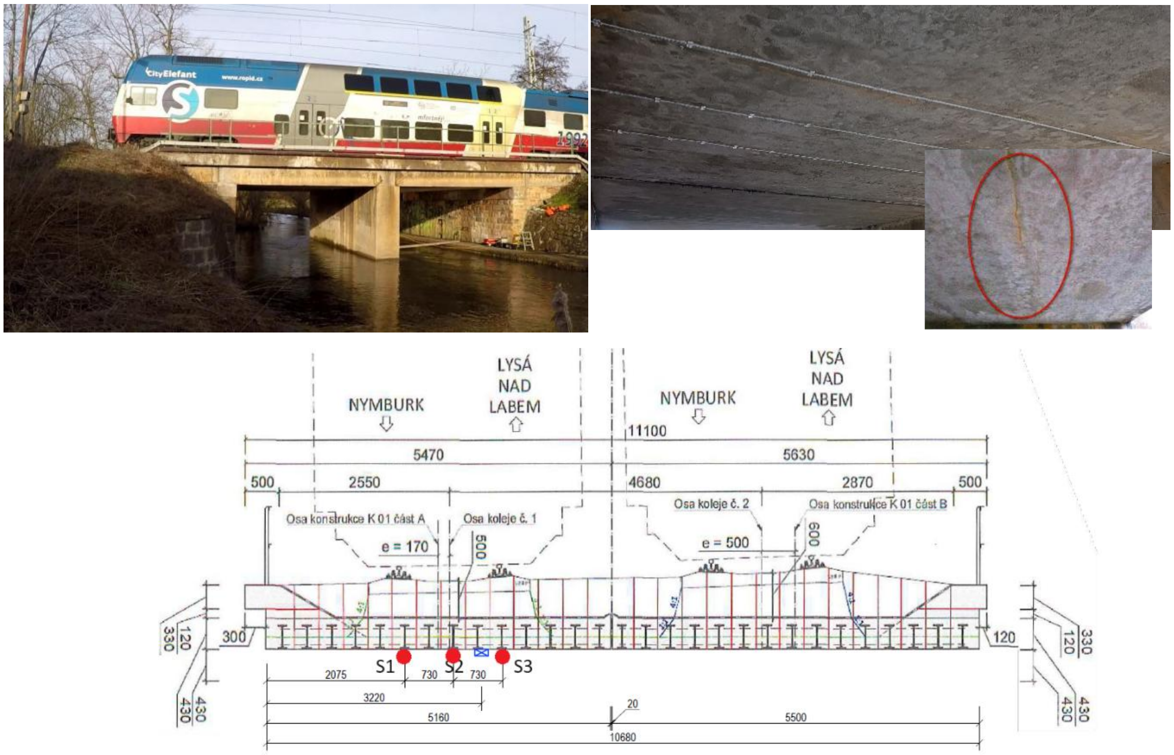


Fig. 8: Railway bridge at Kostomlaty, Czech Republic showing the sensor location S1, S2 and S3.

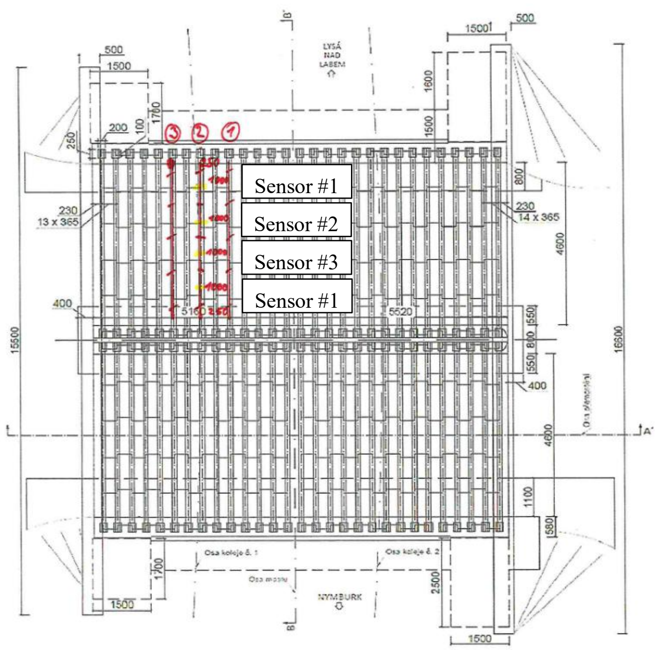


Fig. 9: Kostomlaty pilot bridge application example showing the top view with the sensor locations.

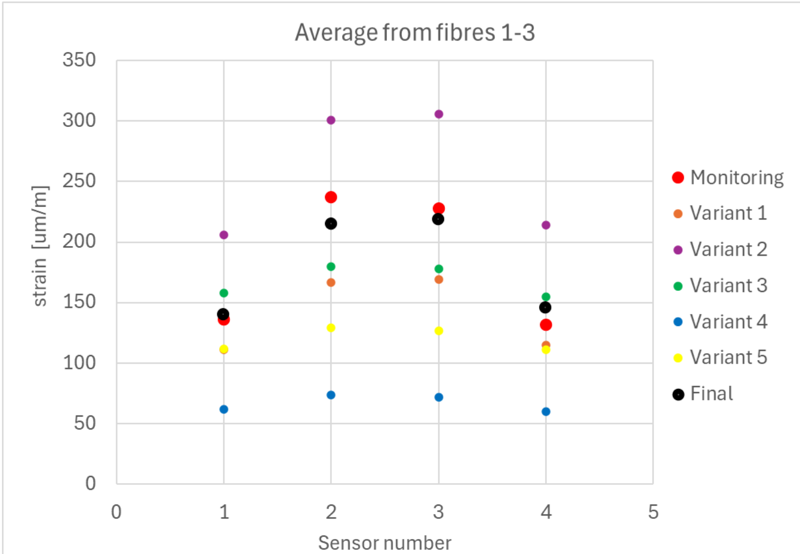


Fig. 10: Example of data fitting and parameter identification process for Kostomlaty railway bridge.

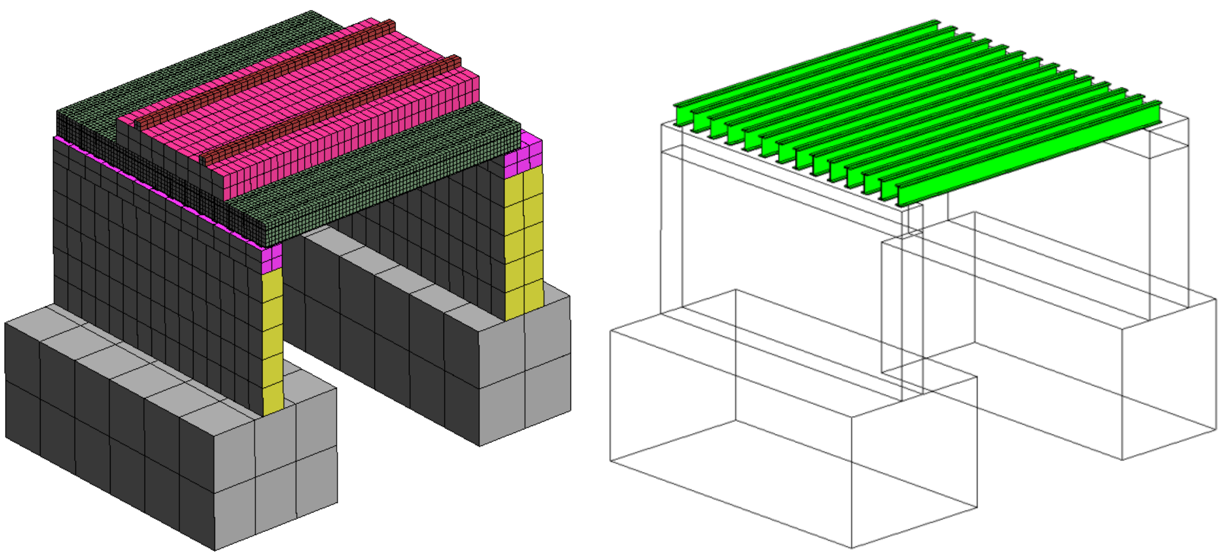


Fig. 11: Finite element model of the quarter section of the model, right figure shows the location of the internal I steel beams.

It is essential to recognize that the structural response of the studied bridge is highly nonlinear, owing to its hybrid system of embedded steel beams within plain concrete. As illustrated in Fig. 14, microcracking is observed even under the action of self-weight, prior to the application of service loads. These microcracks further propagate under thermal loading, underscoring the complex interaction between temperature variation, restraint effects, and the inherent material nonlinearity of concrete. Capturing such effects with traditional linear approaches would be infeasible, whereas ANN-based surrogates trained on nonlinear simulations can efficiently account for them.

In general, any engineering quantity of interest for the investigated bridge can be evaluated using an appropriately trained ANN-based surrogate model. Conceptually, such models can be expressed in the generic functional form:

$$\bar{R}_{n,i} = \Phi_{Eng}\left[\boldsymbol{f_{Ti}}(t_{i-24}, t_i), T_{Avg}(t_{i-72}, t_{i-24}), S_{n,i}\right] \tag{3}$$

This flexible formulation highlights the adaptability of ANN surrogates for diverse monitoring objectives, paving the way for their broader integration into Digital Twin frameworks for predictive, data-driven infrastructure management.

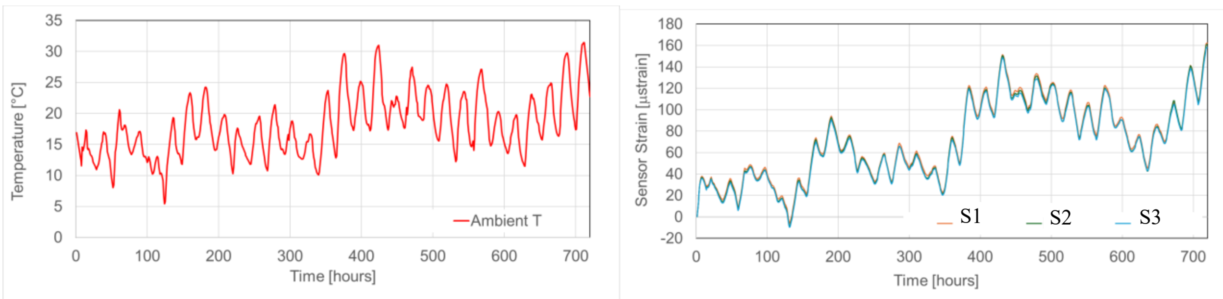


Fig. 12: The left graph shows the evolution of ambient temperatures at the bridge location in the investigated month June 2023. The right graph shows the predicted average sensor strains along optical fibers S1-S3 due to thermal loads.

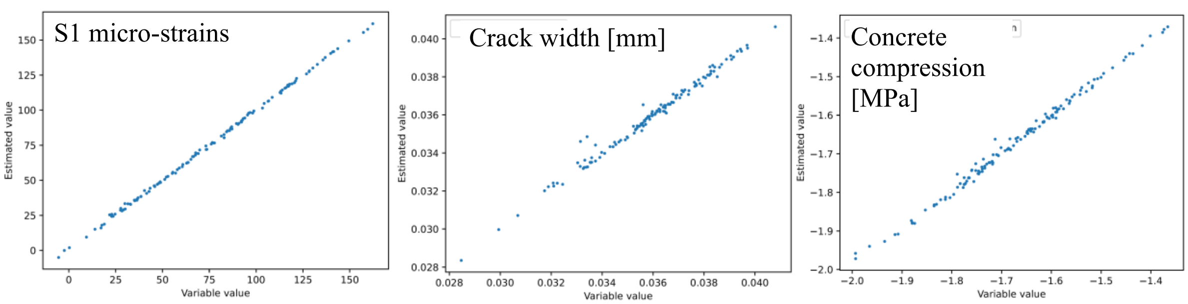


Fig. 13: The prediction accuracy of ANN surrogate model for selected engineering quantities based on 3 days history of ambient temperature.

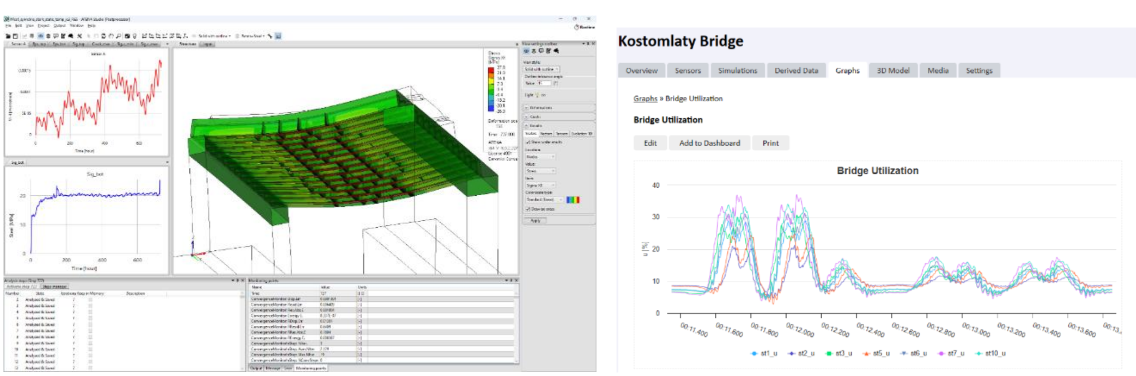


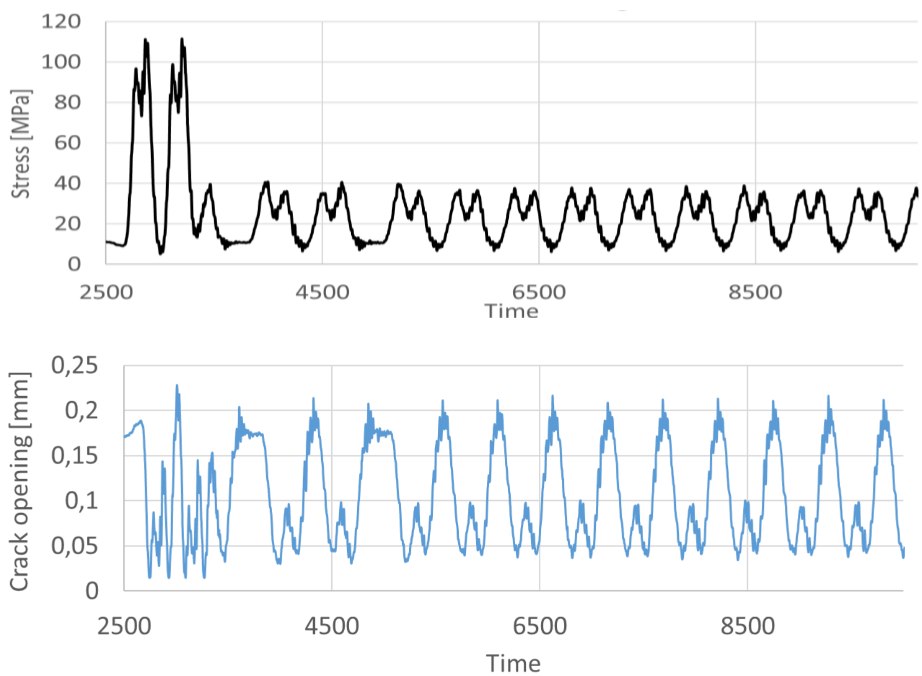
Fig. 14. The railway bridge deflection due to thermal loads showing the evolution of strains at sensor 204, tensile stresses at the I-beam bottom flange and bridge deflections with cracks (left), the evaluation of bridge utilization using the fast response surrogate model during train overpass.

Following the successful training of the ANN using the numerical model illustrated in Fig. 11, the fast-response surrogate model introduced in Section 3 was deployed to predict a range of engineering quantities that are directly relevant for bridge assessment and maintenance planning. These outputs, integrated within the prototype Digital Twin platform, provide infrastructure managers with rapid and interpretable indicators that go far beyond raw sensor measurements. Selected screenshots from the developed platform are presented to demonstrate the potential of this approach in supporting decision-making processes.

As an example, Fig. 14 displays the evolution of the bridge utilization ratio during a train overpass. This metric quantifies the proportion of the load-bearing capacity currently mobilized by the structure, offering an immediate measure of how close the bridge is operating to its design limits. Such information is invaluable for real-time risk evaluation and for planning traffic restrictions or load management strategies during critical periods.

In addition, Fig. 15 highlights two further predictive outputs derived from sensor readings and ANN-based surrogate calculations during the same train crossing. The first is the distribution of maximum stresses in the bottom steel flange, which plays a key role in ensuring structural safety under repeated live loads. The second is the estimation of anticipated crack widths within the concrete slab, an important serviceability criterion that influences durability, long-term stiffness, and maintenance requirements. By providing these parameters in near real time, the surrogate model enables engineers to not only monitor structural safety but also anticipate degradation mechanisms that affect the bridge's life-cycle performance.

Collectively, these examples illustrate the versatility of the ANN-based surrogate approach. By transforming sensor inputs into actionable engineering metrics, the Digital Twin platform enhances operational awareness, supports proactive maintenance strategies, and contributes to the sustainable management of ageing infrastructure.



(a)

(b)

Fig. 15: Prediction of bridge bottom flange stresses in steel I section (a) and crack opening and closure in concrete slab (b) during train overpass.

5 Example of durability assessment of reinforced concrete road bridge

The overarching goal of this research is to employ ANN-based surrogate models for the predictive assessment of the life-cycle performance, durability, reliability, and safety of reinforced concrete structures. This capability is essential for moving beyond reactive maintenance toward proactive, data-driven infrastructure management. To illustrate the practical application of this approach, a second pilot case study is presented, focusing on the Vogelsang Bridge in Esslingen, Germany, which spans the Neckar River.

The Vogelsang Bridge represents a complex structure composed of eight partial sections built using three different construction methods. Erected between 1971 and 1973, the bridge has a total length of approximately 595 m and covers an overall deck area of 9,744 m^2, including its approach ramps. For the purposes of monitoring and analysis, two representative spans of 13.8 m + 13.2 m were selected. Structurally, this section corresponds to a continuous, non-prestressed reinforced concrete beam with a structural depth of 0.6 m.

As part of the European cyberBridge project (www.cyberbridge.eu) an extensive in-situ monitoring campaign was carried out over a period of 61 days, from January to March 2019. The monitoring system employed was the iBWIM (Bridge-Weigh-In-Motion) technology, developed by PEC – Petschacher Consulting ZT-GmbH. This innovative system enables the continuous recording of structural responses under real traffic conditions without interrupting service.

The monitoring setup consisted of deflection measurement units coupled with a laser rangefinder used for accurate vehicle detection (see Fig. 16). These units were installed on the underside of the bridge, ensuring that installation and operation did not interfere with traffic flow. Each unit integrated both strain gauges and a data acquisition module, allowing for the precise measurement of strain responses under varying traffic loads. The strain gauges were strategically arranged in both the transverse and longitudinal directions, providing a comprehensive picture of load distribution, stress transfer, and overall structural behavior.

The virtual numerical models were developed using the finite element (FE) simulation platform ATENA [3]. Calibration of the models was performed against monitoring results from the bridge, supplemented by reference loading tests with calibration trucks of known weight (see Fig. 17). Once calibrated, the FE model was able to reproduce the key behavioral characteristics of the real structure, not only under short-term loading but also considering the long-term deterioration mechanisms that govern the service life of reinforced concrete bridges. These ageing mechanisms were incorporated into the model through a mechano-chemical framework, which explicitly accounts for the accelerated progression of damage in the presence of mechanical cracking. The degradation model itself has been described and validated in earlier work [10] and is therefore only summarized here.

The nonlinear response of the concrete was modeled using the fracture–plastic constitutive material law [5] implemented in ATENA software [3]. This advanced formulation captures the main aspects of reinforced concrete behavior, including tensile cracking, compressive crushing, reinforcement yielding or rupture, and potential bond failure between steel and concrete. One of the most critical deterioration processes for such structures is the long-term action of deicing salts, which are regularly applied during winter maintenance. Chloride ions from these salts penetrate into the porous concrete matrix, gradually diffusing towards the reinforcing steel. As chloride concentration increases, the pore solution pH decreases and the alkalinity of the concrete cover is reduced. Once the protective alkaline environment is lost, reinforcement corrosion is initiated, leading to progressive cross-sectional loss of steel and, ultimately, reduction in load-carrying capacity.

Fig. 16: View and instrumentation of the selected section of the Vogelsang bridge, Esslingen, Germany.

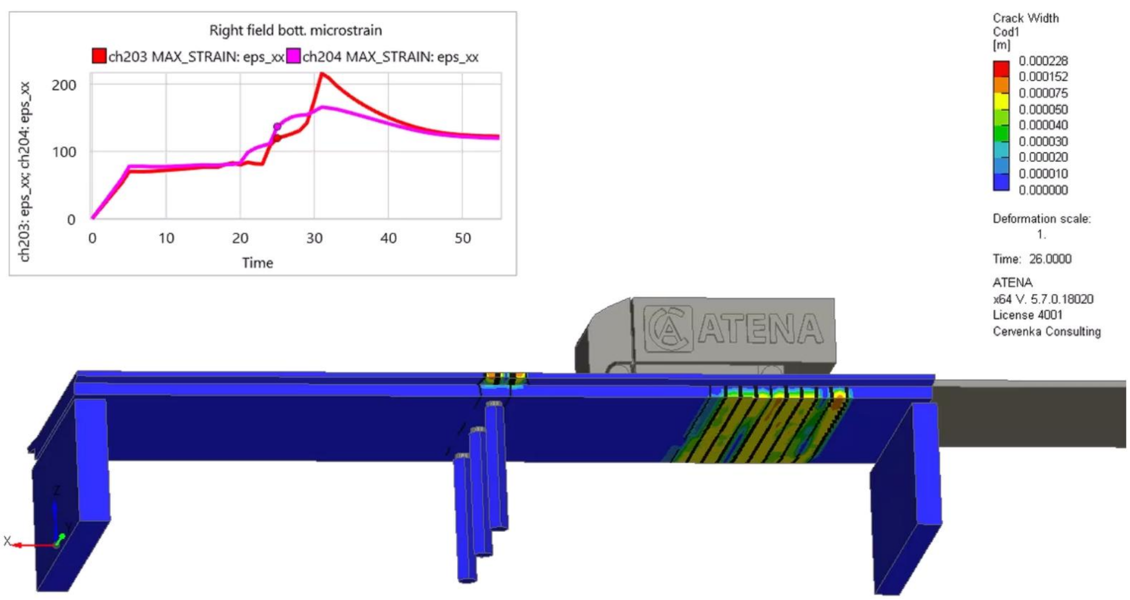


Fig. 17: View of the crack development and strain sensor data from the truch overpass during the model calibration process.

In the finite element simulation, this process is modeled by coupling a chloride ingress model with a reinforcement corrosion model. Chloride transport through the porous medium is represented as a combined diffusion and binding process, where ions are partly absorbed by the C-S-H gel or precipitated as secondary compounds [11]. In engineering applications, this is typically represented through a diffusion equation with a time-dependent coefficient. Importantly, the presence of cracks caused by loading accelerates chloride transport, a phenomenon captured in the model by updating the diffusion rate as a function of crack width. The diffusion process itself is represented as a one-dimensional transport mechanism, which allows efficient application even in large-scale simulations.

At each reinforcement location, modeled using the discrete embedded reinforcement approach [12], the chloride concentration is tracked over time. When the chloride content at the depth of reinforcement exceeds a critical threshold, corrosion is initiated. The corrosion rate is then calculated as a function of chloride concentration, exposure temperature, and elapsed time. The simulation proceeds in incremental steps: in each step, the corrosion depth is estimated and the steel cross-sectional area is reduced accordingly. A new static equilibrium is computed, updated crack widths are evaluated, and these in turn accelerate chloride ingress in the subsequent step. This iterative coupling between mechanical damage and chemical deterioration allows the model to realistically capture the long-term degradation process.

The numerical implementation builds upon the mechanistic formulations of Liu and Weyers [13] and the guidelines established in the DuraCrete project [14]. The effect of reinforcement corrosion on bond strength is also explicitly considered. Here, the bond–slip law was defined according to the fib Model Code 2010 [15], while the reduction of bond properties due to corrosion was implemented following the empirical relationships proposed by Bhargava et al. [16].

For structural assessment using nonlinear FE analysis, it is essential to define a load history that reflects both the actual sequence of actions on the real bridge and the combinations prescribed by design codes. In addition to permanent and live loads, the long-term deterioration due to chloride ingress and reinforcement corrosion must be included. A representative load sequence used in the Vogelsang Bridge case study is as follows:

- Step 1: Application of design dead loads (self-weight and superimposed dead loads).
- Step 2: Application of design live loads, including concentrated and distributed traffic effects.
- Step 3: Removal of the live loads applied in step 2.
- Step 4: Simulation of chloride-induced degradation and associated corrosion effects. (Fig. 18)
- Step 5: Re-application of live loads to overload conditions.

Chloride attack was simulated for progressive durations of 25, 50, 75, 100, 125, and 150 years within step 4. Partial reloading of dead and live loads was included during this interval to replicate the realistic service conditions under which chloride penetration occurs, excluding partial safety factors. After deterioration simulation, the structure was subjected to increasing live loads until failure, generating a set of load–displacement curves (see Fig. 20) corresponding to different stages of ageing. This figure demonstrates the effect of reinforcement corrosion on the load-carrying capacity of the bridge. It is possible to observe how the strength of the bridge is gradually decreasing over the years.

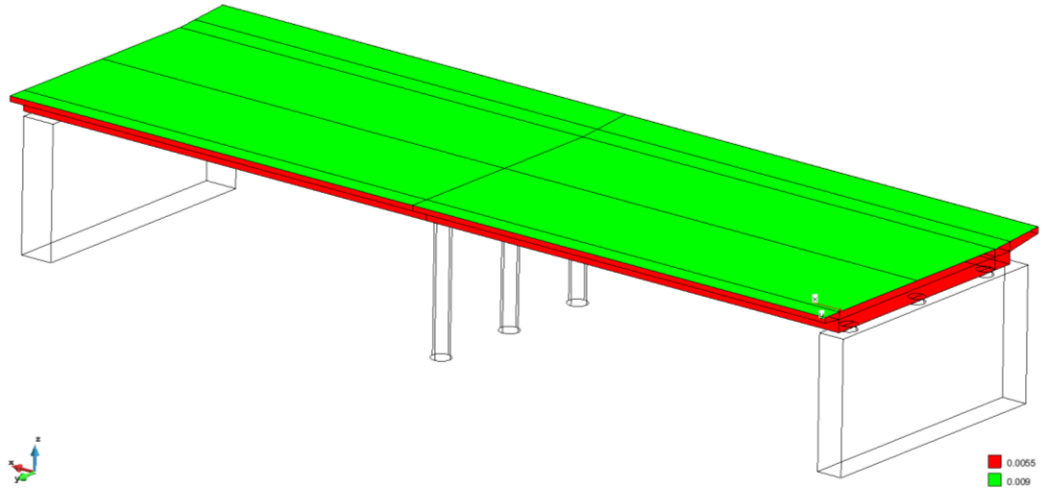


Fig. 18: Numerical model of the Vogelsang bridge with the indication of the assumed chloride concentrations at the bottom at top bridge surfaces.

The global resistance evaluation followed the ECoV approach originally proposed in [17] and later adopted in fib Model code 2010 [15], which requires paired analyses with mean and characteristic material parameters. The resulting time-dependent resistance evolution is plotted in Fig. 21. For the Vogelsang Bridge, the model predicts a life expectancy of approximately 132 years.

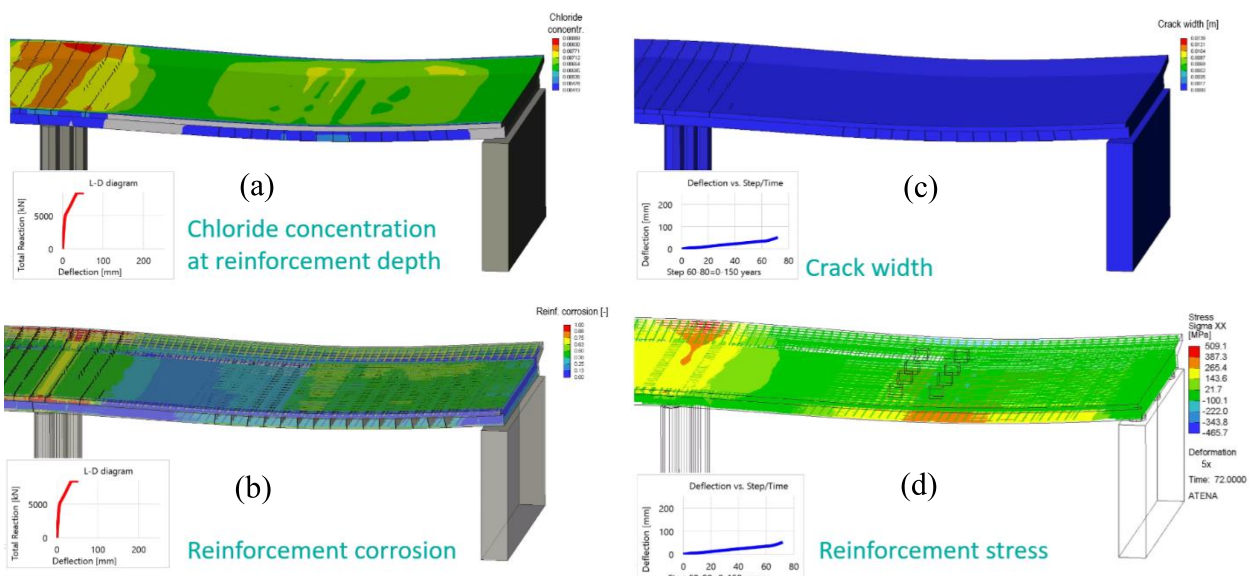


Fig. 19: The evolution of chloride concentration (a), resulting reinforcement corrosion (b), crack development (c) and reinforcement stresses (d) at the time of 135 years during the durability numerical simulation.

The most interesting and unique results from the presented long term and durability behavior or this reinforced concrete bridge are summarized in Fig. 19. This figure shows various interesting quantities at the time of 135 years of the bridge life. The evolution of chloride concentration at the depth of the reinforcement cover is shown in Fig. 19a. The resulting reinforcement corrosion using the briefly described chloride ingress and corrosion model [10] is depicted in Fig. 19b. The reinforcement corrosion is indicated as a relative cross-sectional area that is lost due to corrosion. This means that the value of 0 indicates no corrosion, and the value of 1 means that the whole reinforcement cross-sectional area has been lost due to the corrosion. The loss of reinforcement area results in the increase crack propagation, which is shown in Fig. 19c as well as in the higher reinforcement stresses in Fig. 20d.

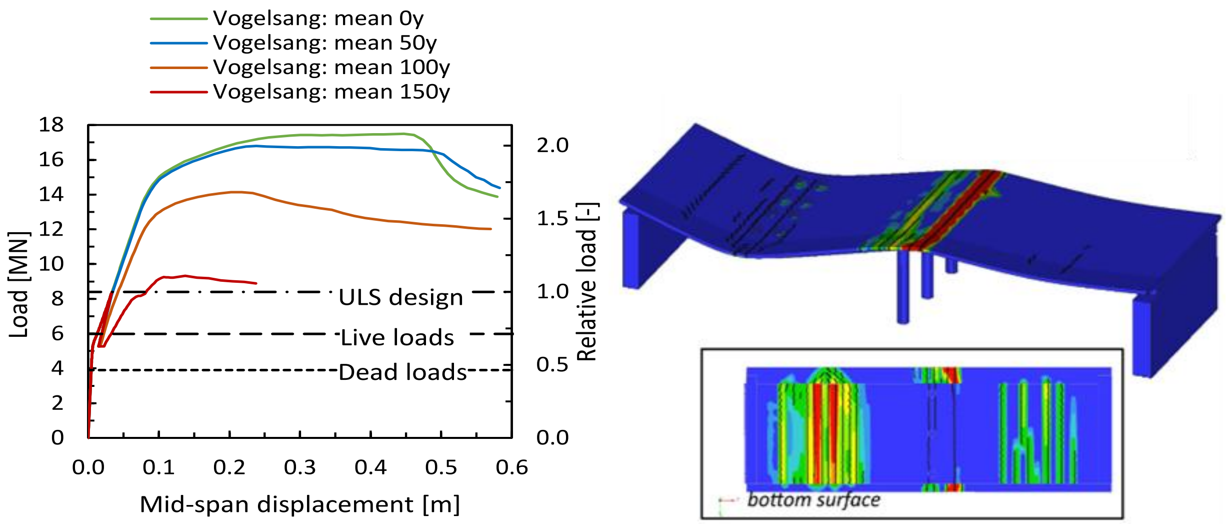


Fig. 20: Load-displacement curves for loading up to failure after several years of corrosion process (left), crack pattern at failure load for the highest exposure of 150 years (right).

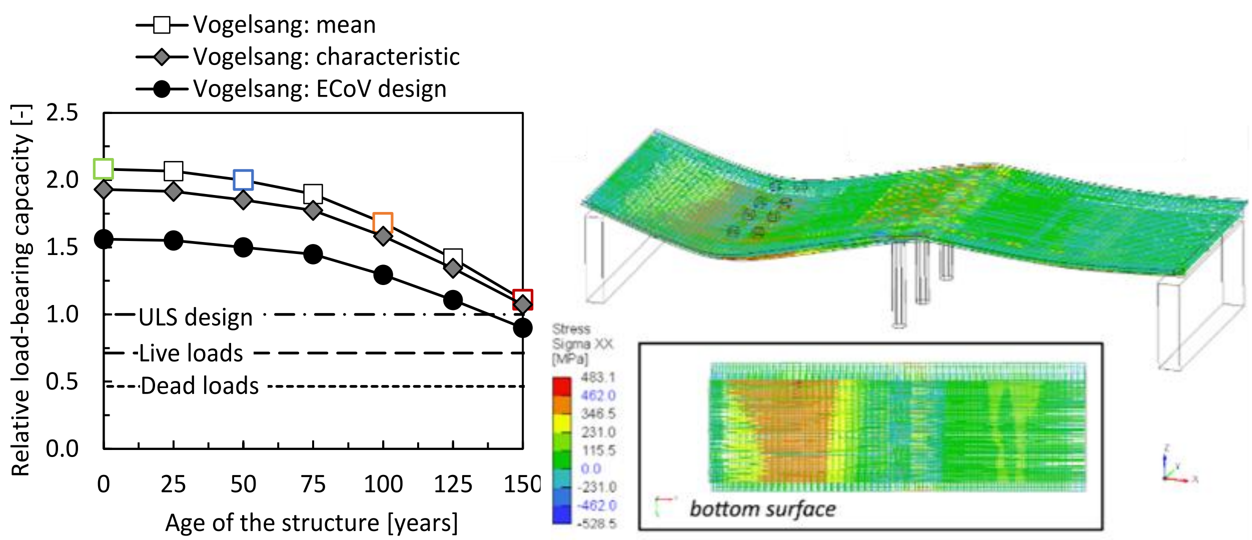


Fig. 21: Evolution of Vogelsang bridge capacity depending on years of chloride exposure (left), Stresses in the corroded reinforcement at the peak load for the most critical scenario of 150 years of exposure (right).

6 Conclusions

This study has investigated the integration of Artificial Neural Networks (ANNs) into a Digital Twin framework for the structural analysis and monitoring of reinforced concrete bridges. Within the proposed methodology, ANNs serve a dual role: first, in the calibration of the virtual twin, ensuring that the numerical model reliably reproduces the behavior of the physical structure; and second, in the development of fast-response surrogate models that enable near real-time translation of raw sensor data into actionable engineering quantities. These surrogate models provide direct estimates of performance indicators such as utilization ratios, stress levels, and crack widths, thereby bridging the gap between continuous monitoring data and engineering decision-making.

A central advantage of the approach lies in addressing a persistent limitation of conventional monitoring systems: while modern sensing technologies can generate vast amounts of data, operators often struggle to interpret these measurements in terms of structural safety, reliability, and serviceability. By embedding physics-informed ANN models into a Digital Twin environment, the proposed framework offers a pathway to transform overwhelming raw data streams into interpretable and decision-relevant information, ultimately enhancing the efficiency and accuracy of infrastructure management.

Beyond short-term monitoring, this work has also highlighted the integration of durability and ageing models into the Digital Twin concept. By coupling mechano-chemical formulations for chloride ingress and reinforcement corrosion with nonlinear FE simulations, and subsequently embedding these results into ANN surrogates, the framework is extended toward predictive life-cycle assessment. This capability enables not only the evaluation of current structural condition but also the forecasting of long-term degradation processes, thereby supporting proactive maintenance planning and sustainable asset management.

Overall, the combination of AI-driven surrogate modeling, durability simulation, and Digital Twin technology marks a significant advancement in structural health monitoring. It paves the way for intelligent, data-driven infrastructure systems that can anticipate deterioration, optimize resource allocation, and ensure the long-term safety and reliability of critical bridge networks.

This work is part of a research project supported by the Czech Technology Agency under the project TM04000012 “BRIHIS - A concrete bridge health interpretation system based on mutual boost of big data and physical mechanism” within the Delta 2 Programme. The financial support is greatly acknowledged.

Reference

[1]. OECD. Infrastructure maintenance (indicator). 2021.

[2]. Haag S, Anderl R. Digital twin – Proof of concept. Manuf Lett. 2018 Jan 1;15:64–6.

[3]. Červenka, V., Červenka, J. & Jendele, L. 2023. ATENA Program Documentation, Part 1: Theory, 2023, Cervenka Consulting s.r.o., www.cervenka.cz

[4]. Červenka J, Červenka V, Eligehausen R (1998) Fracture-plastic material model for concrete, application to analysis of powder actuated anchors. In: Proceedings FRAMCOS (3). pp 1107-1116

[5]. Červenka J, Papanikolaou VK (2008) Three-dimensional combined fracture-plastic material model for concrete. Int J Plast 24:2192-2220

[6]. Červenka V, Červenka J, Kadlec L (2018) Model uncertainties in numerical simulations of reinforced concrete structures. Struct Concr 19:2004-2016

[7]. Drahý V, Explainable neural networks, Diploma thesis, Czech Technical University, Faculty of Electrical Engineering, Dep. Of Computer Science, 2023.

[8]. Drahy V.,. Maen. https://github.com/drvojtex/Maen/, 2023.

[9]. Leonhardt and Walther, Schubversuche an einfeldringen Stahlbetonbalken mit und Ohne Schubbewehrung, Deutscher Ausschuss fuer Stahlbeton, Heft 51, Berlin 1962, Ernst&Sohn.

[10]. Hajkova K., Smilauer V., Jendele L., Cervenka J.: Prediction of reinforcement corrosion due to chloride ingress and its effects on serviceability. Engineering Structures, 2018, Vol. 174: 768-777.

[11]. Taylor, H. F. W., 'Cement chemistry', Cement chemistry. doi: 10.1680/cc.25929

[12]. Jendele, L., Cervenka, J., Modelling Bar Reinforcement with Finite Bond, Computers and Structures, 84, 1780-1791, 2006.

[13]. Liu Y, Weyers E. Modeling the time-to-corrosion cracking in chloride contaminated reinforced concrete structures. Mater J 1998;95(6):675-80.

[14]. The European Union-Brite EuRam III (2000) Probabilistic performance based durability design of con-crete structures: Final technical report of Duracrete project.

[15]. International Federation for Structural Concrete (2013) fib Model Code for Concrete Structures 2010.

[16]. Bhargava, K. et al. (2007) 'Corrosion-induced bond strength degradation in reinforced concrete-Analytical and empirical models', Nuclear Engineering and Design, 237(11), pp. 1140-1157. doi: 10.1016/j.nucengdes.2007.01.010.

[17]. Červenka, V., 2008, Global Safety Format for Nonlinear Calculation of Reinforced Concrete. Beton- und Stahlbetonbau 103, Special Edition, Ernst&Sohn. pp. 37-42.

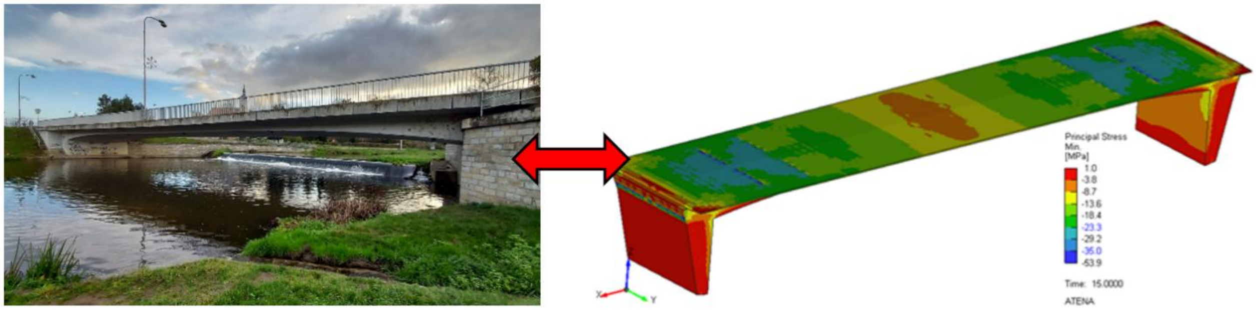


Fig. 1: Bridge digital Twin is typically a combination of monitoring of real structural response and a numerical model that exchange data to provide predictions and information on structural health and reliability.

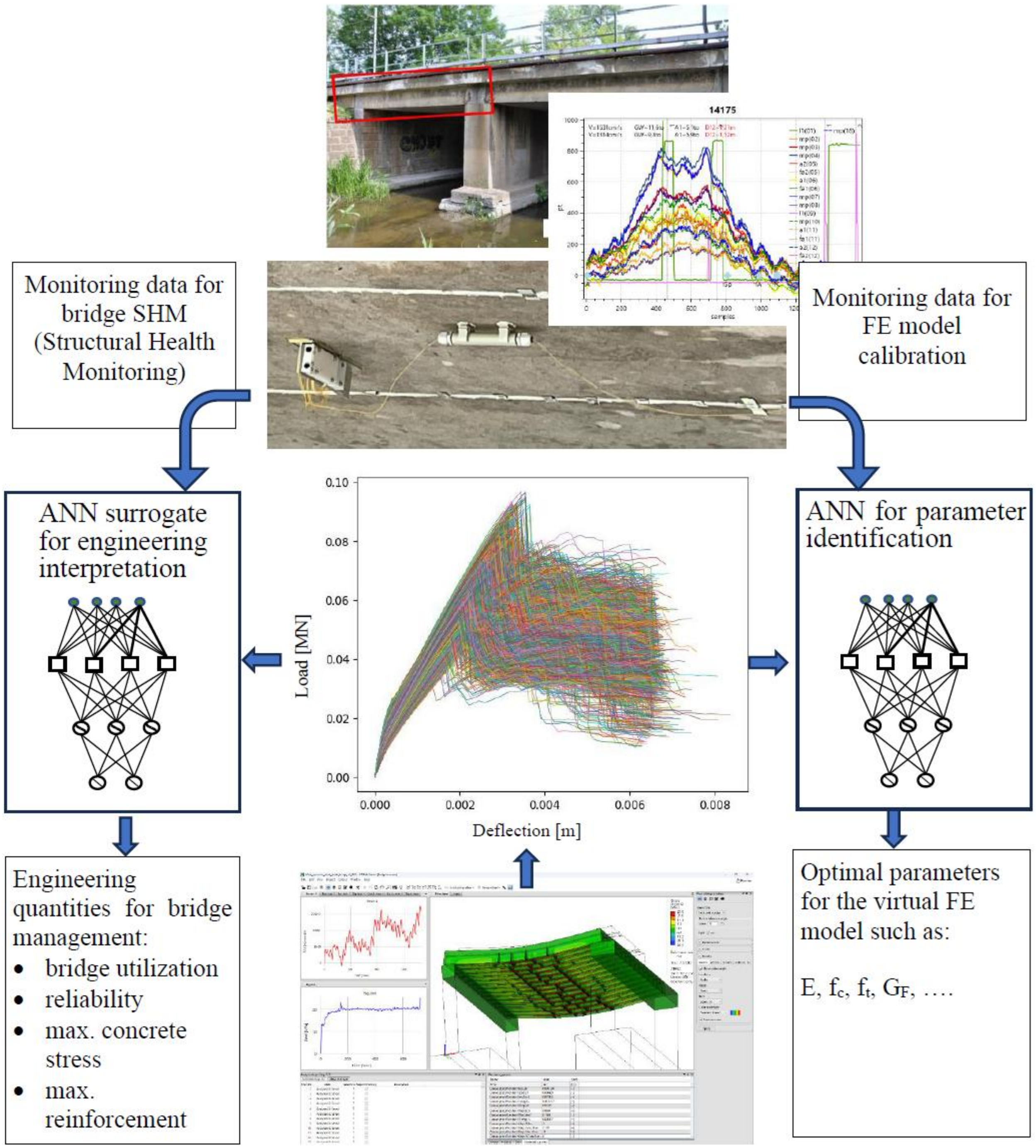


Fig. 2: Digital twin schema: ANN surrogate model is used for two purposes: ANN on the right for model calibration, i.e., parameter identification, and ANN on the left provides real-time engineering data for maintenance decisions.

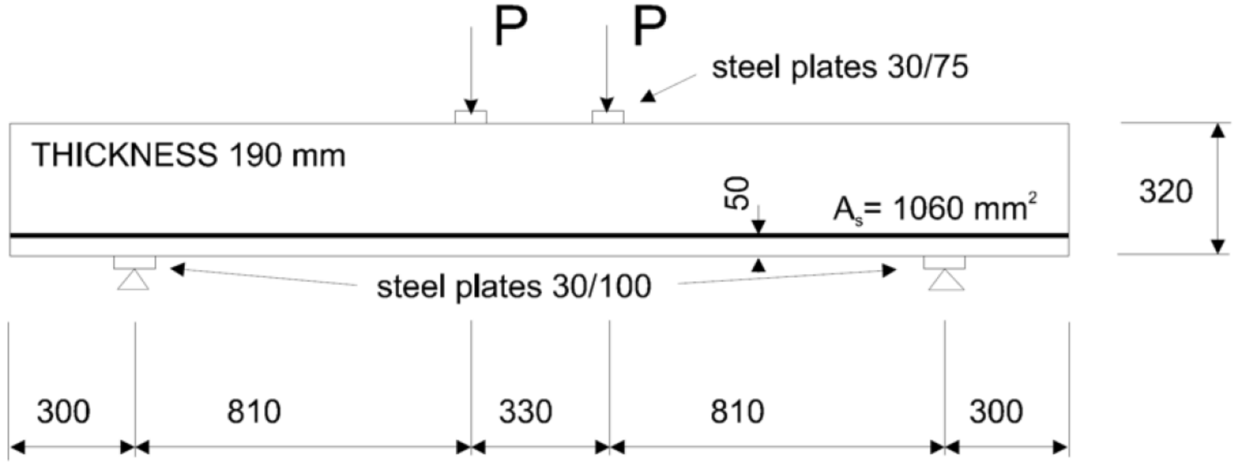


Fig. 3: The geometry of shear beam test [9] for the study of ANN accuracy for the model parameter identification and surrogate modelling. Units are in mm.

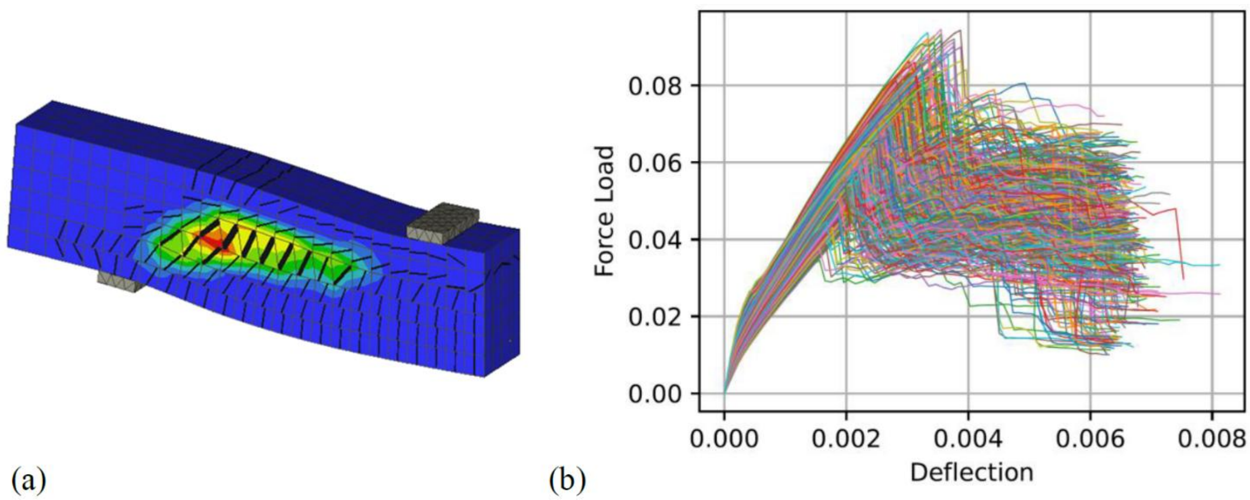


Fig. 4: (a) Shear failure mode for the shear beam [9], (b) load-displacement diagrams of 1000 training and testing samples.

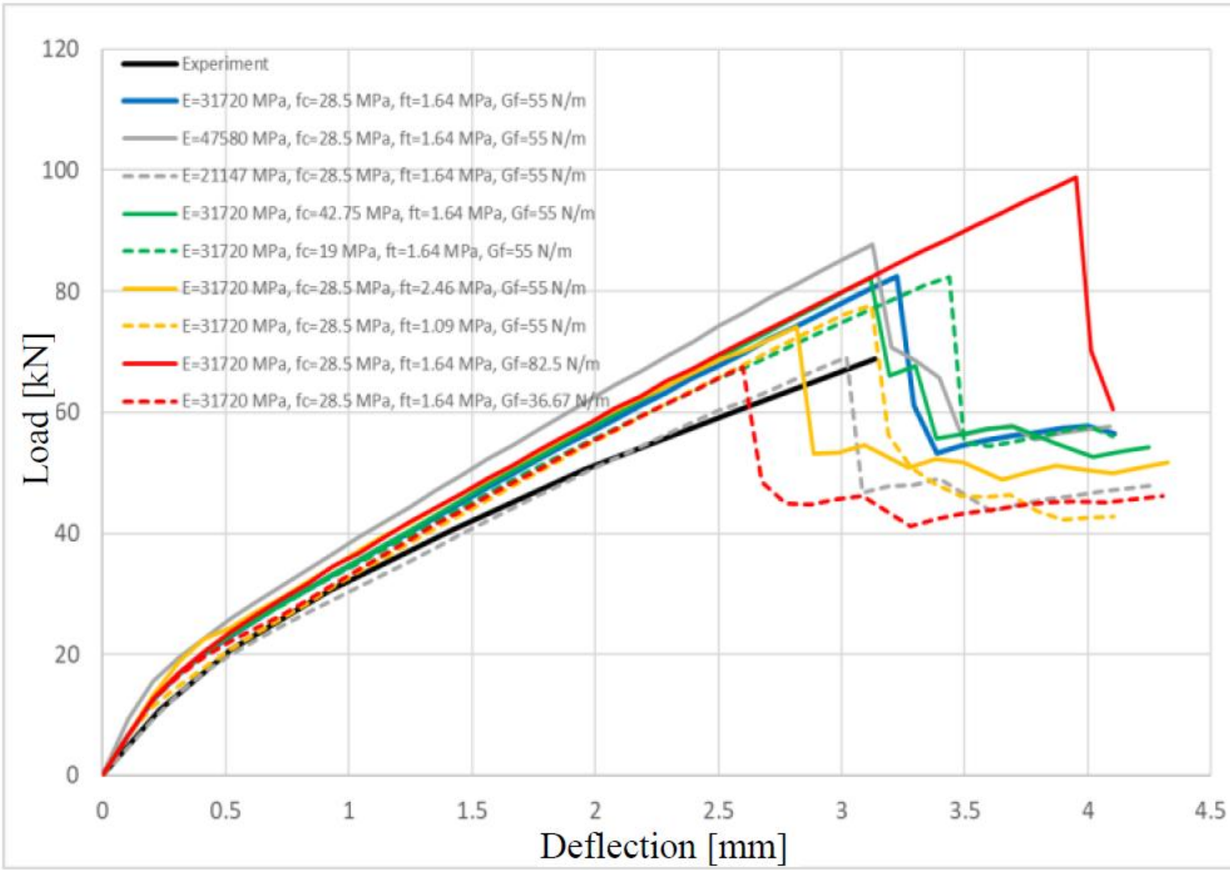


Fig. 5: Shear beam test experimental result with selected analyses with the closest match.

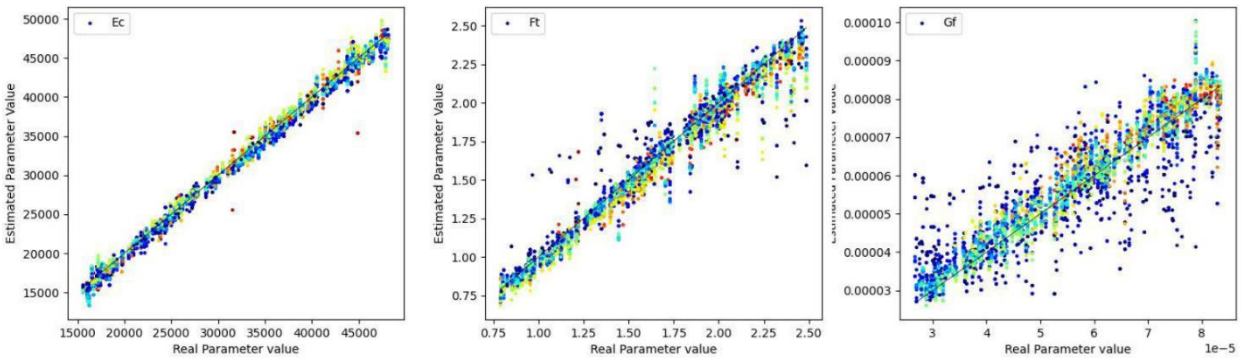


Fig. 7. ANN model accuracy for parameter identification of the critical material parameters for 1000 training dataset.

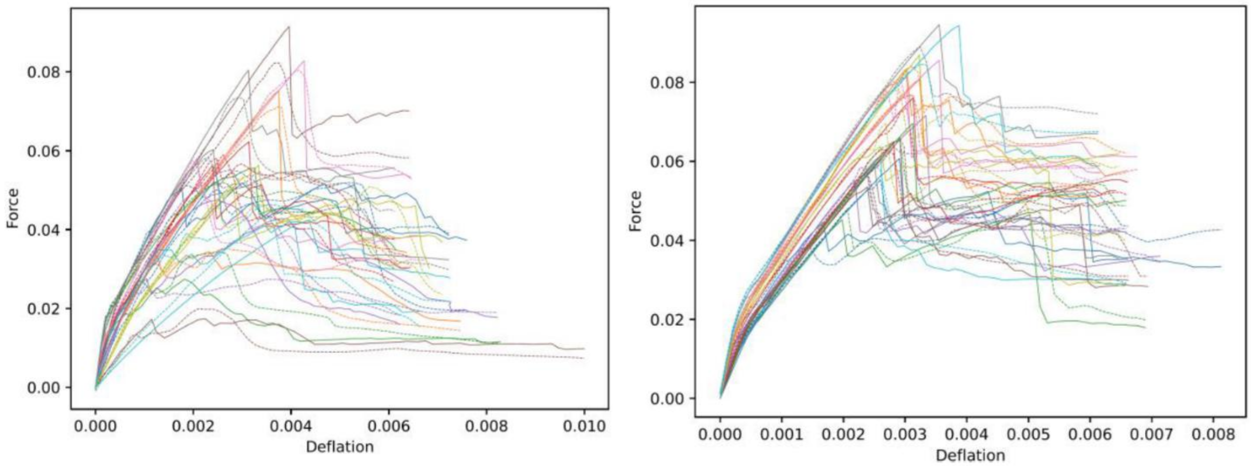


Fig. 7. Capability of the ANN surrogate model to predict the load-displacement curves of the shear beam model, (lef) Dataset A – 100 samples, (right) Dataset B – 400 samples.

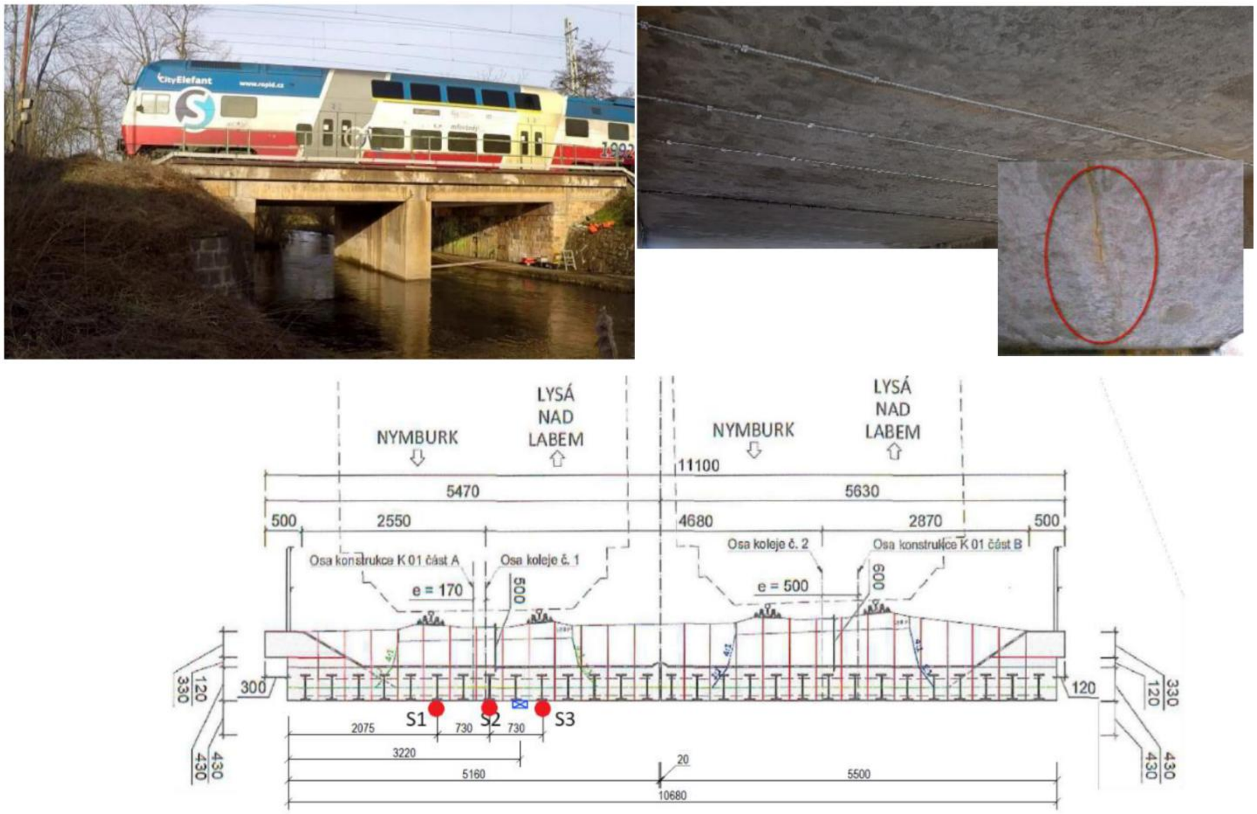


Fig. 8: Railway bridge at Kostomlaty, Czech Republic showing the sensor location S1, S2 and S3.

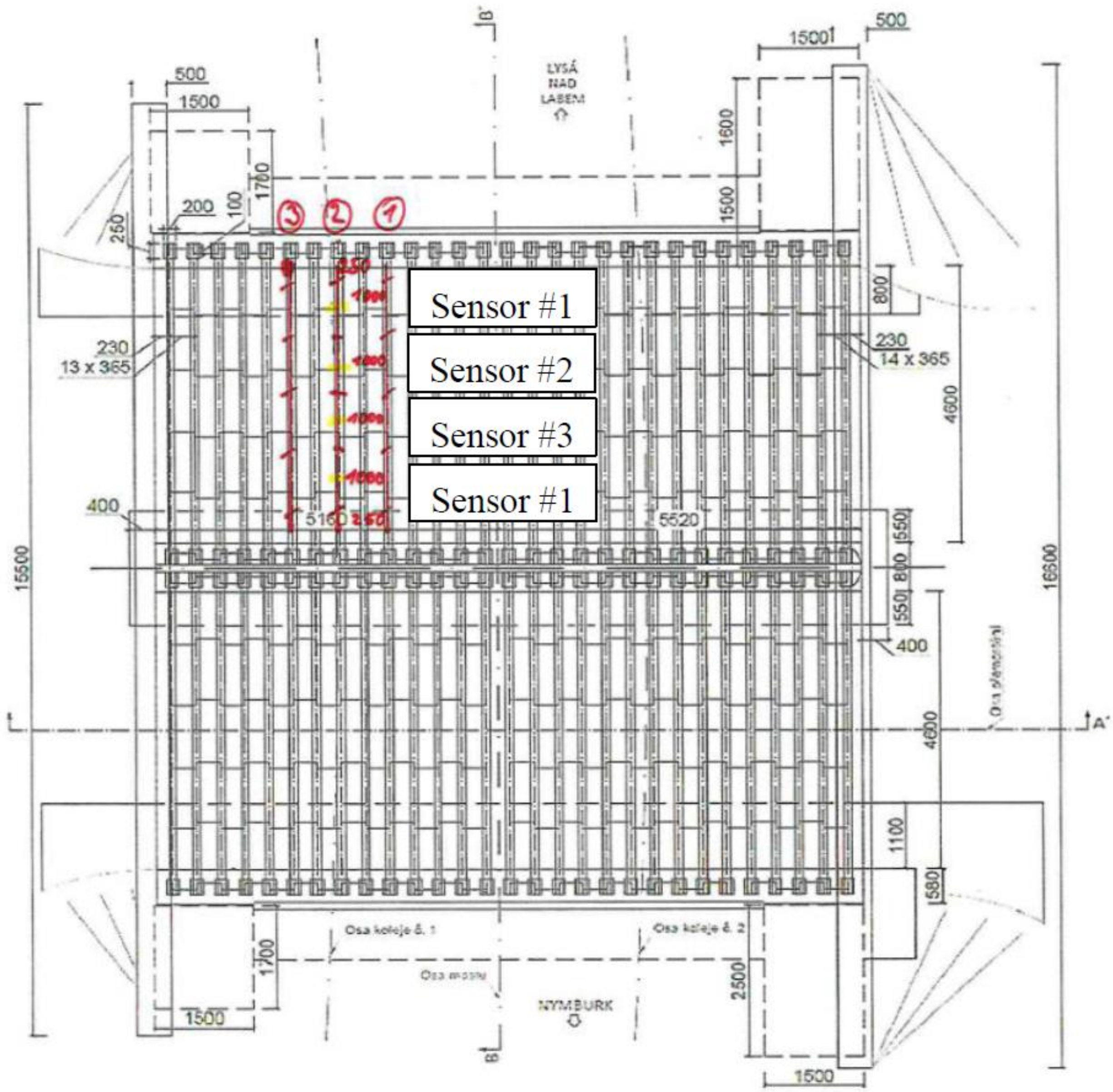


Fig. 9: Kostomlaty pilot bridge application example showing the top view with the sensor locations.

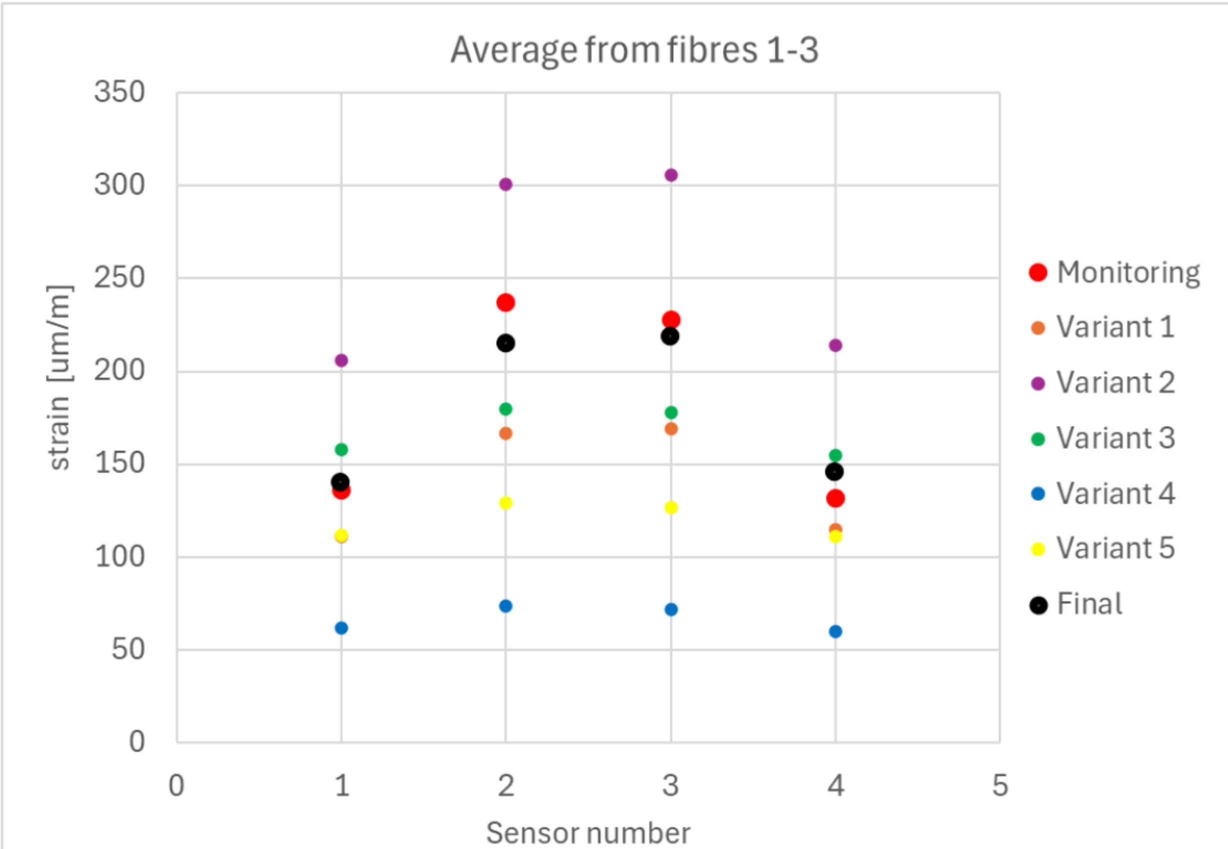


Fig. 10: Example of data fitting and parameter identification process for Kostomlaty railway bridge.

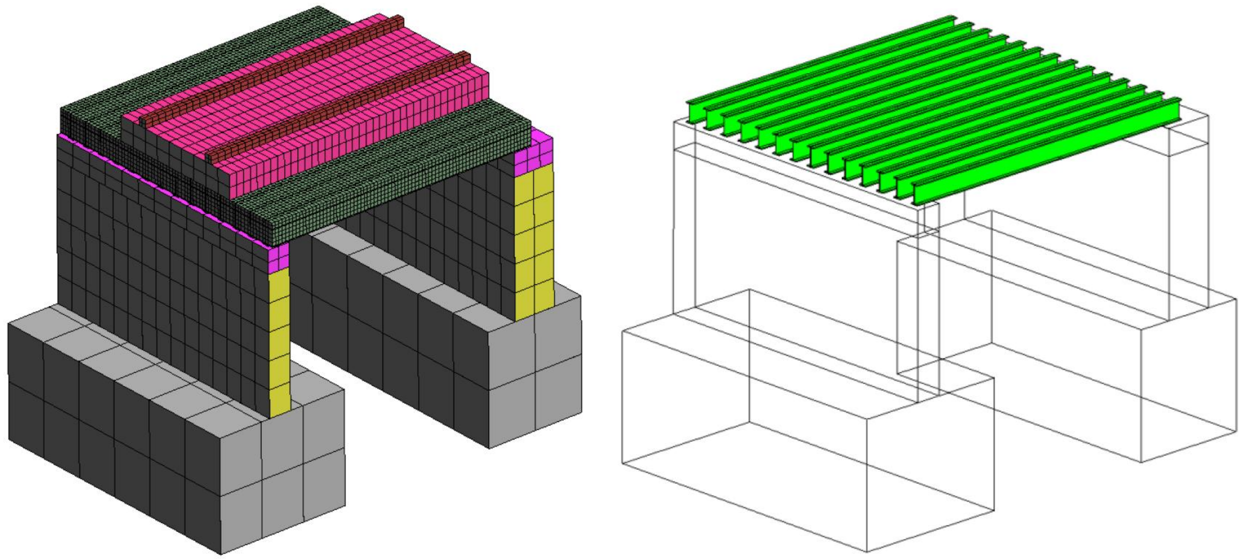


Fig. 11: Finite element model of the quarter section of the model, right figure shows the location of the internal I steel beams.

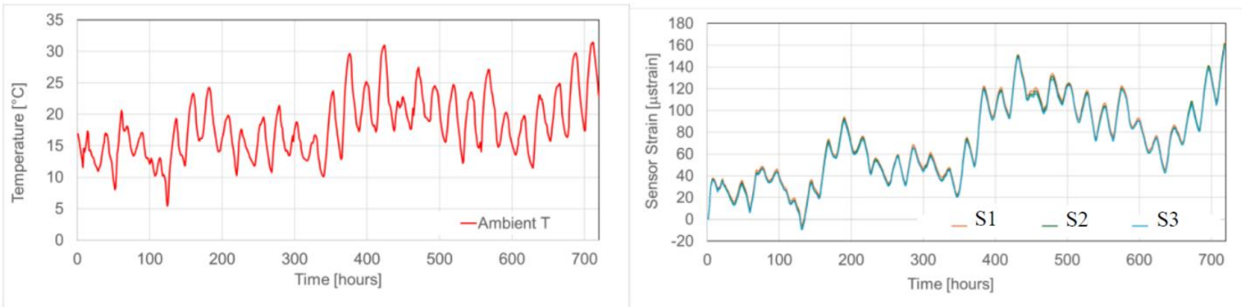


Fig. 12: The left graph shows the evolution of ambient temperatures at the bridge location in the investigated month June 2023. The right graph shows the predicted average sensor strains along optical fibers S1-S3 due to thermal loads.

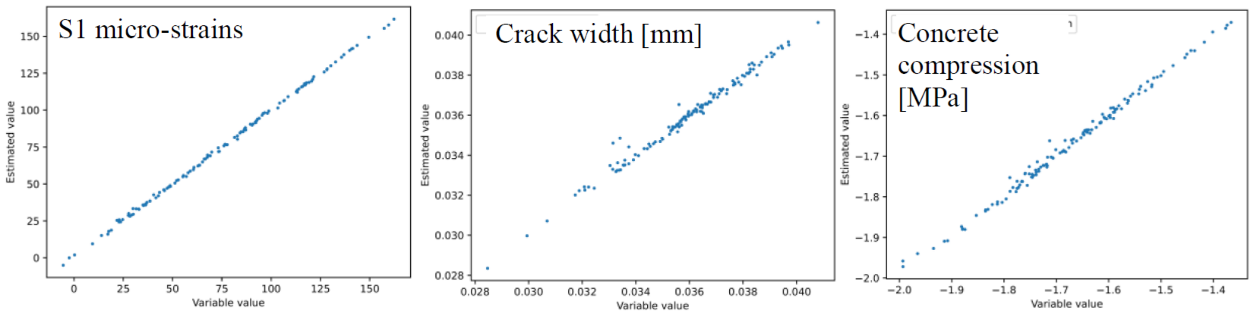


Fig. 13: The prediction accuracy of ANN surrogate model for selected engineering quantities based on 3 days history of ambient temperature.

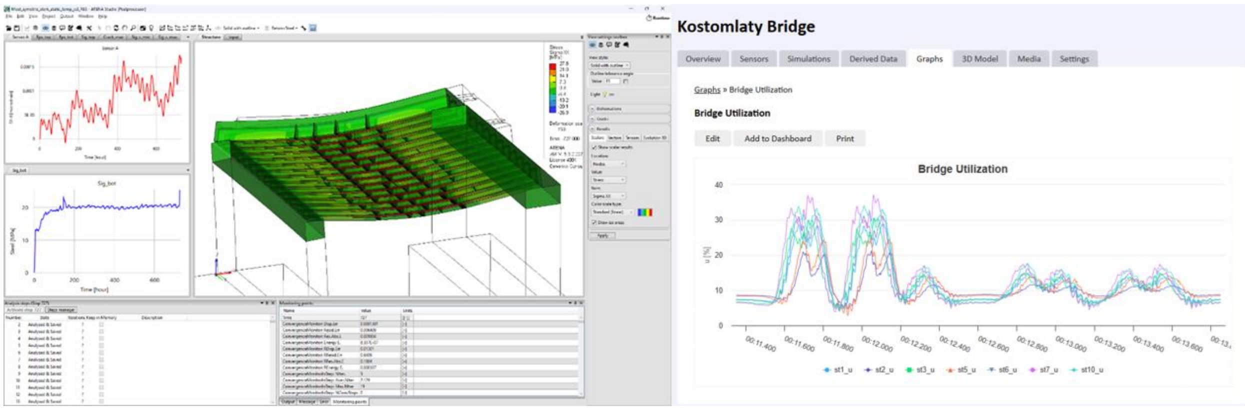
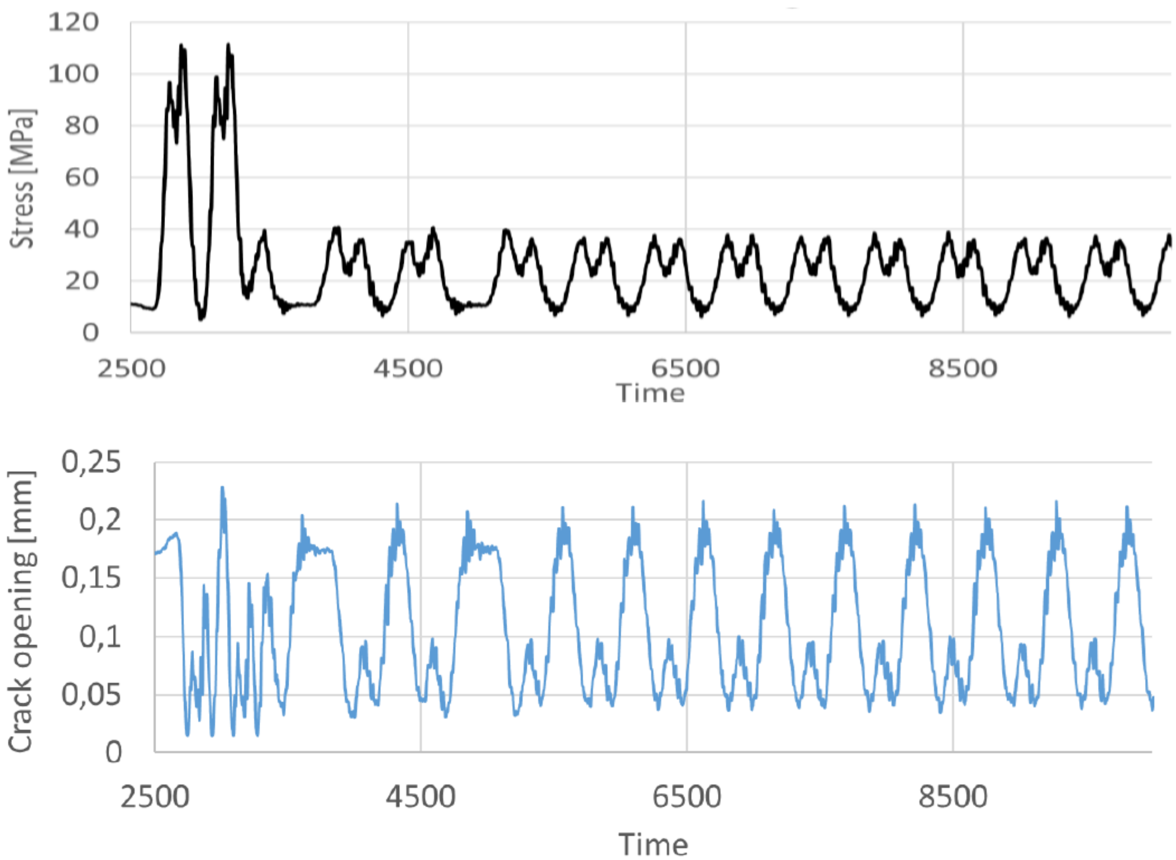


Fig. 14. The railway bridge deflection due to thermal loads showing the evolution of strains at sensor 204, tensile stresses at the I-beam bottom flange and bridge deflections with cracks (left), the evaluation of bridge utilization using the fast response surrogate model during train overpass.

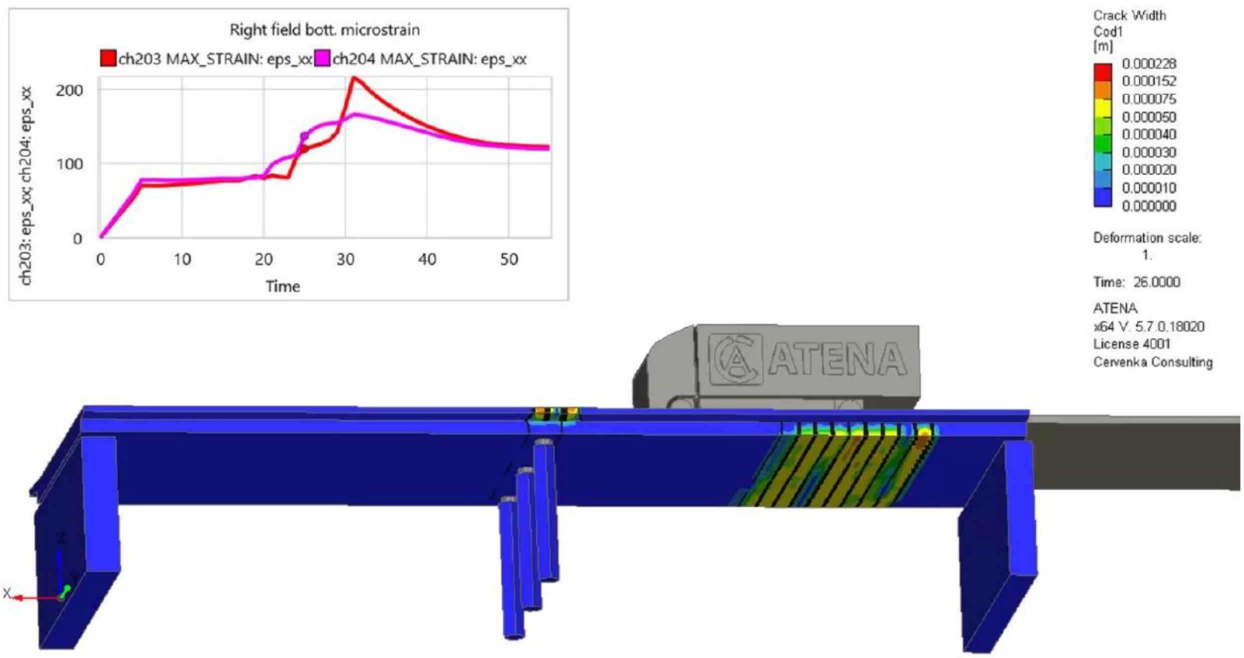


(a)

(b)

Fig. 15: Prediction of bridge bottom flange stresses in steel I section (a) and crack opening and closure in concrete slab (b) during train overpass.

Fig. 16: View and instrumentation of the selected section of the Vogelsang bridge, Esslingen, Germany.



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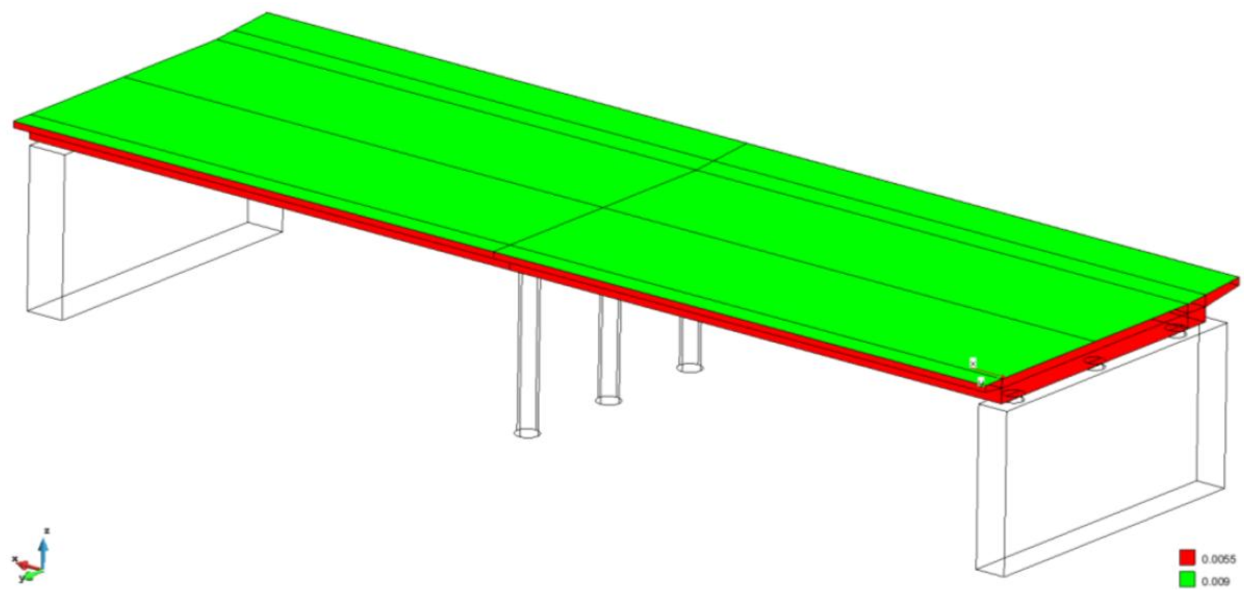

Fig. 18: Numerical model of the Vogelsang bridge with the indication of the assumed chloride concentrations at the bottom at top bridge surfaces.

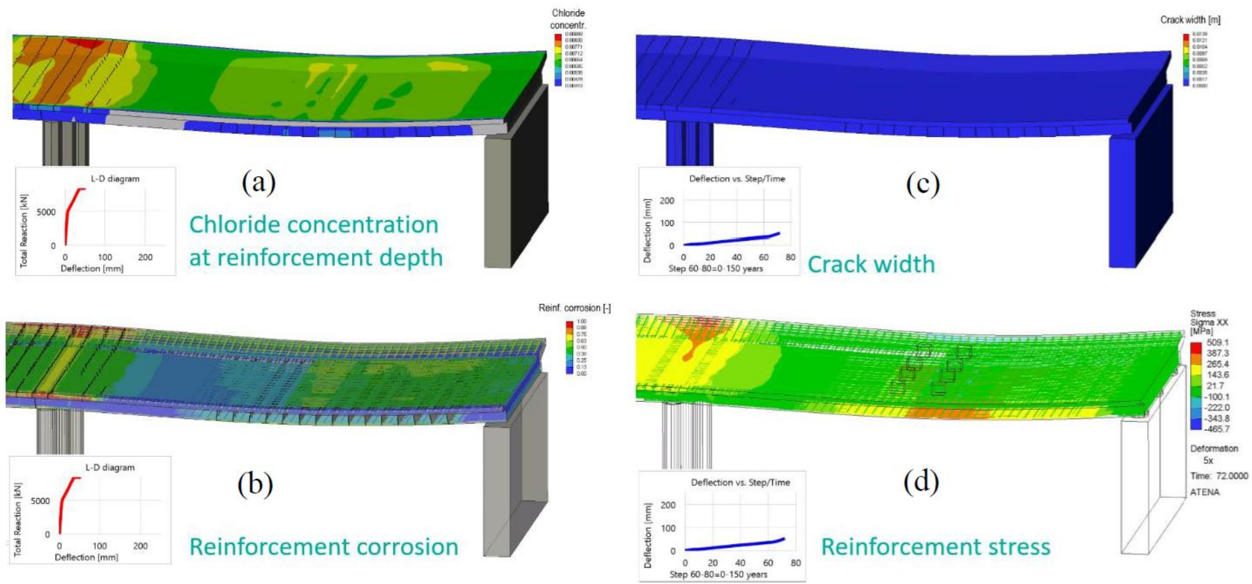

Fig. 19: The evolution of chloride concentration (a), resulting reinforcement corrosion (b), crack development (c) and reinforcement stresses (d) at the time of 135 years during the durability numerical simulation.

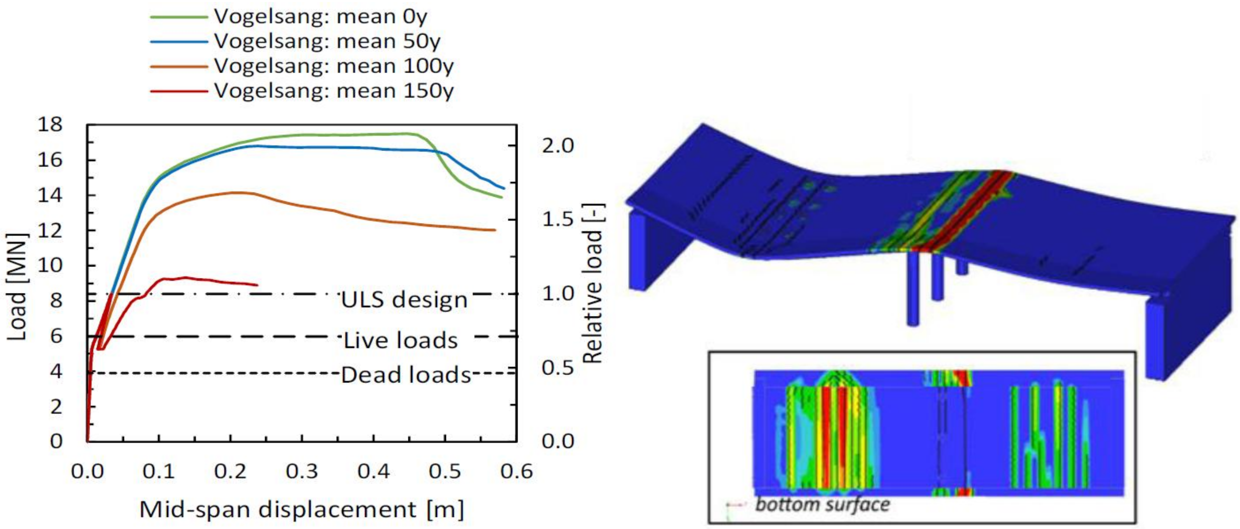

Fig. 20: Load-displacement curves for loading up to failure after several years of corrosion process (left), crack pattern at failure load for the highest exposure of 150 years (right).

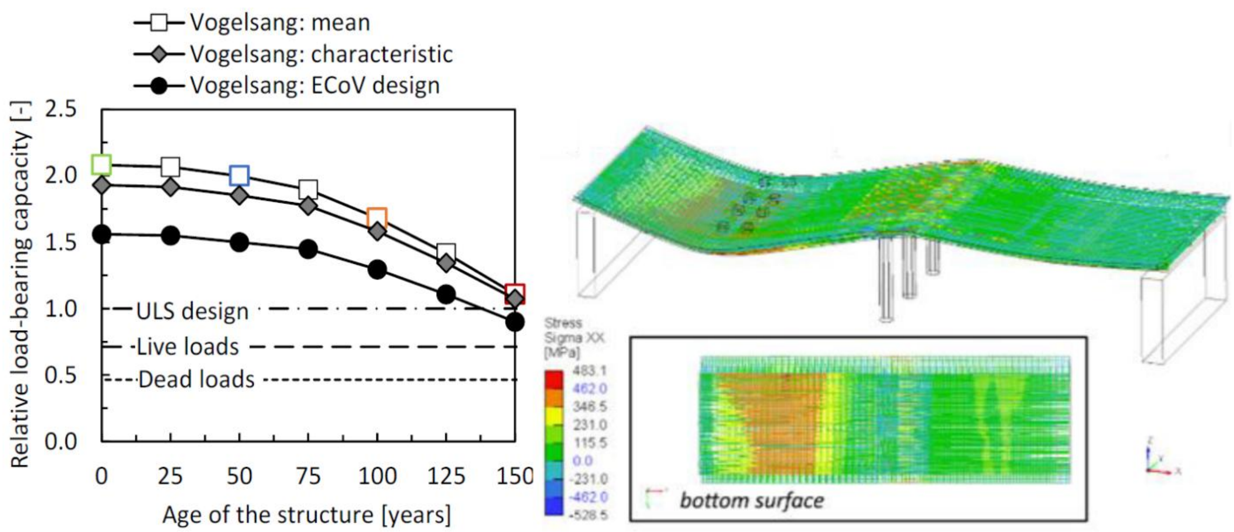

Fig. 21: Evolution of Vogelsang bridge capacity depending on years of chloride exposure (left), Stresses in the corroded reinforcement at the peak load for the most critical scenario of 150 years of exposure (right).