Structural Utilization Prediction for the Health Monitoring of Tunnel Linings by Means of an Artificial Neural Network Ensemble

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ABSTRACT

The continuous expansion of underground structure networks and the necessity of guaranteeing the safety and functionality of the already built tunnels pose the necessity of developing techniques and methods to efficiently achieve these aims. Normally, measured data of different nature are available for tunnels due to sensors installed in the lining. However, adequate procedures have to be implemented to obtain valuable information out of the monitored data.

A new method has been developed to achieve a real-time assessment of the stress state in segmental tunnel lining, given specific measured quantities as input. The method is based on the combination of finite element (FE) analyses and feedforward neural networks, which permits to exploit the advantages of both physics-based simulations, representative of the structure considered, and the predictive capabilities of machine learning tools. The FE model of the tunnel lining plays an important role for the reconstruction of the missing quantities, which are not available from monitoring campaigns, but which can be generated by numerical analyses. A Monte Carlo sampling procedure is performed for the definition of multiple sets of the input parameters used in the FE model for the generation of the training data of the metamodels. An ensemble of neural networks is created and assembled into a framework, which is validated against a full scale test where its predictive performances are investigated.

INTRODUCTION

The underground infrastructure network is steadily expanding around the world, arising the issue of guaranteeing both, the safety and the operational conditions of existing

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tunnels over their life. There have been a rising awareness of the importance of monitoring the health of tunnel linings in the long term, which will result in an increase in the amount of recorded data. This poses the perfect conditions for the development of automatic systems capable of extracting information out of the available recorded data.

A new method for the estimation of the structural utilization level in segmental tunnel linings is presented. The concept is based on the combination of finite element (FE) simulations, artificial neural networks (ANNs) and monitoring data. An example of using strain measurements from tunnel linings for their structural analysis is performed in [1], [2], wherein analytical formulations and finite element simulations are employed in a traditional framework of back analysis. Analytical methods for the study of segmental tunnel linings based on the theory of curved arches are provided in [3], [4], however limitations in the general applicability of the approaches arise due to the reduced load configurations that can be considered for the loads acting on the lining.

Artificial neural networks find large application in civil engineering, thanks to their capability of learning correlations from the data related to highly non linear problems, during a learning process called training. For the elaborated method, feedforward neural networks (FNNs) are used, which are thoroughly expounded in [5], [6], [7]. The application of ANNs in civil engineering is well documented in [8], where a description of their use for structural monitoring is given.

The encapsulation of FNNs in the developed method permits to achieve real-time estimations of the maximum bending stresses in the tunnel lining for the determination of its structural utilization given a set of stress input measurements.

INTELLIGENT STRUCTURAL HEALTH MONITORING FRAMEWORK FOR TUNNEL LININGS

The availability of monitoring data represents a source from which information about a structure can be obtained. It is required to interpret these data which, in some cases, can build up enormous database. The deployment of machine learning models gives valuable insights about what and in which fashion monitored data can be used for the estimation of the utilization level of a tunnel lining.

The method developed aims at the prediction of the maximum stresses due to bending actions recorded in the lining based on stress values obtained from strain gauges positioned in the structure. These target quantities are selected for the quantification of the utilization level of the segmental lining.

The approach consists of two steps, an offline and an online stage. In the former, the combination of FNNs and FE analyses is carried out. Specifically, the synthetic data used for the training of the metamodel are generated by numerical simulations of the tunnel lining subject to manifold loading scenarios. Ranges of variation for the input parameters of the FE models are determined and used for the investigation of the structural responses. In the online stage, the actual application of the method takes place by feeding the FNNs, developed in the offline stage, with input measurements from a monitored tunnel lining ring.

The developed approach represents an intelligent framework for real-time structural health monitoring of segmental lining, consisting in an automated system for the assessment of the maximum stress states in the structure and their position. The advantage of

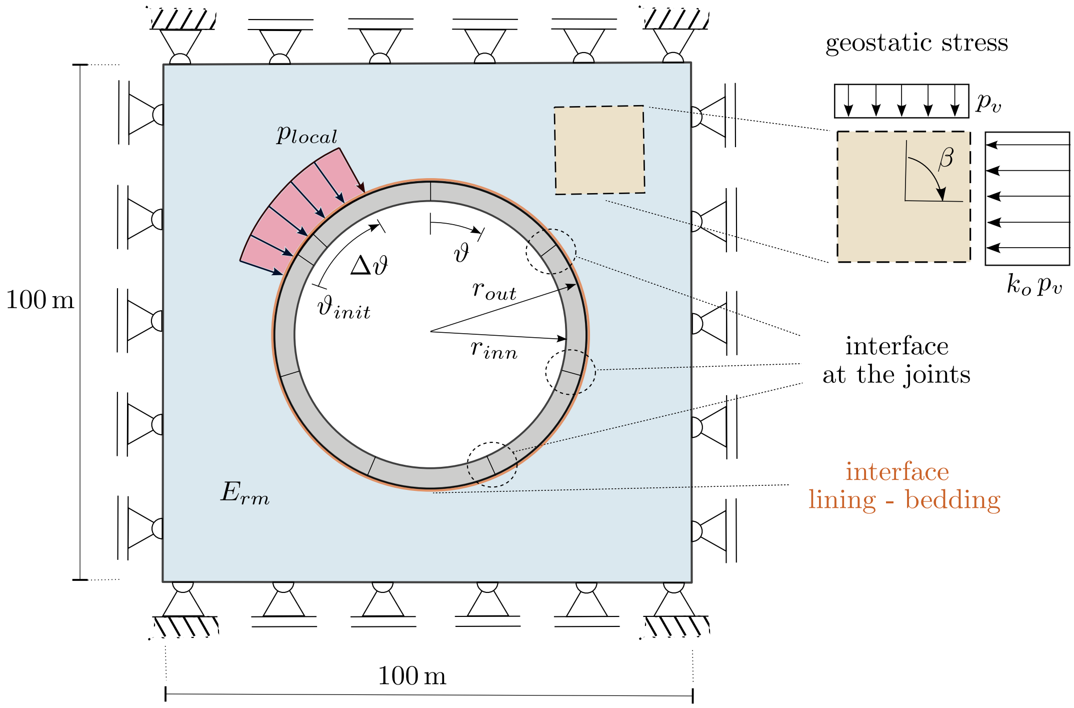

Figure 1. The structural model used for the analysis of the segmental lining response.

this approach lays not only in the swift system response capabilities, but in a further step into digitalization thanks to the automated elaboration of monitoring data for tracking the structural response and its health state. This permits to plan maintenance in advance and to better follow the long term behavior of segmental linings in tunnels.

OFFLINE PHASE - *FE MODEL*

The offline phase is the stage in which the method algorithm is generated for the investigated problem. Initially, the data necessary for the training of the artificial neural networks are produced by means of FE analyses of the tunnel lining.

The method is going to be tested using the monitored data from a full scale lining test carried out at TU Delft (see [9], [10]), wherein all the boundary conditions are known. However, in real applications to deep tunnels excavated in rock, high uncertainty affects the identification of the boundary conditions. For that reason, a FE model of the lining representing general bedding conditions is defined and depicted in Figure 1. The finite element software for multiphysics analyses KRATOS [11] is employed for the numerical analyses of the structure.

The lining is modeled embedded in an elastic continuum, representing the surrounding ground mass, in a domain, which is fixed along all its edges. A plane strain condition is considered for the analysis of the tunnel, where bi-linear Lagrange elements are used for the discretization of the model. The load acting on the lining is indirectly caused by the geostatic stress, applied as a prestress, in the surrounding bedding domain. The reinforced concrete lining segments are modeled as linear elastic. This assumption is

TABLE I. INPUT PARAMETERS RANGES FOR THE FE MODEL.

	Parameter		Range	Unit
Ground	Young's modulus	E_{rm}	$[5.0; 105.0]$	MPa
in-situ stress state	in-situ vertical stress	p_v	$[0.2; 1.5]$	MPa
	principal stress ratio	k_0	$[0.5; 1.1]$	$-$
	vertical stress inclination	β	$[0.0; 180.0]$	$^\circ$
Local load	amplitude	p_{local}	$[0.0; 300.0]$	kPa
	extension	$\Delta\vartheta$	$[10.0; 80.0]$	$^\circ$
	position	ϑ_{init}	$[0.0; 360.0]$	$^\circ$

valid for this study, since in the full scale test used for validation, the tensile strength of concrete is not reached. The mutual interaction between the segments at the joints and the contact between segments and bedding is taken into account with interface elements [12]. While at the joints between segments, the contact is modeled using a simple Coulomb frictional law, a simple cohesive law is assigned at the interaction between bedding and lining.

In order to take into account manifold potential loading scenarios, a localized radial load is applied at different positions and with varying amplitude along portions of the lining, see Figure 1. The main idea is to reproduce possible unforeseen loads which might arise due to late activation of localized faults in the rock mass or sudden rock-block detachments as aftermath of tunnel excavation. The geostatic stress and the aforementioned localized load are considered acting simultaneously in the FE simulations.

OFFLINE PHASE - *FNNs*

For the tuning of the feedforward neural networks (FNNs) deployed in the method, it is necessary to have data according to which the relationships between input and output of the metamodel can be learned. Synthetic data obtained by FE simulations are used in this study. Ranges of variation of the main parameters of the model are defined, assuming that the properties and features of the full scale test used as reference scenario are known with uncertainty. In a real situation, these ranges might be defined based on project reports or engineering experience. Intervals were defined for the geostatic stress, the Young's modulus of the bedding material and for the localized load, as it is shown in Table I. Multiple sets of input parameters for the FE model are chosen using Latin hypercube sampling within the defined ranges and deployed for the FE analysis of the structure. Overall, 4000 scenarios are computed, and the corresponding results are reorganized for the learning process of the networks.

The final aim is to use FNNs for the prediction of the maximum bending stresses at the lining extradox and the location where these are recorded, starting from 5 circumferential stresses monitored at the extradox of the middle cross section of each consid-

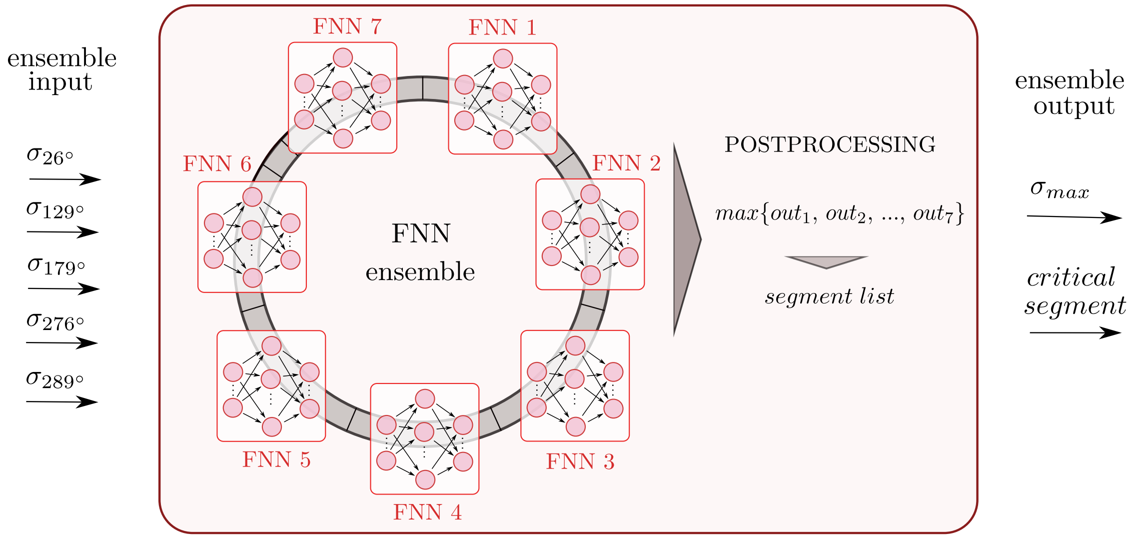

Figure 2. Ensemble of FNNs used in the presented monitoring framework.

ered segment (see Figure 3). By removing the axial component from the total recorded stresses, it is possible to isolate the bending portion. Artificial neural networks are universal approximators of any function and can learn correlations among the data supplied during the training process of the network [7]. Among the different types of neural networks, FNNs are featured with multiple layers of neurons, the processing units of the machine learning model, wherein each of them is mutually connected with all neurons of the previous and following layer. The signal from the input layer, to which the input data are given, travels through the network structure and it is modified by the neurons during its journey to the output layer, where the predictions computed by the network are shown.

Several architectures for the FNNs are investigated in order to explore their prediction performances. While the networks can be trained to predict the maximum bending stress of the structure starting from 5 input stresses at selected monitoring locations, this does not hold for the determination of the position of the maximum bending stress. To overcome this issue, a different approach based on a FNN ensemble is developed. More specifically, a FNN is trained for each segment to predict its maximum bending stress, obtaining in total as many models as the number of segments. Afterwards, the 7 neural network predictions are combined and postprocessed and the maximum bending stress along with its position are calculated as the ensemble response. That way, it is possible to break down the ensemble task into subproblems, addressing each of them with single neural networks (see Figure 2). The determination of the target quantities for the whole structure is accomplished and the utilization level can be obtained.

The single FNNs are featured with 5 input neurons, 2 hidden layers with respectively 10 and 2 neurons, and one single output which is the maximum bending stress predicted for the segment. Overall, 7 neural networks are combined together in the ensemble, since the keystone is not considered herein. For the learning process, the samples are randomly divided into 60% for training, 20% is used to control the early stop algorithm (to avoid overfitting) and 20% for testing. A batch of 10 metamodels is trained for each segment, using every time different initial weights and sample subsets so as to verify the

TABLE II. COEFFICIENTS OF DETERMINATION FOR EACH FNN BATCH.

	$Seg.1$	$Seg.2$	$Seg.3$	$Seg.4$	$Seg.5$	$Seg.6$	$Seg.7$	Avg
R_b^2	0.983	0.954	0.986	0.984	0.963	0.996	0.958	0.975

general performances of the models. The R^2 computed for the testing samples is used to measure the goodness of each model, and the batch average R_b^2 is then obtained with the following expression:

$$R_b^2 = \frac{\sum_{k=1}^{N_b} R_k^2}{N_b} = \frac{1}{N_b} \sum_{k=1}^{N_b} \left(1 - \frac{\sum_{i=1}^{N_{ts}} \left(\sigma_{max,i} - \hat{\sigma}_{max,i}\right)^2}{\sum_{i=1}^{N_{ts}} \left(\sigma_{max,i} - \bar{\sigma}_{max,i}\right)^2} \right) \tag{1}$$

where N_b is equal to 10 and it is the number of models trained in each batch, N_{ts} are the used testing samples, $\hat{\sigma}_{max,i}$ is the predicted maximum bending stress for scenario i, $\sigma_{max,i}$ are the corresponding target values and $\bar{\sigma}_{max,i}$ their average. The results are reported in Table II.

The training occurs successfully for all the segments, although different performances are shown by the networks for the considered segments. These depend on the stress states observed in the segments, and how well the networks can learn the sought relationships from the synthetic data.

ONLINE PHASE - *APPLICATION AND VALIDATION*

The application of the methodological approach takes place in the online phase. Once the algorithm has been created and tuned based on the data generated with the FE models, it can be deployed on the actual field by feeding it with the real measurements. That way, it is possible to obtain in real-time predictions of the maximum bending stresses in the structure and their position. It is crucial that the synthetic data used for the training of the FNNs are representative of the physics of the problem and that the algorithm is not extrapolating while being used. The issue of extrapolation has been thoroughly addressed in [13] for the case of a four point bending test, where displacement measurements were used as input to predict the maximum bending moments in the structure.

For the validation and testing of the method, a full scale lining test performed at TU Delft is considered [9], [10]. This consisted of three rings of a segmental reinforced concrete lining assembled one upon the other in a staggered manner. Each ring was made out of 7 segments and a keystone. The lining was subject to a radial load applied by means of hydraulic jacks, as it can be observed in Figure 3. The load was increased monotonically, applying initially a confinement pressure and afterwards was adjusted to produce an ovalization of the lining. The boundary conditions were known in the experiment, since the structure was deformed under load-control.

The stresses measured at the selected positions (see Figure 3) are used as input to predict the maximum bending stresses recorded in the test and at which position they occur. Since the training of the neural network ensemble is performed 10 times, this coincides with the validation tests carried out. By analyzing the responses obtained by the developed framework, very good agreements are achieved both for the predicted

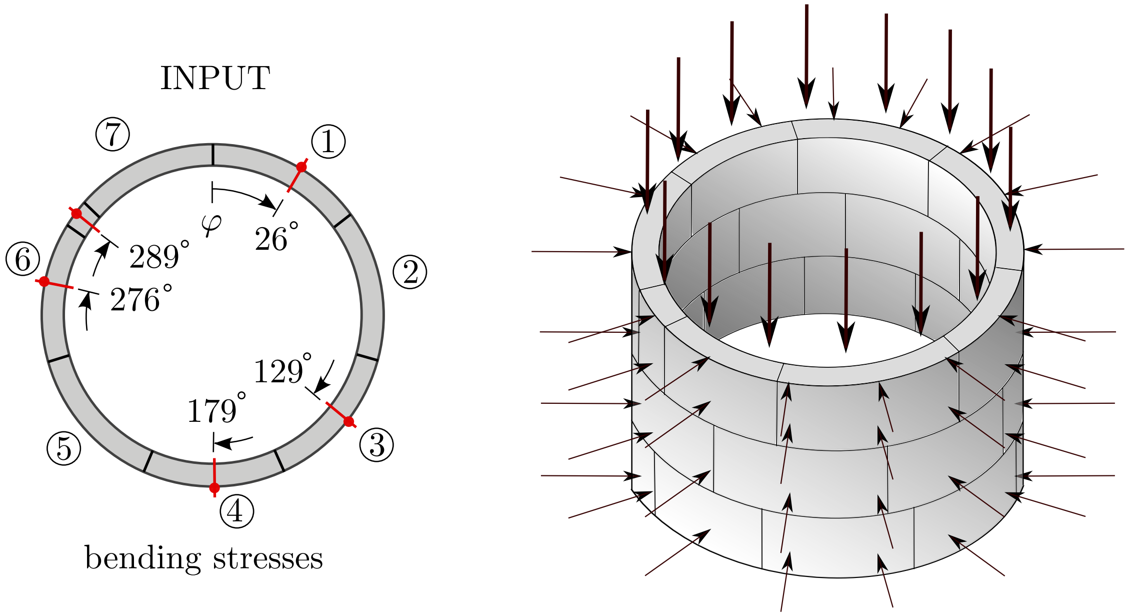

Figure 3. On the left, locations of the five input stresses, on the right, a sketch of the full scale lining test setup (see [10]).

TABLE III. PREDICTION RESULTS FOR THE ANALYZED NETWORK ENSEMBLES.

$Test$	1	2	3	4	5	6	7	8	9	10	Avg	σ^2
$\hat{\sigma}_{max}$ [MPa]	5.55	5.29	5.19	5.51	5.27	5.22	5.37	5.25	5.42	5.29	5.34	0.0135
$Segm.$	5	2	2	5	5	2	5	2	2	5	50% -5 50% -2	
$Err\,\%$	10.4	5.4	3.7	9.6	5.1	4.2	6.9	4.8	7.9	5.5	6.3	4.69

maximum stress $\hat{\sigma}_{max}$ and its position, in comparison with the measured value. As it can be seen from Table III, an average error of 6% is reached for the 10 tested responses of the network ensemble. Also the average predicted $\hat{\sigma}_{max}$ and its variance over the predictions is computed, to verify the accuracy of the neural networks, which provide similar responses when fed with the same input data.

It is worth noting in Table III, that the predictions of the segment in which the maximum stress should appear seem to be inconsistent, since segment 5 is indicated as critical for some tests, while in other cases segment 2 is pointed as the most loaded structural member. In fact, the behavior of the approach is meaningful, because in the full-scale test the lining was loaded symmetrically, achieving the maximum bending stress at two symmetric locations in the structure (respectively at segment 2 and 5). When the ensemble outputs are evaluated for the 10 tests performed, slightly difference responses are obtained by the FNNs of the ensemble, yet for each validation test new metamodels are trained and new initial weights and biases are considered. As a consequence, for each generated ensemble slightly different maxima are computed by the framework, ending up, as a result, with different location predictions for the maximum stress.

CONCLUSIONS

A framework for the real-time estimation of the maximum bending stresses and their location in a segmental tunnel lining was presented. The method is based on the combination of feedforward neural networks, used to achieve a real-time response and FE analyses, which were deployed for the generation of the samples required for the training of the FNNs. It was shown that an ensemble of metamodels allows to break down the problem into subtasks, which are simultaneously solved by each neural network. Each output is then postprocessed to retrieve the global structural response. That way, it was possible to successfully obtain predictions not only of the magnitude, but also of the location of the maximum stresses.

Even though the performances of the FNNs were promising on the synthetic data, the framework was additionally validated with a full scale test of a ring of segmental lining. By using the measured input data, the algorithm provided good estimations of the target quantities proving its performances on real data. Furthermore, several sets of FNNs were trained to track the behavior of the models. In all cases, similar responses from the framework were obtained and potential extensions to the method were highlighted, such as improvements for the detection of multiple maxima in case of symmetric responses of the structure.

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