

## AI Based Surrogate Model for Digital Twins in Reinforced Concrete

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### Abstract:

Artificial Intelligence (AI), particularly using Artificial Neural Networks (ANNs), is increasingly integrated into various domains of human activity and industrial applications. A significant area of application is the development of real-time, fast-response surrogate models within the digital twin framework for structural health monitoring. Within the presented framework, ANNs serve two primary functions. First, during the calibration phase, ANNs ensure that the virtual twin accurately reflects the behavior of the physical structure. Once calibrated, the virtual twin facilitates the training of the ANN through physically informed deep learning, utilizing data derived from sensitivity analyses conducted via nonlinear finite element analysis using ATENA software. The second function involves deploying the trained ANN as a fast-response surrogate model, providing critical safety information for the ongoing structural health monitoring of bridges. This paper outlines the development of an efficient and accurate ANN-based surrogate model, emphasizing the advancements in physically informed deep learning methodologies for structural analysis and life cycle assessment of infrastructures.

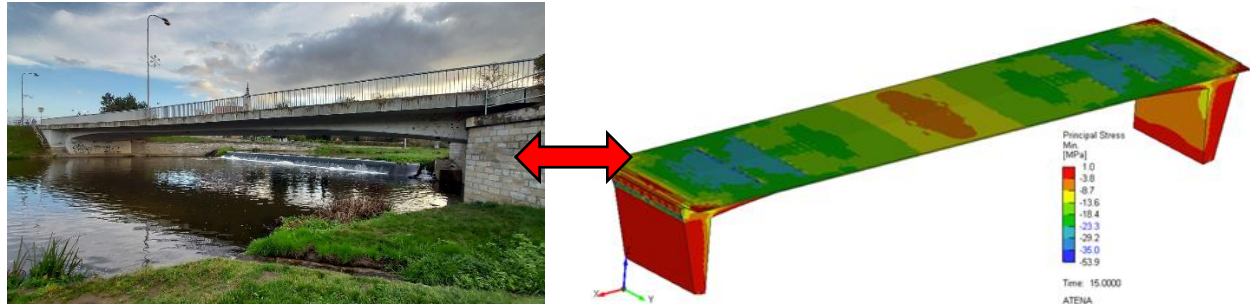
**Keywords:** artificial intelligence, deep machine learning, digital twin, reinforced concrete bridges, reinforced concrete modelling, nonlinear simulation.

### 1 Introduction

A well-functioning transport infrastructure is a crucial element of a productive modern economy in both developed and developing nations. Within the European Union, the road and rail networks are essential for the movement of goods and people. Much of this infrastructure was constructed during the post-World War II economic expansion, meaning that many structures are now over 50 years old. As a result, the ageing transport system places a considerable financial strain on public

authorities. Data from 22 selected OECD countries [1] indicates that between 1997 and 2016, the annual cost of infrastructure maintenance rose by 1.78 billion euros.

The concept of a digital twin has recently been introduced across various engineering disciplines, including structural design [2].



**Fig. 1 Digital Twin consists of a real structure equipped with monitoring sensors and a virtual replica with data exchange about structural health and reliability.**

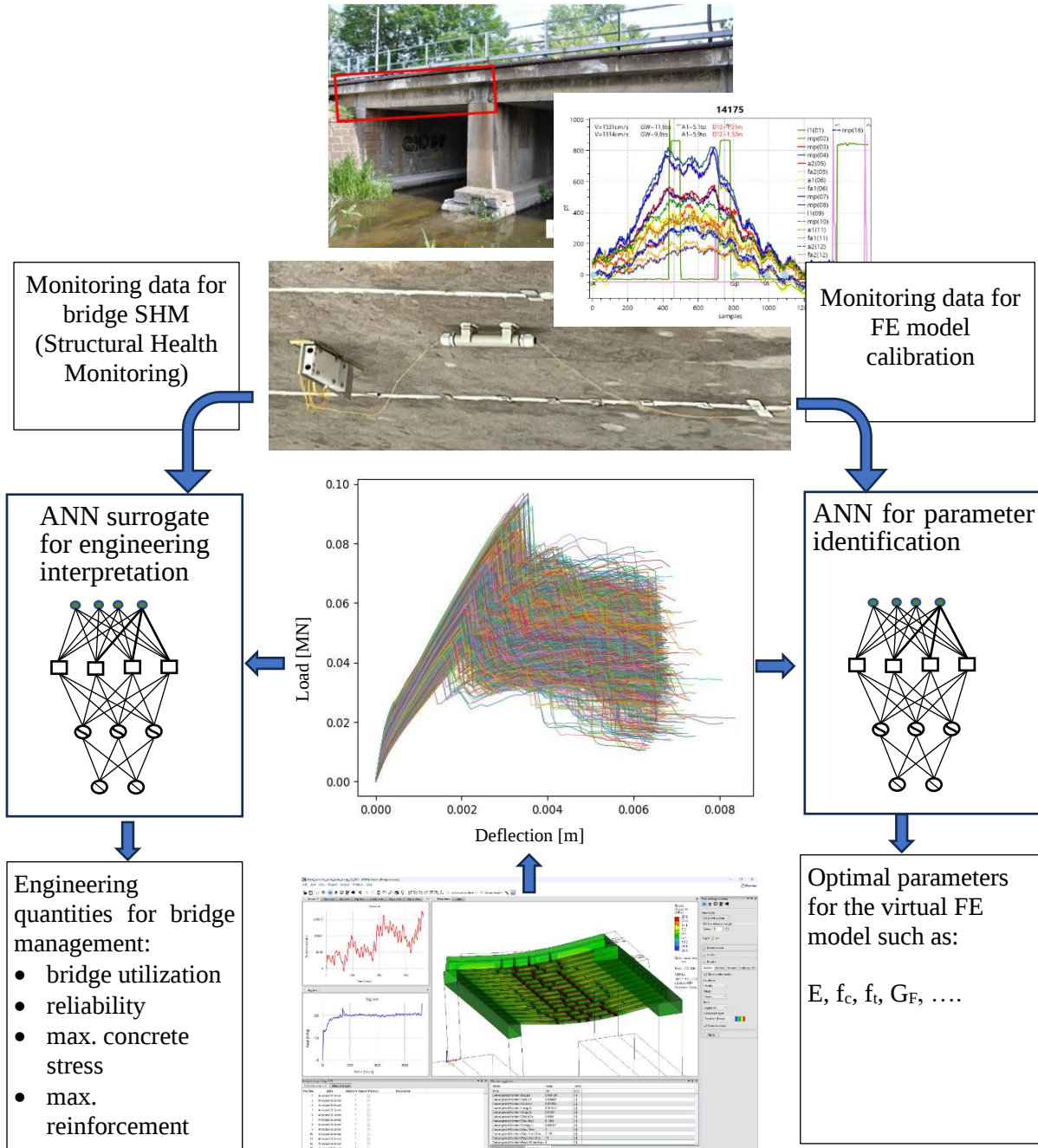
This approach involves calibrating a computational model based on data collected from the physical structure, ensuring that the digital representation accurately reflects all critical aspects of the real-world counterpart. In structural engineering, this includes simulating the response to both dead and live loads as well as evaluating durability performance. Once properly calibrated, the digital twin enables the assessment of the structure's current condition and facilitates predictions about its future behavior. When combined with regular inspections, it serves as a valuable tool for managing the ageing process of structures.

Artificial Intelligence (AI), particularly through the use of Artificial Neural Networks (ANNs), is increasingly transforming various industries and human activities. One prominent application lies in the development of real-time, fast-response surrogate models within digital twin frameworks for structural health monitoring. The digital twin concept revolves around creating a dynamic digital replica of a physical structure or product (see Fig. 1). This virtual counterpart, often represented by a sophisticated numerical model, engages in continuous data exchange with its real-world counterpart. In the field of reinforced concrete structures, digital twins play a critical role in assessing safety, durability, and reliability. The objective of this approach is to address one of the most critical issues in the current monitoring systems, when the infrastructure owner is often overloaded with large amounts of data that he is not able to process and draw meaningful engineering or maintenance decisions.

Within this framework, ANNs serve two primary purposes:

1. **Calibration of the Virtual Twin:** During the calibration phase, ANNs ensure that the digital twin accurately replicates the behavior of the real-world structure. This involves physically informed deep learning, where the ANN is trained using sensitivity analyses conducted on the virtual model. The underlying numerical simulations leverage nonlinear finite element analysis powered by the ATENA software [1] ([www.cervenka.cz/products/atena](http://www.cervenka.cz/products/atena)).
2. **Real-Time Structural Health Monitoring:** Once trained, the ANN functions as a fast-response surrogate model, delivering critical safety insights for continuous structural health monitoring particularly for bridges. By providing rapid assessments, this AI-driven approach enhances decision-making in maintenance and risk management.

The integration of AI and digital twin technologies marks a significant leap in structural health monitoring, enabling efficient, data-driven decision-making and improving the long-term sustainability of infrastructure.



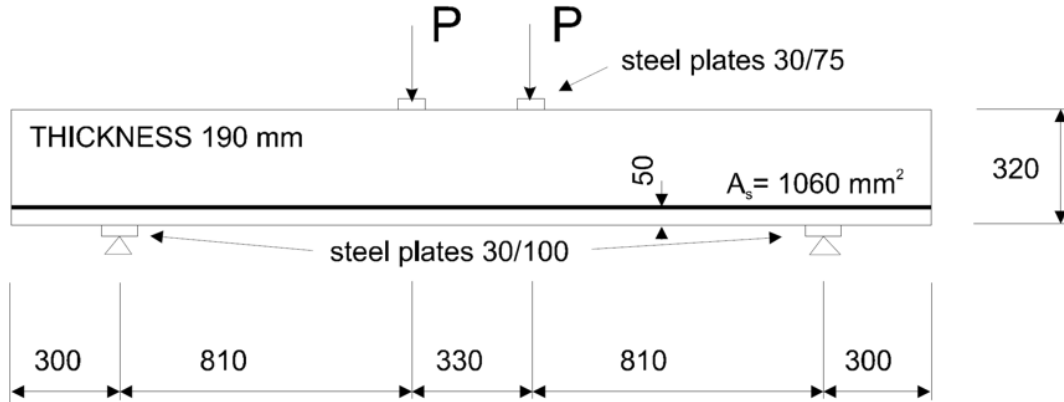
**Fig. 2 ANN surrogate model is applied in two ways: ANN on the right is used for model calibration, i.e., parameter identification, and ANN on the left provides real-time data for engineering interpretation of the obtained monitoring data.**

## 2 ANN Model for Parameter Identification

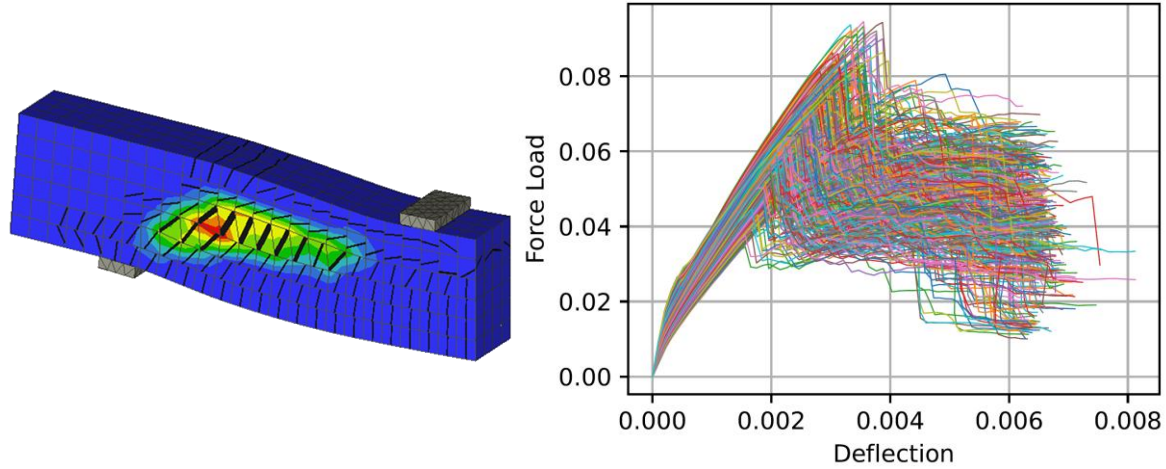
Ensuring the accuracy of a Digital Twin is crucial. In the presented work, this means developing a numerical model of a real-world bridge, which was developed in the finite element simulation system ATENA [3]. The software can simulate the nonlinear behavior of reinforced concrete bridges, including 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  $\mu_\theta=0.979$  and a coefficient of variation  $V_\theta=0.081$ , defining the required accuracy for parameter identification.

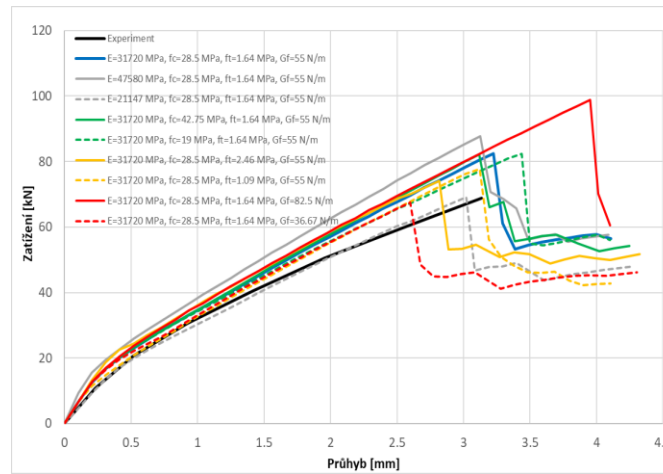
The parameter identification process using ANN was verified using a shear beam example (Fig. 3), based on beams tested by Leonhardt [7]. The goal is not to match experimental data but to assess whether an ANN can accurately identify input parameters—compressive strength ( $f_c$ ), tensile strength ( $f_t$ ), 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 example [7] used for the evaluation of ANN accuracy for the model parameter identification and surrogate modelling.**



**Fig. 4 Typical failure model for the shear beam test example [7] and load-displacement diagrams in the dataset of 1000 training and testing samples.**



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

### 3 Surrogate Engineering Model

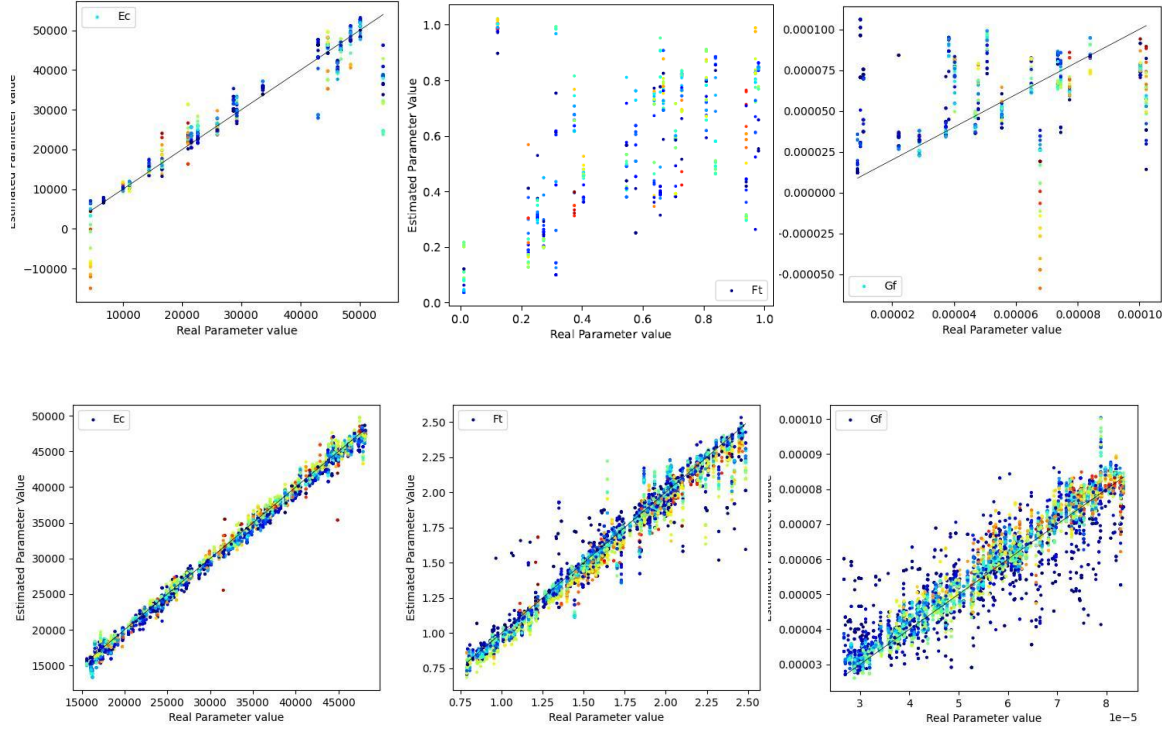
In standard applications of bridge monitoring systems, a substantial volume of data is typically gathered from an array of sensors installed throughout the structure. These sensors continuously collect real-time measurements of various physical quantities such as strain, displacement, temperature, and acceleration. In many cases, certain threshold values of these sensor readings are predefined to trigger warnings or alarms, thereby alerting bridge operators to potential issues. While this method provides a basic level of safety monitoring, it presents a fundamental limitation: there is often no explicit or easily interpretable correlation between the raw sensor data and high-level engineering metrics that are directly meaningful for decision-making.

Such engineering metrics may include, for example, the structural reliability index, the probability of structural failure or collapse, or the utilization ratio of specific elements under loading. These indicators are more informative for engineers and operators because they relate to the actual performance and safety of the bridge, rather than to isolated sensor readings.

This gap between sensor data and engineering insight can be effectively bridged by employing a surrogate model. A surrogate model acts as a computationally efficient proxy that translates raw sensor inputs into comprehensible, actionable engineering quantities. It provides rapid, near real-time estimations based on complex relationships embedded in the underlying data, enabling better-informed operational decisions.

To validate this concept, the same shear beam example discussed earlier is utilized. Dense Neural Network (Dense NN) model is applied. This model architecture consists of four hidden layers. The role of the surrogate model here is to replicate the output of a more computationally intensive nonlinear simulation. Specifically, the surrogate model represents a functional mapping, denoted as  $\Phi_p$ , which estimates the load  $\bar{F}_i$  given the input parameters. These inputs include deflection values  $D_i$  and material properties such as the modulus of elasticity  $E$ , compressive strength  $f_c$ , tensile strength  $f_t$ , and fracture energy  $G_F$ . This surrogate function enables rapid load estimation, significantly enhancing the utility and responsiveness of the bridge monitoring system.

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

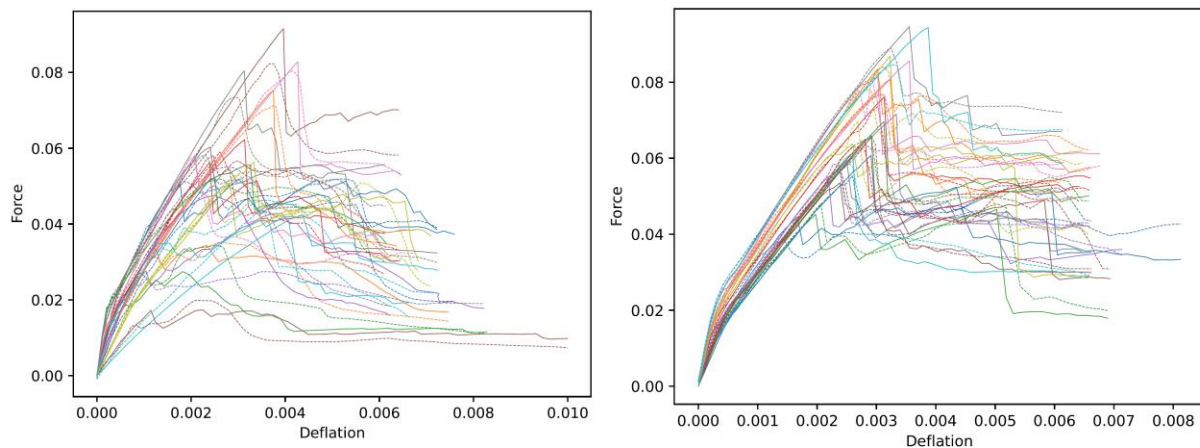


**Fig. 6 The evaluation of the accuracy of ANN model parameter identification of the critical material parameters.**

Fig. 7 presents the training of the surrogate model the pilot example of the shear beam (Fig. 3), specifically for two different cases referred to as Dataset A and Dataset B, containing 100 and 400 samples, respectively. These datasets were generated through finite element (FE) simulations and captured the relationship between structural deflection and applied load under varying material properties. The objective was to use these datasets to train an artificial neural network (ANN) model to serve as a computationally efficient surrogate for the full numerical simulations.

Fig. 7 illustrates the performance of the surrogate model by comparing its predictions with the original FE results for unseen test data. These test samples were intentionally excluded from the training process to objectively evaluate the generalization capability of the ANN model. In the load-displacement diagrams shown, the solid lines denote the results from the original finite element simulations, while the dotted lines correspond to the predictions made by the surrogate model. Even in the case of Dataset A, which comprises only 100 training samples, the ANN model demonstrates a reasonably good approximation of the FE results. Although slight deviations can be observed, the model successfully captures the overall trends and nonlinear behavior of the system. When trained with Dataset B, consisting of 400 samples, the predictive accuracy improves significantly. The higher quantity of training data enables the neural network to better learn the complex mapping between input parameters and structural response, thereby enhancing its reliability and precision.

The broader motivation behind this modeling effort lies in its application within the framework of Digital Twin technology. In such a context, the ANN-based surrogate model can be deployed in real-time to continuously evaluate the structural health and operational safety of the bridge. One particularly valuable output is the utilization ratio, a quantitative measure of how close the structure is to reaching its failure threshold under current loading conditions. This predictive capability enables proactive maintenance, early warning systems, and optimization of load management, ultimately contributing to safer and more efficient infrastructure management.



**Fig. 7. Accuracy of ANN surrogate model in predicting the response of the testing shear beam structure, (left) Dataset A – 100 samples, (right) Dataset B – 400 samples.**

## 4 Example of Application

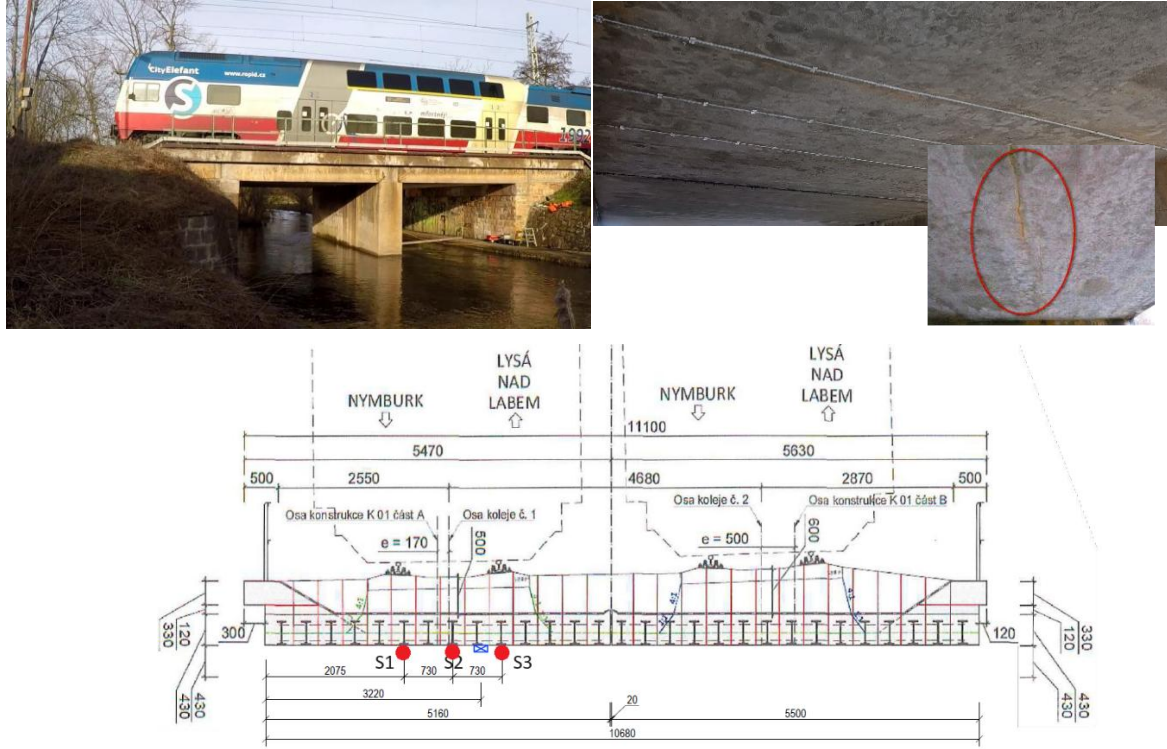
This section presents a pilot application of the proposed Digital Twin framework, incorporating ANN-based surrogate models, applied to a real-world engineering structure. The case study involves a small railway bridge located near the village of Kostomlaty in the Czech Republic. The bridge is a modest two-span concrete structure, consisting of four concrete slabs reinforced with embedded steel I-sections, as illustrated in Figure 9. Constructed in 1946, the bridge exhibits visible signs of aging and structural degradation. Notably, longitudinal cracks have developed along the underside of the concrete slabs, indicating potential issues with structural integrity (see Figure 9). While the bridge marginally meets the required Ultimate Limit State (ULS) load capacity, it significantly underperforms in Serviceability Limit State (SLS) assessments, particularly in terms of deflection and cracking criteria. Due to these concerns, the bridge was selected for continuous monitoring and designated as a pilot structure within the Digital Twin research

project. Its structural condition and simplicity make it an ideal candidate for testing and validating the practical implementation of Digital Twin technologies in combination with AI-driven surrogate modeling.

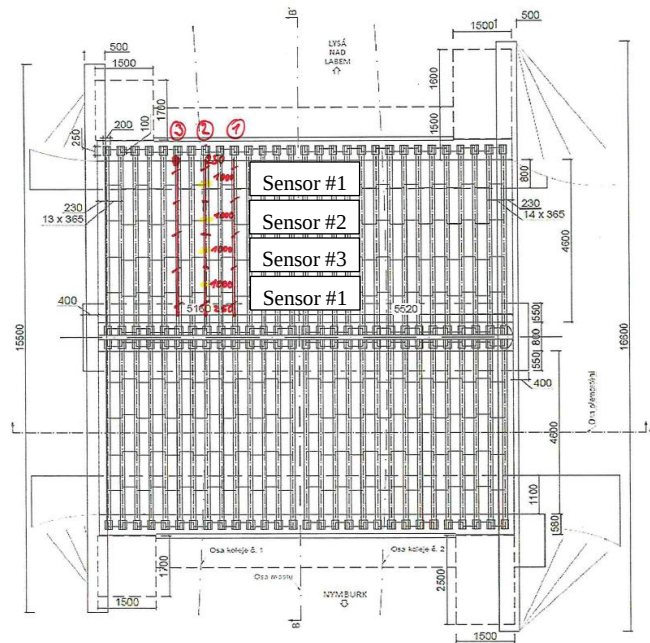
The ANN-based surrogate model from Section 2 is applied to evaluate the thermal response of the bridge. Trained on nonlinear FE simulations, the model estimates sensor readings resulting from ambient temperature variations. Typical hourly temperature profiles such as the June example in can be easily sourced from meteorological data. Bridge response is monitored using fiber-optic sensors placed longitudinally, as shown in Fig. 8 and Fig. 9. These sensors measure strain at four points along the bottom deck; this study focuses on mid-span results. Fig. 12 presents FE-predicted strains at sensor locations under the applied temperature history. This historical temperature data is used to train the ANN model, which functions as a surrogate to predict thermal-induced strain responses in real time. The ANN based surrogate model in this case represents a functional:

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

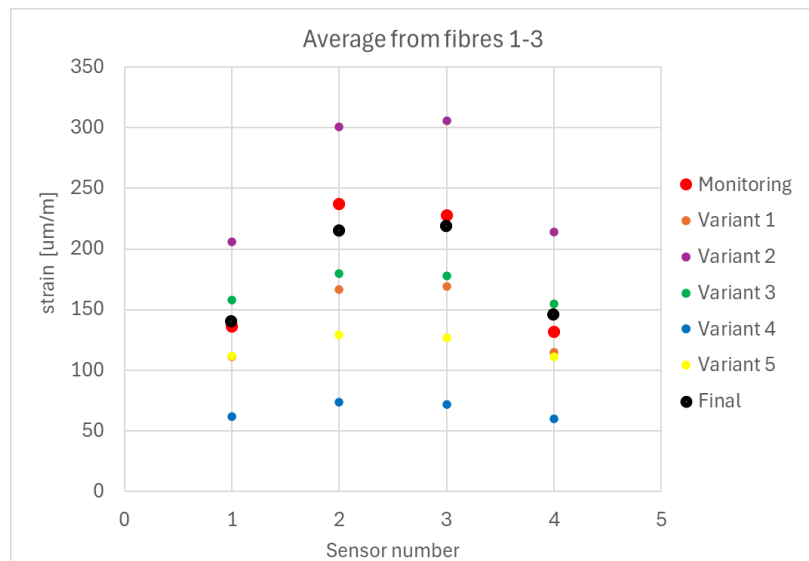
The ANN model estimates the strain value at sensor  $S_n$  at time step  $i$ , using the ambient temperature history over the preceding 24 hours and the current time  $i$ . Additionally, it incorporates the average temperature from the earlier 48-hour period (i.e., between  $i-72$  and  $i-24$ ) to account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



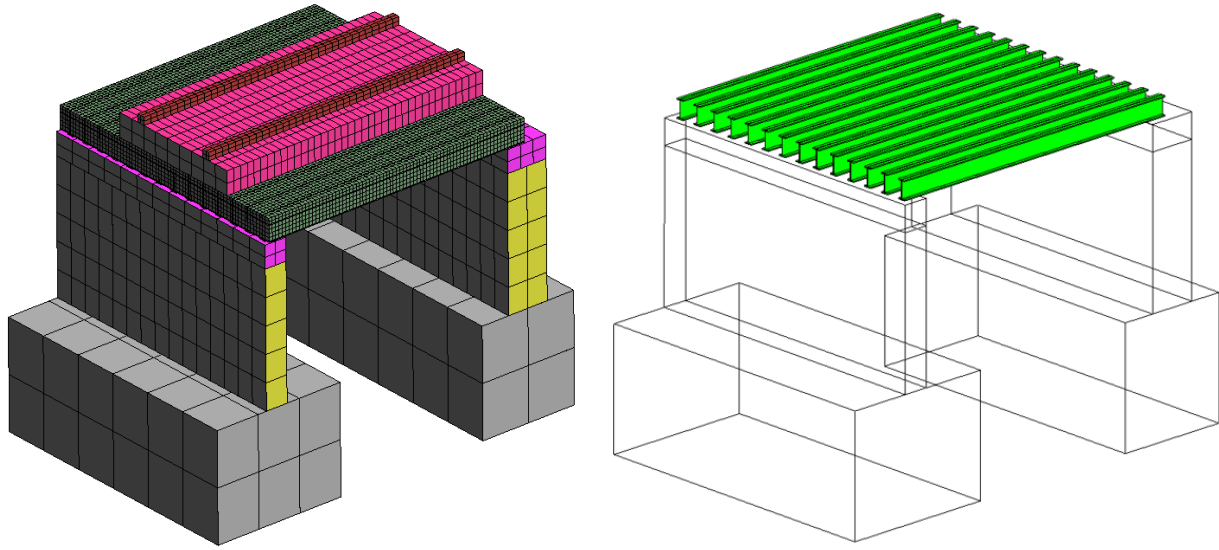
**Fig. 8. Pilot bridge application example, small railway bridge at Kostomlaty, Czech Republic with the sensor location S1, S2 and S3.**



**Fig. 9. Pilot bridge application example, top view with the sensor locations.**



**Fig. 10. Selected data from the fitting and identification process.**

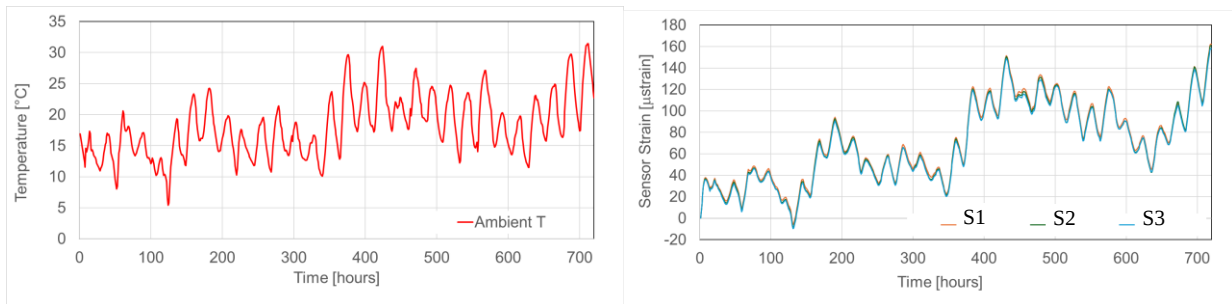


**Fig. 11. Finite element model of the quarter section of the model, right figure shows the location of the internal I steel beams.**

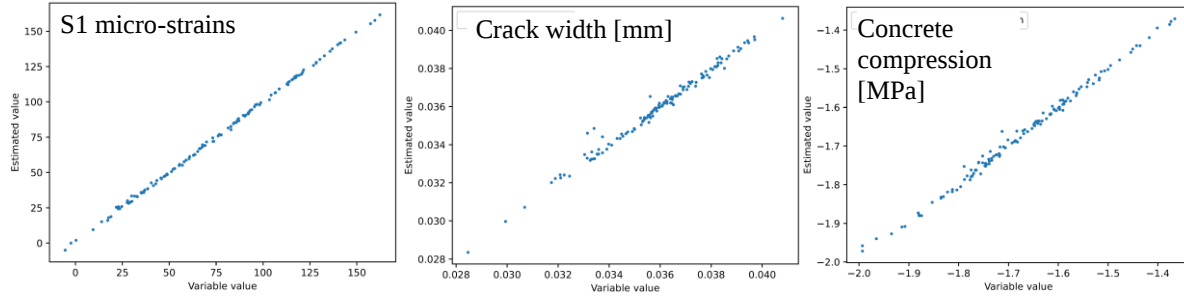
The ANN model provides the estimate of the value at sensor  $S_n$  at time  $i$  based on the temperature history in the interval  $i-24$  hours and the current time  $i$  and based on the average temperature in the previous 2 days, i.e. time interval  $(i-72, i-24)$ . The accuracy of the ANN surrogate model in predicting the correct sensor strain is shown in Fig. 13. The surrogate model can be used to predict other engineering quantities in the structure such as for instance the expected maximum crack width or the highest compressive stresses in the concrete slab (see Fig. 13). It should be noted that the response of the bridge is nonlinear due to the structural system of the steel beams embedded in plain concrete. Microcracks occur already during the self-weight of the structure and during the thermal loading as is shown in Fig. 14.

Any engineering quantity for the investigated bridge can be then evaluated by a suitable trained surrogate model based on ANN, which in general has the form:

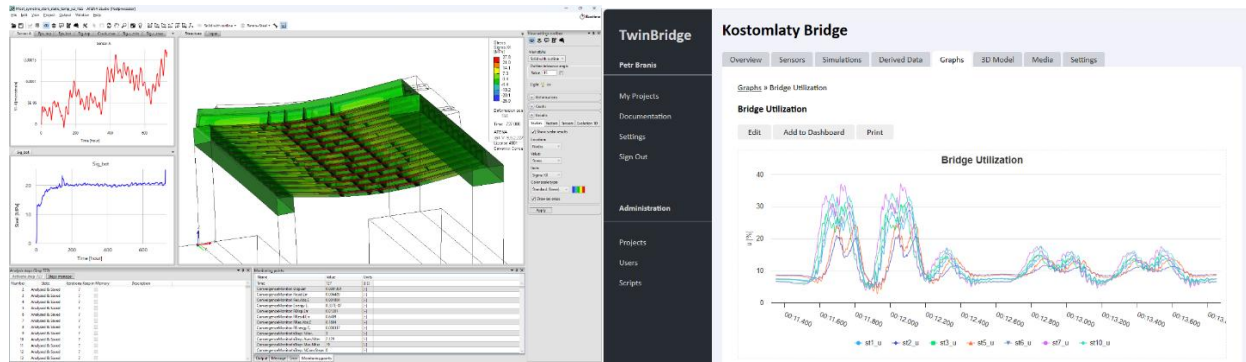
$$\bar{R}_{n,i} = \Phi_{Eng} [f_{Ti}(t_{i-24}, t_i), T_{Avg}(t_{i-72}, t_{i-24}), S_{n,i}] \quad (3)$$



**Fig. 12. (Left) Typical ambient temperature profile at the bridge location in the selected period of the month June, (Right) predicted average sensor strains along optical fibers S1-S3 due to temperature.**

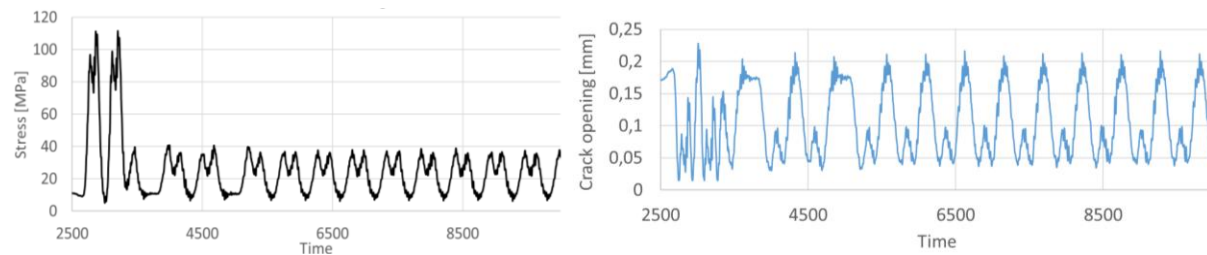


**Fig. 13. Accuracy of ANN surrogate model in predicting engineering quantities based on 3 days history of ambient temperature.**



**Fig. 14. (Left) 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, (Right) prediction of bridge utilization by Digital Twin model during train overpass.**

The results obtained from the trained system are illustrated in the screenshots of the developed Digital Twin platform. Fig. 14 displays the bridge utilization ratio during a train overpass. Similarly, Fig. 15 depicts the highest stresses in the bottom steel flange and the anticipated crack widths, derived from sensor readings during a train overpass.



**Fig. 15: Prediction of bridge bottom flange stresses during train overpass.**

## 5 Conclusions

This paper explores the use of Artificial Neural Networks (ANNs) within a Digital Twin framework for structural analysis and monitoring. ANNs are first applied to calibrate the virtual twin, i.e., the numerical

model representing the physical structure, and are later used to create fast, real-time surrogate models. These models translate raw monitoring data into meaningful engineering metrics, supporting infrastructure owners in bridge management and maintenance.

The proposed approach tackles a key challenge in structural health monitoring when bridge operators often face an overwhelming volume of sensor data, with limited insight into how these readings reflect structural performance, safety, or reliability, making informed decision-making difficult and error-prone.

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## 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](http://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]. Leonhardt and Walther, Schubversuche an einfeldrigen Stahlbetonbalken mit und Ohne Schubbewehrung, Deutscher Ausschuss fuer Stahlbeton, Heft 51, Berlin 1962, Ernst&Sohn.
- [8]. Drahy V, Explainable neural networks, Diploma thesis, Czech Technical University, Faculty of Electrical Engineering, Dep. Of Computer Science, 2023.
- [9]. Shih-Chung B. Lo, Heang-Ping Chan, Jyh-Shyan Lin, Huai Li, Matthew T., Freedman, and Seong K. Mun. Artificial convolution neural network for medical image pattern recognition. *Neural Networks*, 8(7):1201-1214, 1995. *Automatic Target Recognition*.
- [10]. A.G. Ivakhnenko, V.G. Lapa, V.G. Lapa, and R.N. McDonough. *Cybernetics and Forecasting Techniques. Modern analytic and computational methods in science and mathematics*. American Elsevier Publishing Company, 1967.
- [11]. Sepp Hochreiter and Juergen Schmidhuber. Long short-term memory. *Neural Comput.*, 9(8):1735-1780, nov 1997.
- [12]. Drahy V., Maen. <https://github.com/drvojtex/Maen/>, 2023.