AI Based Surrogate Model for Nonlinear Modelling of Reinforced Concrete

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Abstract. Surrogate models employing Artificial Intelligence (AI) and Artificial Neural Networks (ANNs) are being developed to enhance digital twins for structural health monitoring. Within this framework, the ANN-based surrogate model serves two key purposes. Initially, an ANN model is utilized during the calibration phase of the virtual twin, which is constructed using a nonlinear finite element model in ATENA software. Once calibrated, this virtual twin is employed to develop an ANN-based surrogate model. This model is instrumental in providing real-time, critical safety information essential for monitoring the structural health of bridges. This innovative approach has been implemented on pilot bridges in the Czech Republic.

Keywords: Artificial Neural Networks, Digital Twin, Durability, Finite Element Analysis, Reinforced Concrete Structures, Structural Health Monitoring.

1 Introduction

Artificial Intelligence (AI), particularly using Artificial Neural Networks (ANNs), has become increasingly prevalent across various human activities and industrial applications. One notable application is in developing real-time, fast-response surrogate models within the digital twin framework for structural health monitoring. Such models are being developed in TwinBridge research project by the consortium of partners: Safibra s.r.o., Cervenka Consulting s.r.o. and Czech Technical University in Czech Republic.

The concept of a digital twin involves creating a digital replica of a physical product or structure (see Fig. 1. This virtual counterpart—often a sophisticated numerical model—engages in continuous communication and data exchange with its physical counterpart. In the realm of reinforced concrete structures, digital twins are crucial for evaluating safety, durability, and reliability.

In this context, ANNs are employed within the digital twin framework primarily for two purposes. Firstly, ANNs are used during the calibration phase of the virtual twin to ensure that it accurately replicates the real structure's behavior. Following calibration, the virtual twin supports the training of the ANN through physically informed deep learning, leveraging data from sensitivity analyses conducted using the virtual model. This model utilizes nonlinear finite element analysis facilitated by the ATENA software [1] (www.cervenka.cz/products/atena).

The second use of the ANN within this framework involves deploying the trained model to function as a fast-response surrogate, providing essential safety information for the monitoring of structural health in bridges.

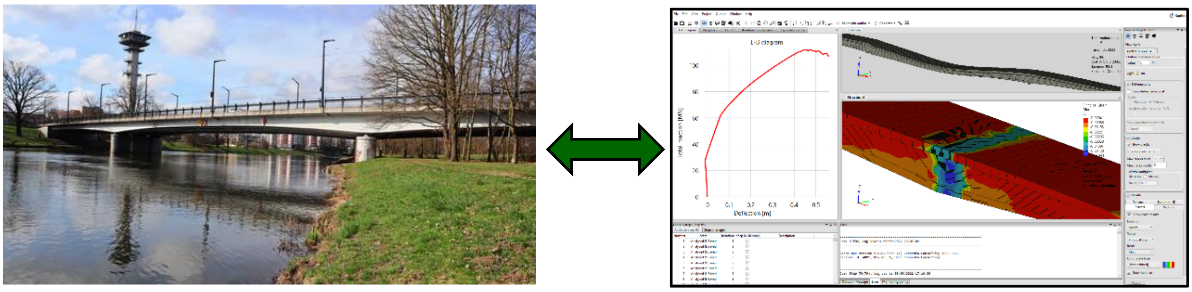

Fig. 1. Digital Twin involves active data exchange between the real structure with monitoring sensors (left) and virtual twin, i.e. its numerical model (right).

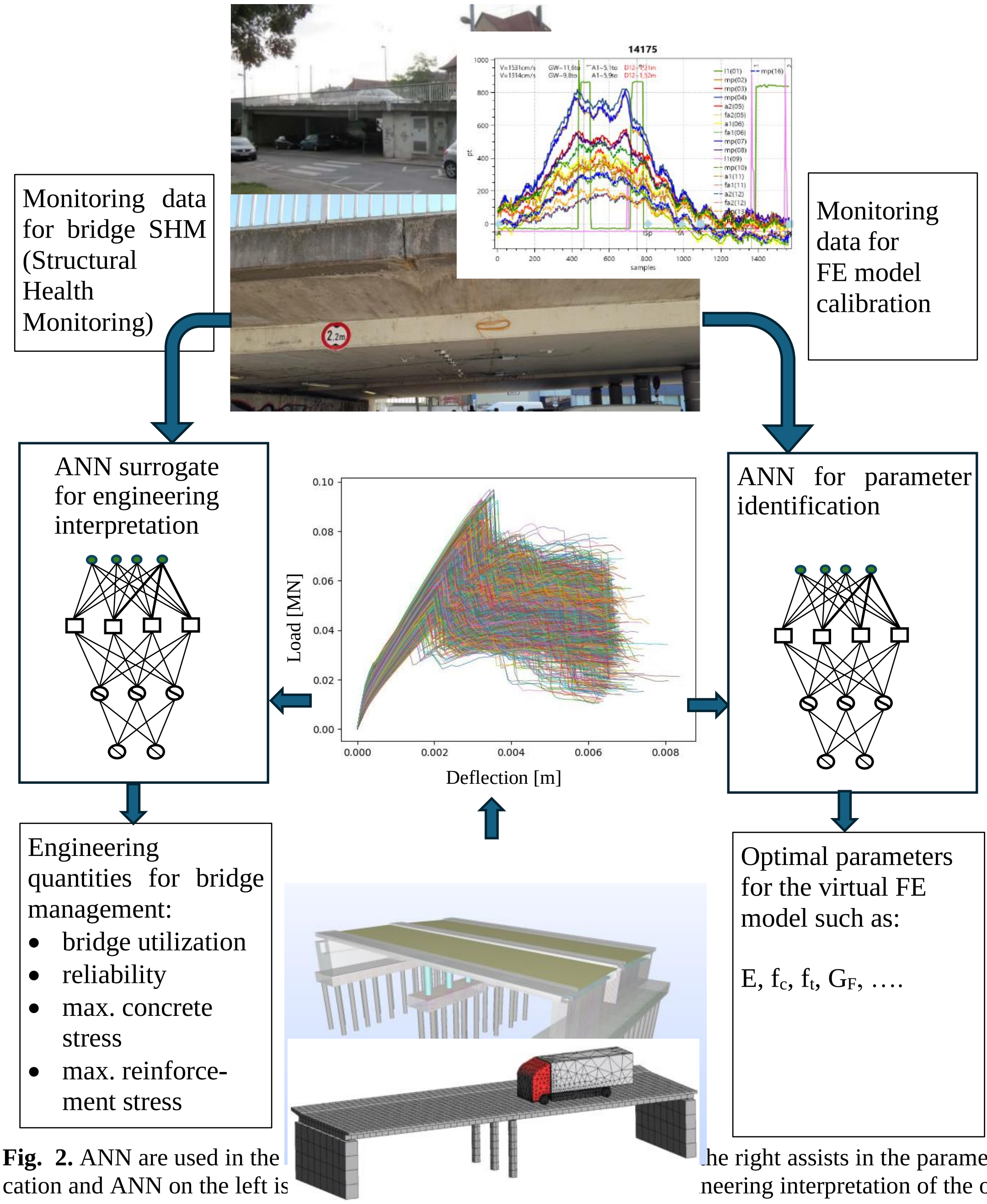

Fig. 2. ANN are used in the … he right assists in the parameter identification and ANN on the left is … neering interpretation of the obtained monitoring data.

This paper presents the development of an efficient and accurate ANN-based surrogate model, highlighting advances in physically informed deep learning methodologies for structural analysis. These two applications of ANN in the digital twin concept are summarized schematically in Fig. 2.

2 Model Parameter Identification

In the development of the Digital Twin, ensuring the validity and accuracy of the virtual twin is paramount. For our purposes, this entails a numerical model of a real-world structure, specifically a bridge. In this study, we employ the finite element simulation system ATENA [1] to model the nonlinear behavior of reinforced concrete bridges. This system is adept at capturing critical aspects of reinforced concrete structural behavior, including concrete cracking, crushing, reinforcement yielding, prestressing, and the bond between concrete and reinforcement.

The details about the fracture-plastic concrete material model were published in the original papers [2][3]. Extensive validation of the model applicability for the simulation of typical failure modes of reinforced concrete structures have been presented in the paper [4], where the model uncertainty partial safety factor has been calibrated. In this publication, the model uncertainty partial safety factor was calibrated, yielding a general value of 1.16 was obtained with the bias $\mu_\theta = 0.979$ and a coefficient of variation $V_\theta = 0.081$. These values define the required accuracy of parameter identification for the virtual twin.

The accuracy of the parameter identification using the proposed approach will be demonstrated on a shear beam example (see Fig. 3). The geometry of the example corresponds to the beams tested by Leonhardt [10]. The matching of experimental data is not the primary objective. The main objective is to verify whether the ANN can identify the suitable set of input parameters, which are represented here by compressive strength f_c, tensile strength f_t, elastic modulus E and fracture energy G_F, for a given load-displacement diagram (see Fig. 3c). Three sets of datasets have been pre-calculated with the number of samples: 100, 400 and 1000 with different random choices of the material parameters (E, f_c, f_t, G_F). For each data set **Fig. 3**d shows the sensitivity of the peak displacement for the largest dataset of 1000 samples for different values of the input parameters.

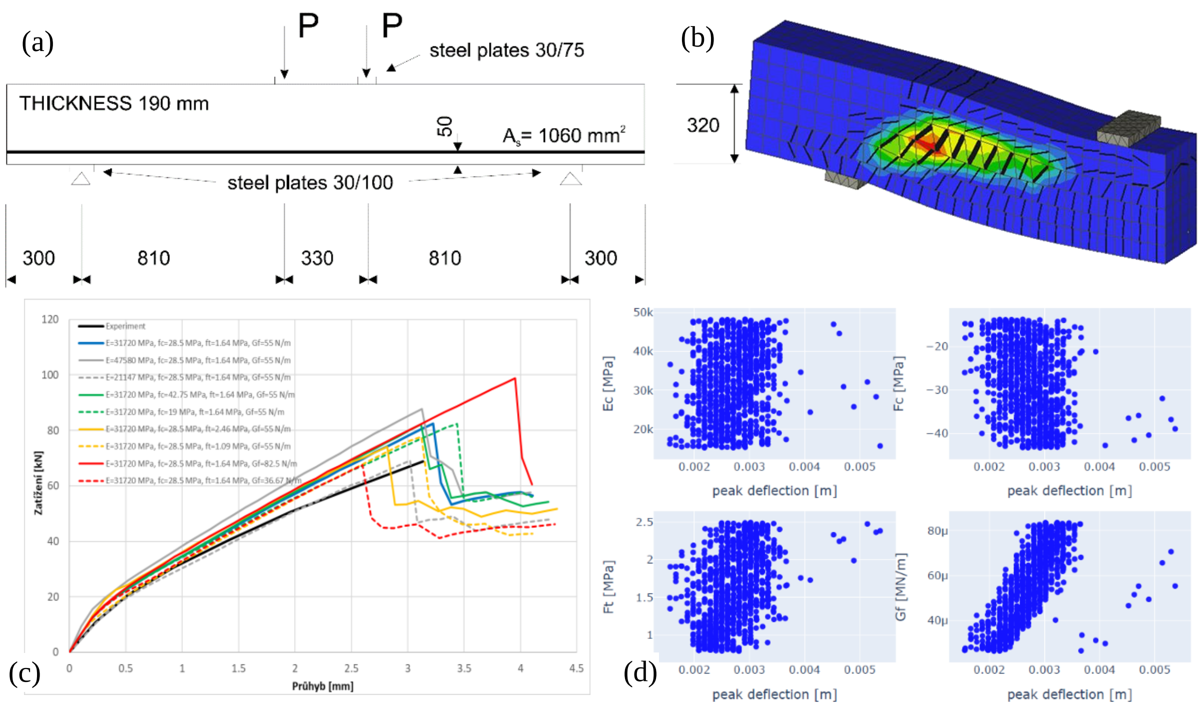

Fig. 3. Shear beam test example [5] used for the evaluation of ANN accuracy for the model parameter identification. (a) geometry, (b) numerical model failure simulation, (c) load-displacement diagrams, (d) distribution of the main parameters in the dataset of 1000 training and testing samples.

To evaluate the performance and accuracy of ANN, several types of neural networks have been tested and evaluated [6]. The investigated ANN models can be divided into two groups: conventional and explainable models and they are summarized in Table 1. Three architectures of explainable neural network models were created based on the distribution of sampling points. Their architecture was implemented in the tool Maen (Multiple agents ecosystem network) developed by V. Drahy [10]. Their architecture is shown in Fig. 4.

Table 1. Summary of ANN model used for the evaluation of the parameter identification [7].

Model	Description	Layers	Parameters
Conventional models			
CNN	Convolution neural network [7]	7	23 904
Dense NN	Fully connected (dense) neural network [8]	5	71 204
LSTM NN	Long/short term memory neural network [9]	6	6 762
Explainable models **Fig. 8** [6][10]			
L-Maen	LSTM Maen	5	12 308
L-A-Maen	L-A-Maen	6	2 600
F-Maen	Feed forward Maen	5	33 028

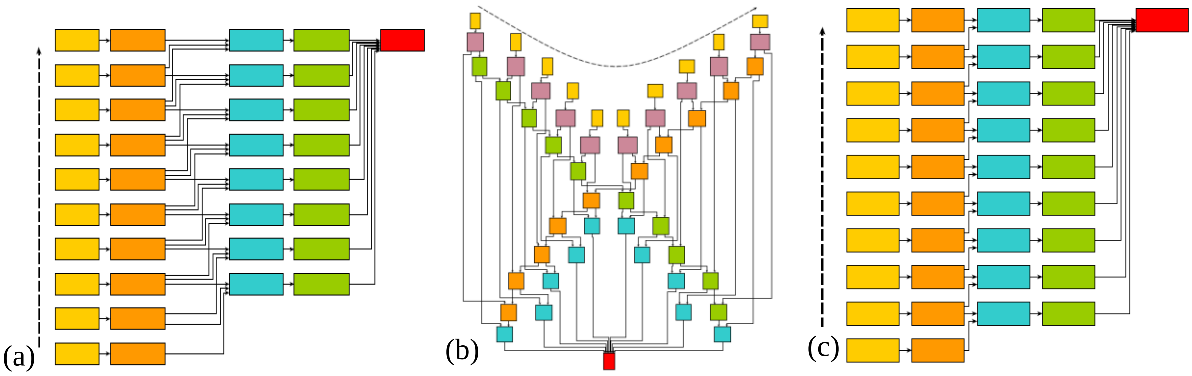

Fig. 4. Schema of explainable ANN models applied during the evaluation of suitable ANN models for parameter identification (a) L-Maen, (b) L-A-Maen, (c) F-Maen.

In each data set 64% samples are used for training, 16% for validation and 20% for testing. The objective of the ANN test samples is to predict the whole load-displacement curve as shown in Fig. 3c based on the provided set of input material parameters (E, f_c, f_t, G_F), which are not part of the training. Mean relative errors for each ANN model are summarized in Table 2 for each data set. Since each model contains different number of layers and trainable parameters an efficiency parameter is defined to facilitate the comparison of their efficiency: $p_e = \frac{1}{n \times m}$, where n is the number of trainable parameters and m is the median relative error. This means higher value represents higher efficiency. As expected, the results show that in general for larger data set lower error is obtained. Interestingly the lowest error is obtained for the standard Dense NN model for the largest set C with 1000 samples.

Table 2. Average relative error of various ANN models for parameter identification.

Dataset	CNN	Dense NN	LSTM NN	L-Maen	L-A-Maen	F-Maen
A – 100	0.279	0.256	0.229	0.224	**0.188**	0.261
B – 400	0.182	**0.123**	0.175	0.228	0.175	0.164
C - 1000	0.176	**0.111**	0.170	0.171	0.161	0.128

Table 3. Performance efficiency of various ANN models for parameter identification.

Dataset	CNN	Dense NN	LSTM NN	L-Maen	L-A-Maen	F-Maen
p_e : A – 100	0.013	0.005	0.055	0.033	**0.184**	0.009
p_e : B – 400	0.019	0.008	0.071	0.032	**0.190**	0.014
p_e :C - 1000	0.019	0.009	0.070	0.039	**0.198**	0.017

The results also show that in the case of small datasets, it is advantageous to develop specialized ANN models, where acceptable error can be obtained even for small training datasets. This is documented in the above tables by the L-A-Maen model, which shows the highest performance indicator and acceptable mean error even for the smallest dataset A (see Table 2, Table 3). It should be noted that sensitivity analysis should be part of a parameter identification process. In this example of shear beam failure, the sensitivity analysis showed that the results are not significantly affected by the value of f_c (compressive strength), which is to be expected. The accuracy of the identification of the other input material parameters (E, f_t, G_F) is shown in a different graphical format in Fig. 5.

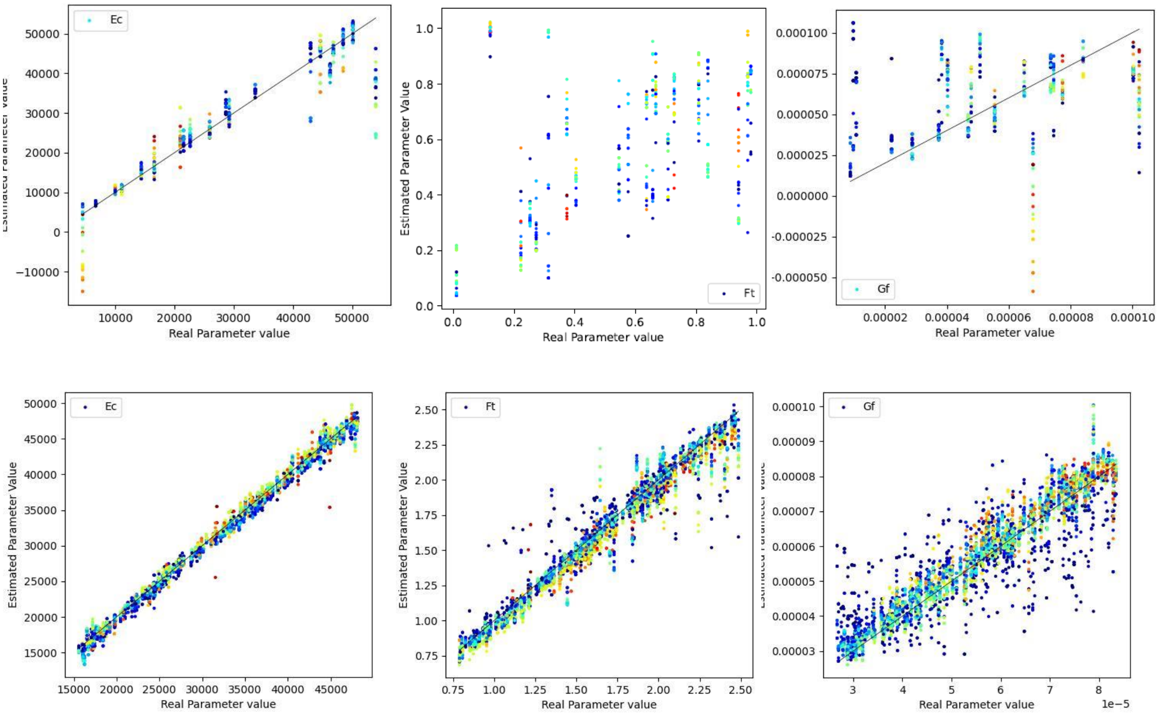

Fig. 5. Accuracy of ANN model parameter identification using the testing samples for Dense NN model.

3 Surrogate Engineering Model

In typical bridge monitoring applications, large amount of monitoring data is usually collected from the installed sensors. Some critical values of the sensor readings are usually identified beforehand as raising an alarm or warning for the bridge operators. The problem with this approach is that there is no direct and clear relationship among the sensor readings and meaningful engineering quantities that would be clearly understandable to the bridge operator such as for instance: reliability index of the bridge, probability of collapse or utilization ratio. This deficiency can be addressed by a surrogate model which provides fast real-time data with clear engineering meaning based on the sensor readings. This approach was again validated using the same shear beam example as in the previous Section 2. This time however only the Dense NN model is used with 4 hidden layers as shown in Fig. 6. The operation of such a surrogate model is to emulate the nonlinear simulation as represented by the following functional Φ_p that calculates the estimate of the load $\bar{F}_i$ for a given input in terms of deflection D_i and material parameters (E, f_c, f_t, G_F):

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

Fig. 7 shows the training data for the surrogate model of the shear beam for the case of dataset A and B with 100 and 400 samples respectively. The surrogate model predictions using the Dense NN model are shown in Fig. 8. The figure shows the predictions of the load-displacement diagrams for the test data samples, i.e. the samples that were not used for the ANN learning. The solid lines represent the original FE results, and the dotted lines are from the ANN surrogate model. It shows that even the predictions obtained by the ANN model for dataset A (100 training samples was quite reasonable. With larger training dataset, the prediction accuracy increases. The motivation is that in the Digital Twin approach the ANN based surrogate model can be used to predict what is the utilization ratio of the structure, i.e. how close is the structure from a possible collapse.

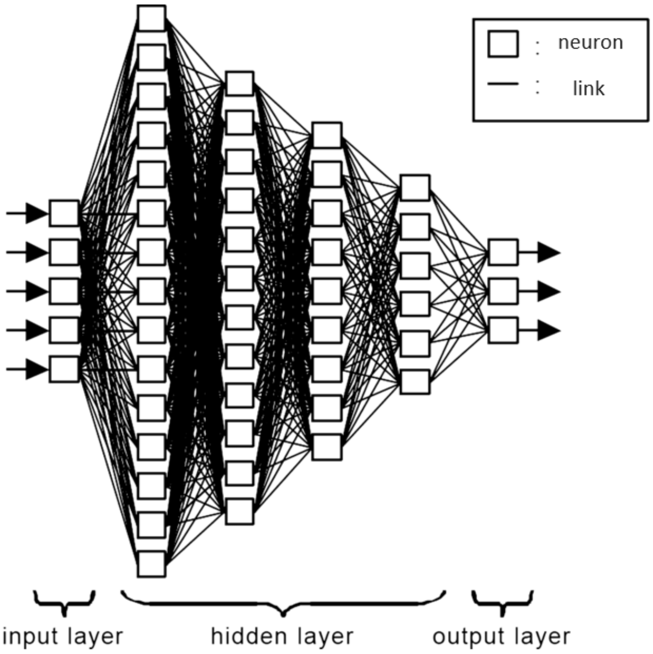

Fig. 6. Dense NN model with 4 hidden layers: 1000, 5000, 500 and 500 neurons in each layer fully connected.

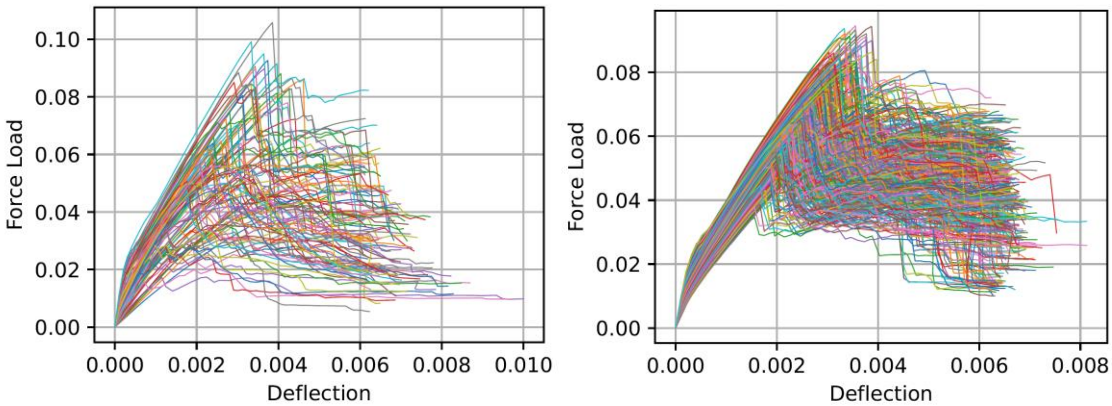

Fig. 7. Simulation data for ANN surrogate model training and testing (left) dataset A with 100 samples, (right) dataset B with 400 samples.

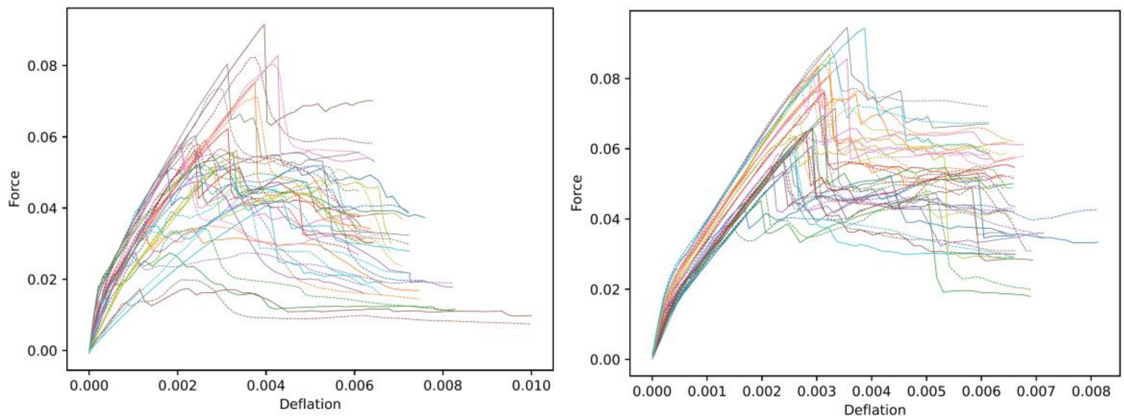

Fig. 8. Accuracy of ANN surrogate model in predicting the response of the testing shear beam structure, (left) dataset A, (right) dataset B, solid lines indicate the response from FE simulation, dotted lines indicate the prediction by the surrogate Dense-NN model.

4 Application Example

This section describes one pilot application of the presented Digital Twin concept and ANN based surrogate models to a practical engineering structure. It is a small railway bridge near the village Kostomlaty in the Czech Republic. It is a simple two span concrete bridge composed of four concrete slabs with embedded steel I sections as shown in Fig. 9. The bridge has been constructed in 1946, and longitudinal cracks are observed at the bottom of the concrete slabs (see Fig. 9). The bridge barely satisfies the required ULS load capacity, but significantly fails SLS checks, therefore it was selected for monitoring and as a pilot bridge candidate in the TwinBridge research project.

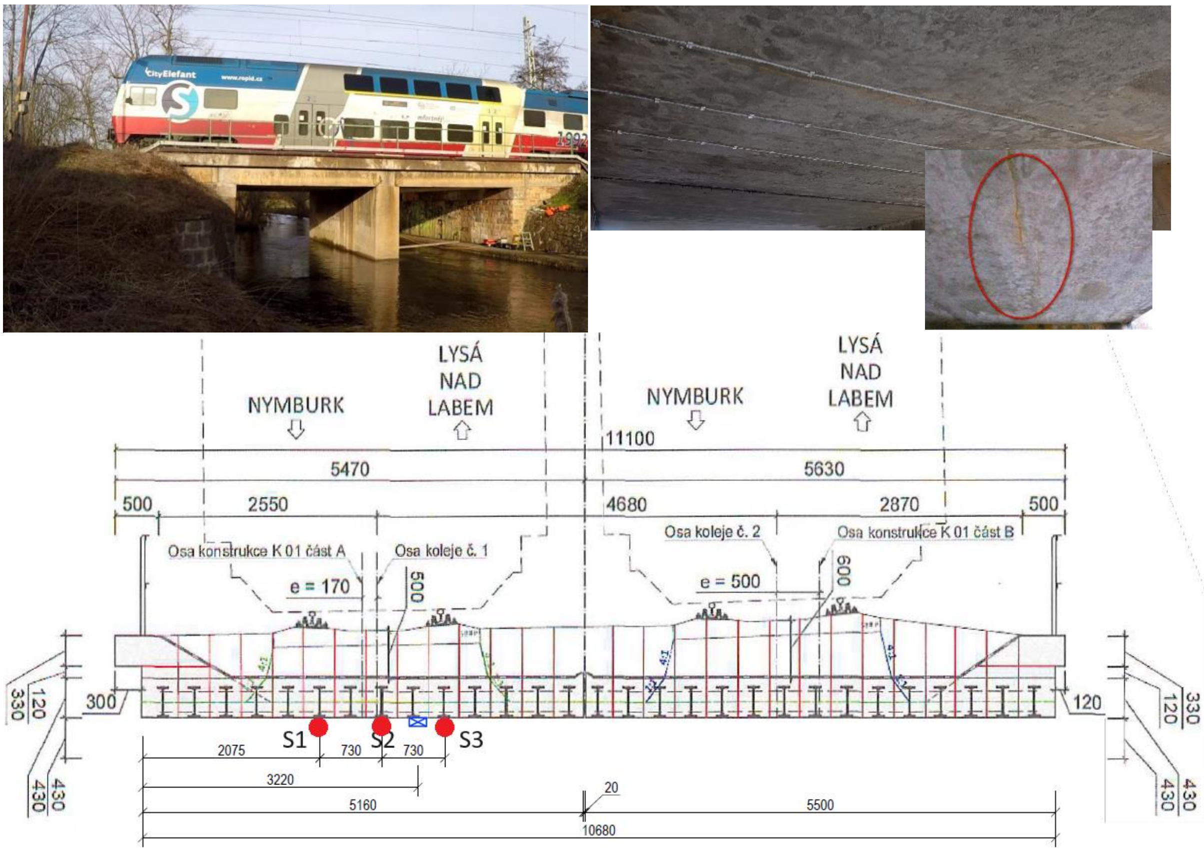

Fig. 9. Pilot bridge application example, small railway bridge at Kostomlaty, Czech Republic with the sensor location S1, S2 and S3.

ANN based surrogate model from Section 3 is applied for the evaluation of thermal response of the investigated bridge. The surrogate model is trained based on the FE nonlinear analysis to estimate the sensor readings due to ambient temperature. The typical hourly profile of ambient temperature at the bridge location can be nowadays easily obtained from existing meteorological services. Such a typical profile for the month June is for instance shown in **Fig. 10**. The bridge response is monitored by fiber-optic sensors located in the longitudinal direction as shown in Fig. 9. The sensors monitor the strain of the bridge bottom deck at four locations in the longitudinal direction, but for the purpose of this paper, the results in the mid-span will be discussed and evaluated. Fig. 11 shows the results from the FE simulation of the strains expected at the sensor location by the applied ambient temperature history. These historical temperature data can be used to train an ANN surrogate model to predict the bridge response due to the ambient temperature history. The ANN based surrogate model in this case 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 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. 12. 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. 12).

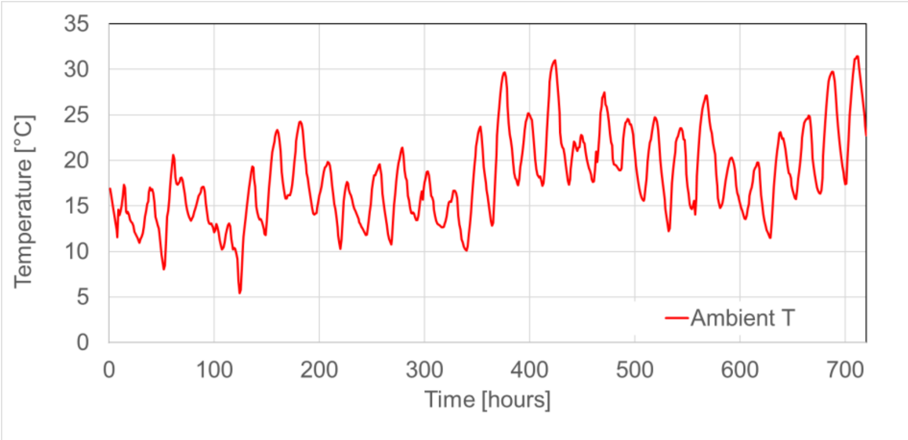

Fig. 10. Typical ambient temperature profile at the bridge location in the selected period of the month June.

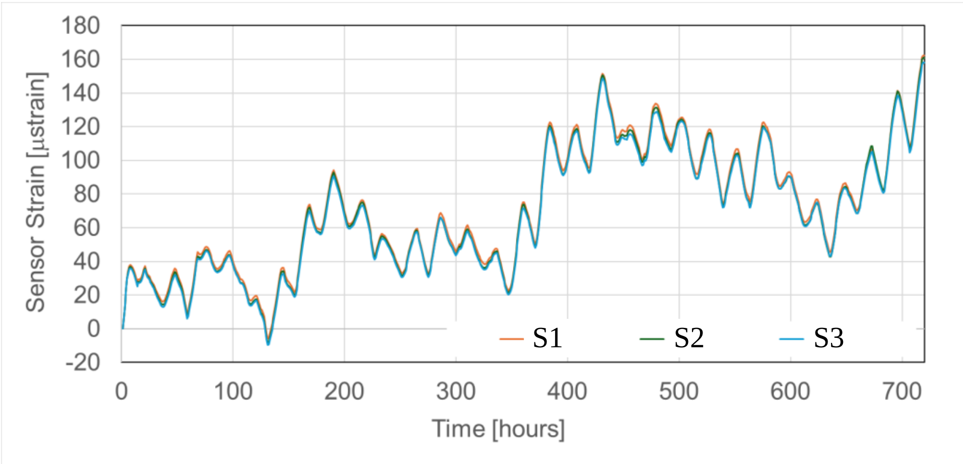

Fig. 11. Simulation of the sensor strains evolution due to measured ambient temperatures.

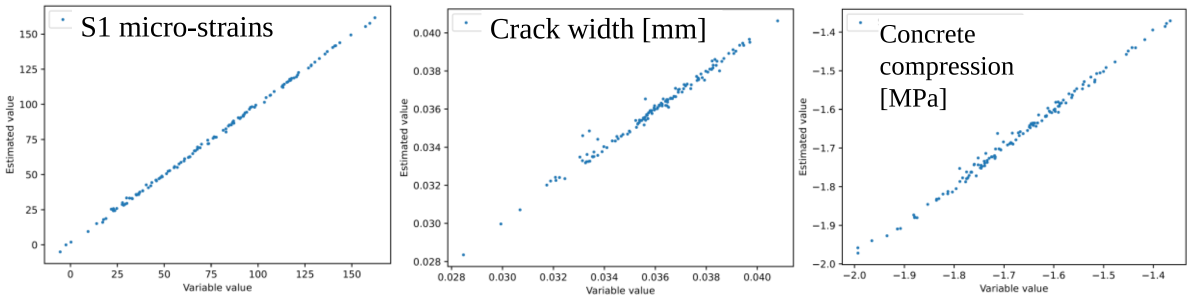

Fig. 12. Accuracy of ANN surrogate model in predicting engineering quantities based on 3 days history of ambient temperature.

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. 13.

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:

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

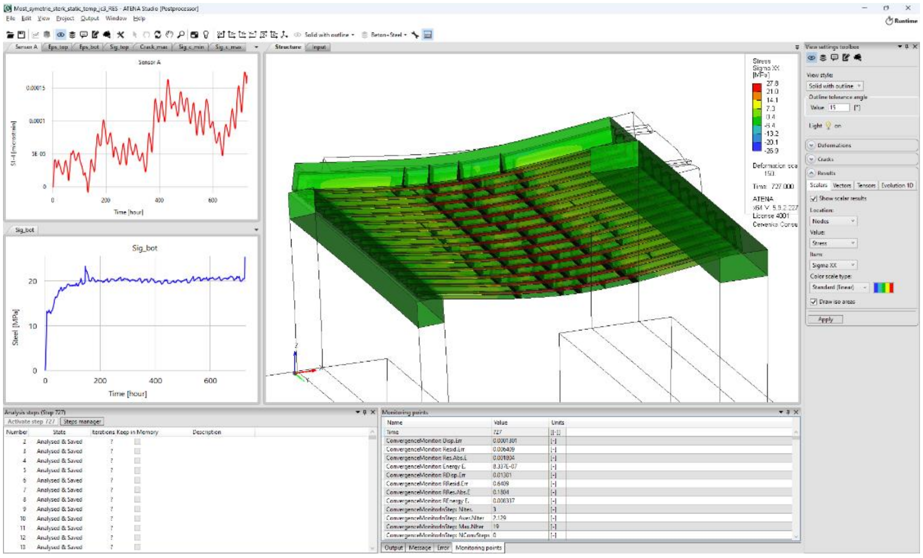

Fig. 13. Bridge deflection due to thermal loads showing the evolution of strains at sensor 204, maximal tensile stresses at the bottom flange of the steel I beams and bridge deflections along with the location of concrete cracks.

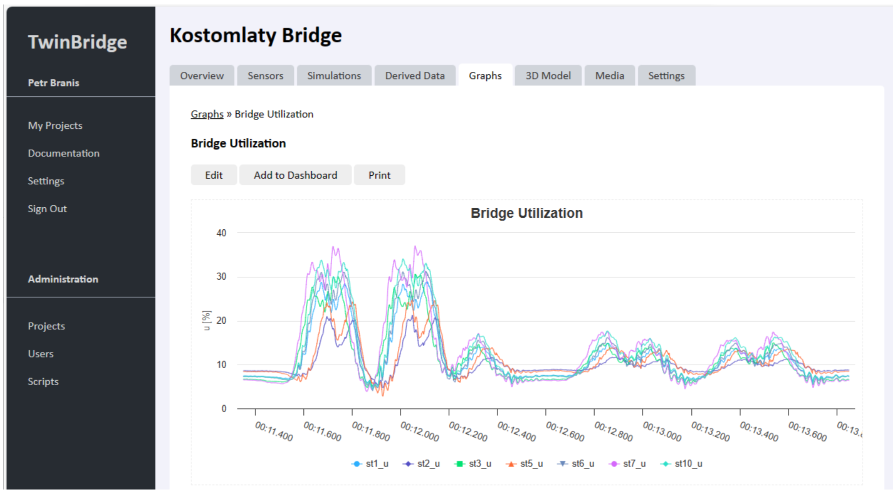

Fig. 14: Prediction of bridge utilization by Digital Twin model during train overpass.

The results obtained from the trained system are illustrated in the screenshots of the developed Twin-Bridge platform. Fig. 14 displays the bridge utilization ratio during a train overpass. Similarly, Fig. 15 and Fig. 16 depict the highest stresses in the bottom steel flange and the anticipated crack widths, respectively, derived from sensor readings during a train overpass.

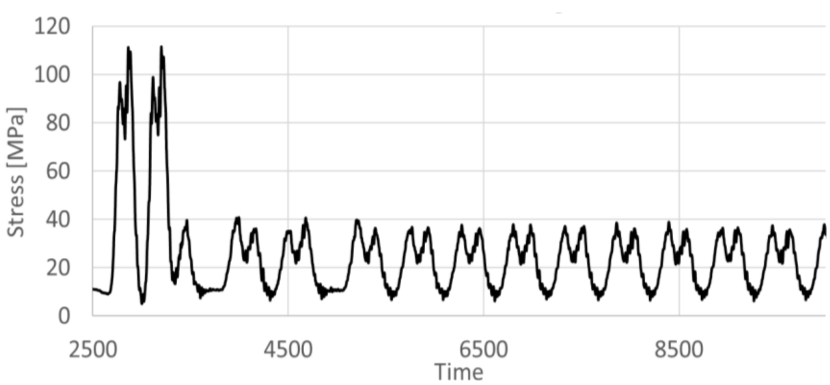

Fig. 15: Prediction of bridge bottom flange stresses during train overpass.

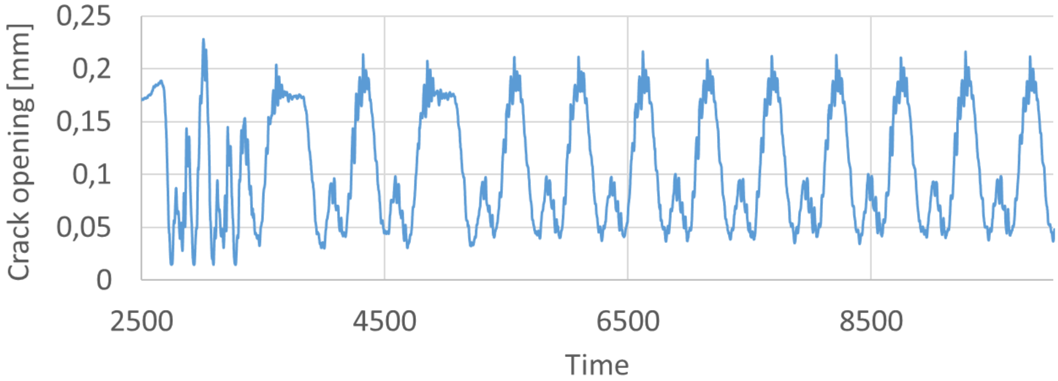

Fig. 16: Prediction of bridge maximum crack openings by Digital Twin model during train overpass.

5 Conclusions

This paper discusses the implementation of Artificial Neural Networks (ANNs) within the Digital Twin framework for structural analysis and monitoring. Initially, ANNs are employed to assist in the calibration of the virtual twin, specifically the numerical model that represents the actual structure. Subsequently, ANNs are utilized to develop fast-response, real-time surrogate models. These models are crucial for converting monitoring data into engineering quantities that aid infrastructure owners in the management and maintenance of their bridge inventory.

The approach outlined in this paper addresses a significant challenge in current structural health monitoring applications: bridge operators are often overwhelmed by the sheer volume of monitoring data collected, without a clear understanding of how these sensor readings relate to the behavior, safety, and reliability of the structure, making informed decisions difficult and susceptible to errors.

The methodologies described are currently being applied to pilot bridges in the Czech Republic. This work is part of a research project supported by the Czech Technology Agency and the Ministry of Transport under the grant CK03000023, titled "Digital Twin for Increased Reliability and Sustainability of Concrete Bridges."

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