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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, as illustrated in Fig. 1.

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

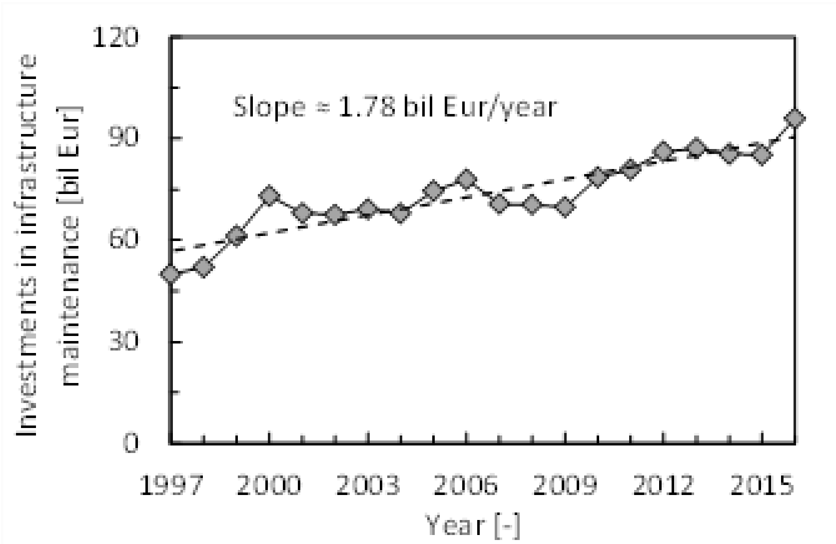


Fig. 1 Infrastructure maintenance cost in selected OECD countries

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. 2). 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.

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).
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.

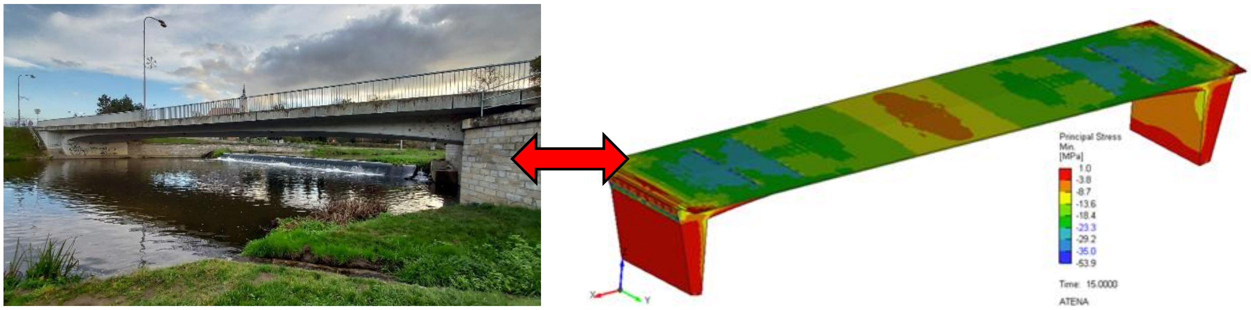
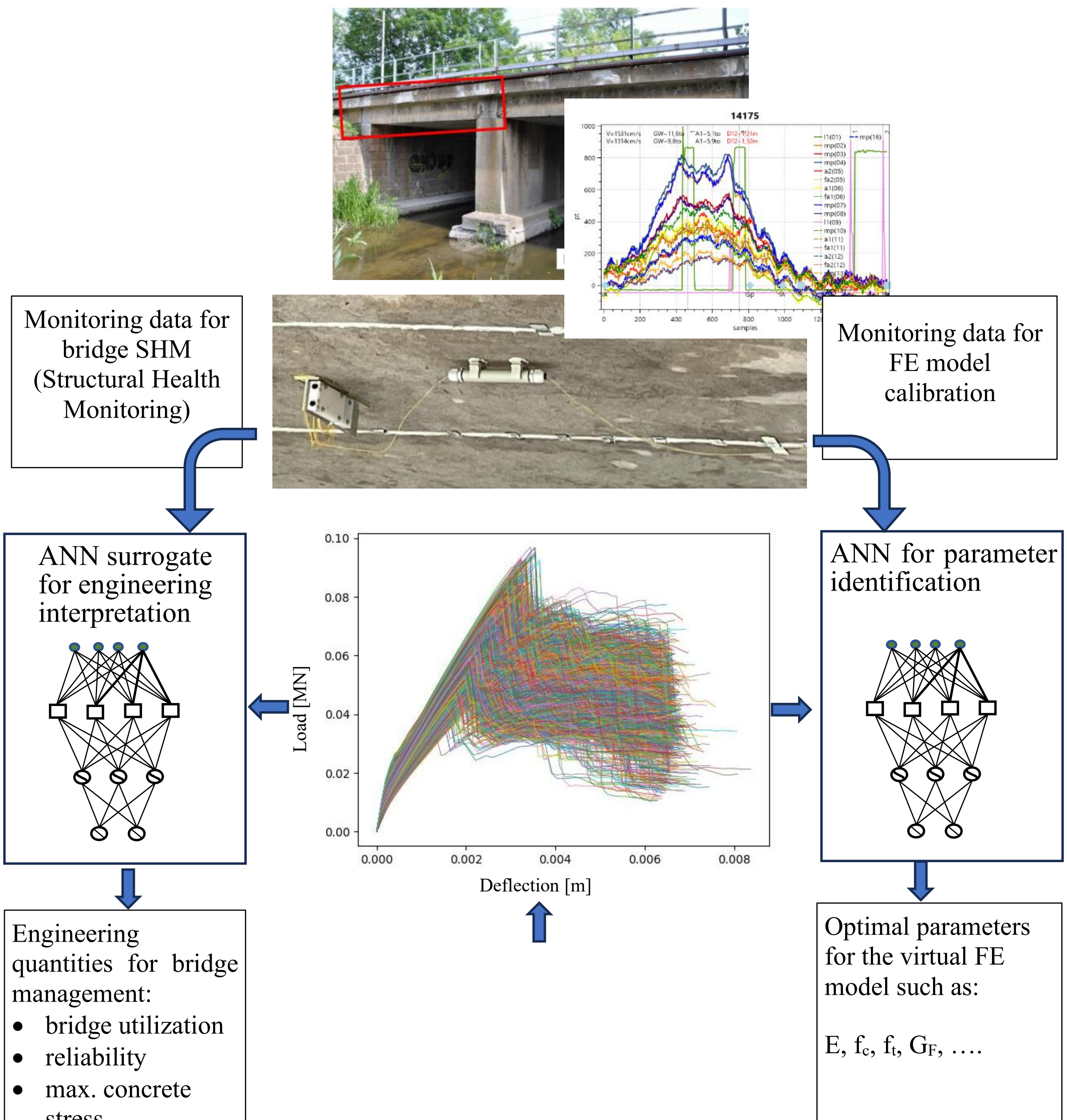


Fig. 2 Digital Twin consists of a real structure equipped with monitoring sensors and a virtual replica, which exchange data and provide real-time engineering information on the structural health and reliability to drive the structural operation or maintenance.



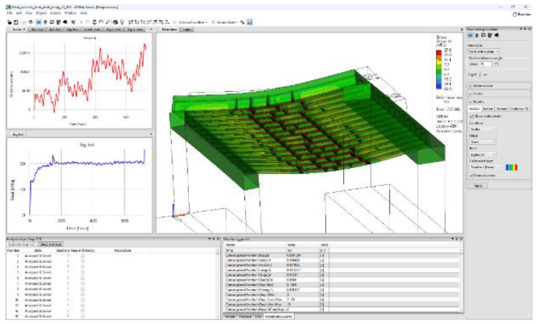


Fig. 3 ANN surrogate model is applied in two ways: ANN on the right is used for model calibration, i.e. parameter identification and ANN on the left provides real time data for engineering interpretation of the obtained monitoring data.

2 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 [**Error! Reference source not found.**] 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.

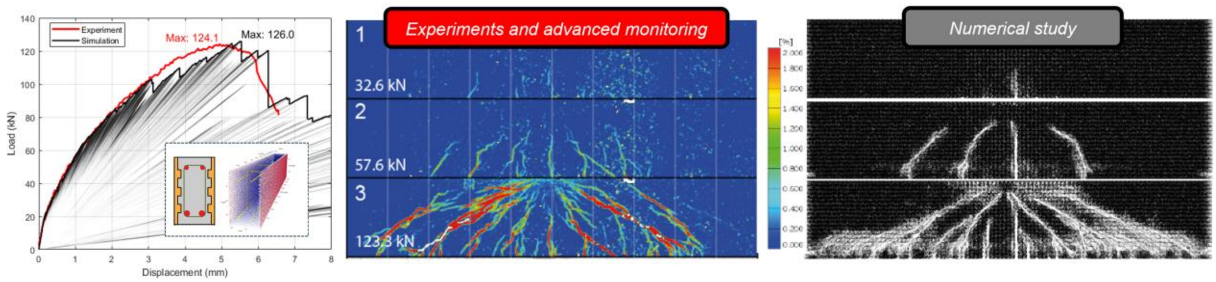
The details about the fracture-plastic concrete material model were published in the original papers [**Error! Reference source not found.**][**Error! Reference source not found.**]. Extensive validation of the model applicability for the simulation of typical failure modes of reinforced concrete structures have been presented in the paper [**Error! Reference source not found.**], 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 **Error! Reference source not found.**). The geometry of the example corresponds to the beams tested by Leonhardt [**Error! Bookmark not defined.**]. 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 **Error! Reference source not found.**c). 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 **Error! Reference source not found.**d shows the sensitivity of the peak displacement for the largest dataset of 1000 samples for different values of the input parameters.

2 Title of the second section

2.1 Title of the subsection

The font of the paper should be Times New Roman 12 and the text should be justified. Use single spacing and normal margins. Define all symbols and abbreviations used. The format of the figure and caption is suggested as in **Fig.1**. Texts referencing to the figures should be bold. The caption should be below the figure, and uses Times New Roman 12 in bold. The figure and caption should both be centered.



(a) (b) (c)

Fig. 1 An example of the figure and caption. Fracture behavior of Strain Hardening Cementitious Composite (SHCC) hybrid concrete structure under bending (a) Load displacement curves, (b) damage patterns observed experimentally and (c) numerically.

Table. 1 An example of the table and caption

Sample name	**Header 1**	**Header 2**	**Header 3**	**Header 4**
Name 1	content	content	content	content
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Name 3	content	content	content	content

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The format of mathematical equation is suggested as the example in **Eq (1)**. The text referencing to the equation should be bold. The font italic Cambria Math 12 is suggested for the equation content. Each variable should be explained below the equation upon its first appearance in this article.

$$\sigma(t) = \int_0^t R(t_0, t)\dot{\varepsilon}(t_0)dt_0 \tag{1}$$

in which σ is the stress; ε is the imposed strain; R is the relaxation modulus; t_0 is the time when the deformation is imposed; t is the current time.

5 Conclusion

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