Expanding Underground. Knowledge and Passion to Make a Positive Impact on the World – Anagnostou, Benardos & Marinos (Eds)

Safety level assessment of segmental linings in rock

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ABSTRACT: The expansion of the underground tunnel network is calling for new methods to allow for their monitoring in an efficient way. A new approach to assess the safety level of segmental lining of tunnels excavated in rock based on discrete monitoring points is developed. Artificial Neural Networks (ANNs) are deployed for the prediction of quantities of interest, chosen for the assessment of the utilization level of the lining, based on input strains. A finite element (FE) model of the lining is created to generate the data required for the training of the ANNs. Eventually, two benchmark scenarios are defined in order to test the approach, by creating FE models representing the excavation process and the lining installation. The predictive model is fed with the input quantities of the testing scenarios and a comparison among predictions and reference quantities is drawn.

1 INTRODUCTION

Over the last decades, a remarkable increase in the number of tunnel projects has been recorded, as a consequence of high speed connections to improve the capacity of the transportation network. With a particular reference to shield tunnels, to guarantee their safety and their operating conditions, the monitoring of segmental tunnel lining plays a key role in providing measurements of pivotal quantities, such as tunnel displacements or strains, by means of the application of a variety of sensors. With the availability of such information, it is important to investigate how these data can be used to increase the knowledge about the lining state, in particular with regards to its level of utilization. Back analyses can be carried out to reconstruct the stress conditions in the segmental lining, as it is reported in (Do et al., 2014), (Fabozzi et al., 2017). However, the recent developments in machine learning have opened up the exploration towards novel approaches and applications of numerical algorithms in tunneling.

The use of Artificial neural networks (ANNs) as machine learning tool, permits to handle considerable amounts of data and to detect relationships and patterns within them. ANNs are considered universal approximators (Bishop, 2006), (Haykin, 1999), (Basheer and Hajmeer, 2000) and can be used to represent highly non linear problems (Basheer and Hajmeer, 2000), finding applications in many fields of civil engineering (Adeli, 2001). In this study, it is investigated how ANNs can be employed for the prediction of the safety level of the lining, starting from a few measurements taken in the structure. The idea is to generate a metamodel, which during its application receives as input strain measurements obtained at discrete locations in the lining, while provides as output a prediction of the target quantities such as internal forces or stresses selected for the utilization level assessment.

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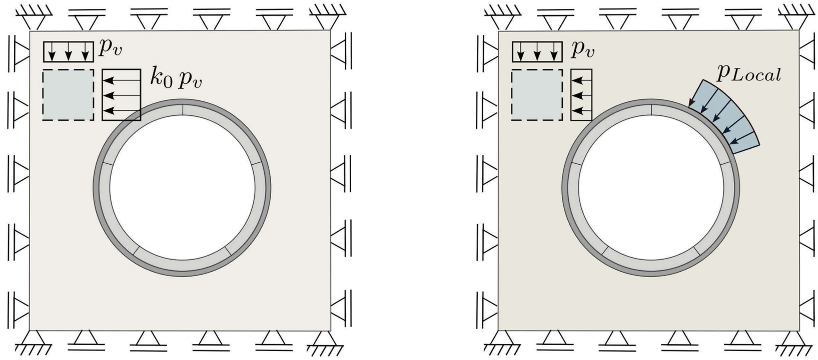
The development of a concept for the real-time estimation of the utilization level of segmental tunnel linings, based on the use of ANNs, is presented. The metamodels are trained on synthetic data generated by finite element models of the tunnel lining, which are computed for different scenarios, in order to create the supporting points to accomplish a good training of the networks. The metamodels are eventually tested on a benchmark example to verify their prediction accuracy.



(a) (b)

Figure 1. a) First benchmark scenario with a representation of the in-situ stress, b) second reference scenario characterized by a localized load is shown.

2 METHODOLOGICAL APPROACH

Considering the availability of strain measurements at certain locations in the lining, obtained from standard monitoring equipped sections of the tunnel, the aim is to obtain a real-time assessment of the utilization level of the segmental ring based on target quantities, here the maximum bending moment and axial force, from which the residual safety of the structure might be computed. The stress resultants are defined as indicators of the stress state in the lining and the concept is developed for deep tunnels in rock.

The methodological approach is based on the combination of finite element simulations, machine learning algorithms and measurements. In the method, there can be distinguished two phases, an offline and an online step. In the former, the numerical analyses and the substeps required for the generation of the metamodel necessary for the prediction of the utilization level of the lining is carried out, while in the latter, the verification and the final application of the concept take place.

Initially, synthetic data are generated by means of a finite element (FE) model of the lining, which is used to analyze multiple loading conditions acting on it and the corresponding stress resultants (bending moments and axial forces) recorded. The analysis results are reorganized into input and output of a neural network, beforehand the training process takes place. The aim is to obtain an adequate metamodel to be used for the lining utilization estimation, from which an evaluation of the residual safety level can be obtained. Finally, the verification is performed by feeding the metamodel with measurements obtained from a benchmark scenario and by comparing the real-time predictions of the network with the reference values.

The creation of an automated procedure for the assessment of the lining utilization level has great advantages, especially in terms of safety for the workers, since no specialized personnel would be required to go inside the tunnel to inspect it. Furthermore, the development of an approach, which employs the measurement types of standard monitoring section configurations used in tunneling, enlarges its range and easiness of applicability and makes the method economically competitive.

2.1 *The benchmark problems*

For the definition of a strategy for the assessment of the utilization level of segmental lining two reference scenarios are generated in order to test the capabilities and the limits of the approach (see Figure 1). The mechanized excavation of a deep tunnel with segmental lining is simulated with a finite element model using plane strain analyses. In the first scenario (Figure 1a), the tunnel is assumed to be bored in a rock mass at a depth $H = 600$m, from which the in-situ stress $\sigma_v = 16.2$MPa can be computed assuming a specific weight $\gamma = 27^3 \mathrm{KN/m}^3$ for the rock mass and $k_0 = 0.7$. In the second scenario (Figure 1b), an isotropic stress field with a localized load acting on one part of the lining is assumed, to simulate the unforeseen detachment of a rock wedge or a localized fault.

Table 1. Material properties of the rock mass, the lining and the grouting.

	Young's modulus	Poisson's ratio	specific weight	friction angle	cohesion
	E	ν	γ	φ'	c'
	GPa	—	$\mathrm{KN/m}^3$		MPa
Rock	2.6	0.3	27	22 (1^{st} scenario) 25 (2^{nd} scenario)	2.8 (1^{st} scenario) 3.2 (2^{nd} scenario)
Segments	40.0	0.2	25	—	—
Grouting	1.0	0.3	20	—	—

The excavation process is simulated by using the convergence confinement method (Panet, 1995), (Carranza-Torres and Fairhurst, 2000), (Vlachopoulos and Diederichs, 2009), (Vlachopoulos and Diederichs, 2014), but instead of using fictitious pressures applied along the excavation boundary to account for the face support to the excavation, the core replacement method is used. This technique is based on a subsequent reduction of the rock stiffness within the excavation boundary to simulate the advance of the tunnel face in 2D analyses. The main stages in the simulated construction sequence are the change of the stress state in the rock mass due to excavation, lining erection with grouting installation and the final stress state reached when the tunnel face is far away (see Figure 2a). For the case where a localized load is simulated another stage is added. As material model for the rock mass, Mohr Coulomb has been used, while a linear elastic behaviour was assigned to the concrete lining segments. All the properties used are summarized in Table 1, while the plasticity indicator evolution is depicted in Figure 2b.

Eventually, the strain values recorded at positions inside the lining, where it is supposed to have strain gauges, are recorded over the excavation process. The strain values obtained in the last excavation stage, i.e. for long term conditions, are the ones used to verify the prediction accuracy of the developed approach (see Figure 3).

2.2 *Generation of the synthetic data: The finite element model*

A fundamental prerequisite for the training of a metamodel is the presence of a data set, that can be made up either of monitored data from existing tunnels, or synthetic data produced by numerical or analytical approaches. A 2D plane strain FE model of the segmental lining of a deep tunnel, embedded in an elastic continuum, is created (see Figure 4). The domain sides are fixed while a prestress is applied in the hosting material. The joints between the lining segments are accurately modeled by means of contact elements, to allow for relative rotations and dislocations between adjacent segments. In this model, a linear elastic behavior is assigned to all its components. For this reason, the model is very similar to a bedded beam model and shares the feature of being fast to be computed. Several load cases are defined and applied to the model to analyze the response of the structure for different combinations of the input parameters. Range of variations, based on engineering judgment or project reports, for k_0, the in-situ stress, the elastic modulus of the bedding continuum and the deconfinement ratio β (quantifying factor for the stiffness reduction of the rock within the excavation boundary) are determined for the analysis of the first scenario. For the identification of the scenario with a localized load, a range of variation of the local pressure is defined, in place of k_0 which is kept constant. Latin Hypercube sampling is used to gain input combinations of parameters, which are fed into the FE model used to analyze the lining response.

The results are collected and for each simulation the strains recorded at specific locations in the lining, where sensors are supposed to be applied, along with the maximum stress

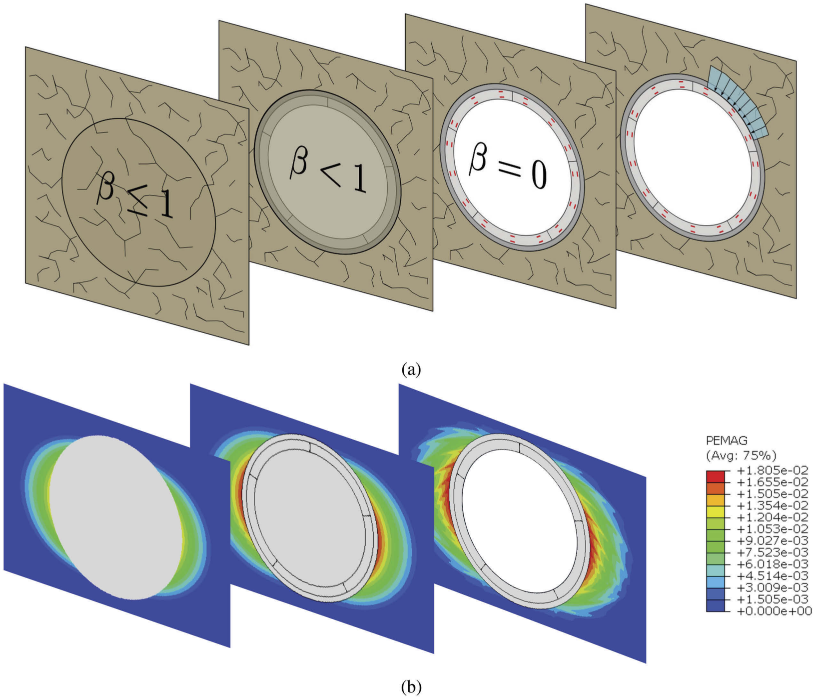


Figure 2. a) Modeling of the sequential tunnel excavation by means of the core replacement method. The main stages which are represented are: reduction of the stiffness in the excavation boundary, lining installation, tunnel face far ahead the considered cross section. As for the second reference scenario, an extra stage featured by a localized load is added. The factor β, which reduces the stiffness of the material within the excavation boundary, diminishes over the excavation steps in order to simulate the decrease of the tunnel face support due to its advancement. b) Plasticized regions around the tunnel for the first loading scenario. The plasticity indicator PEMAG $= \sqrt{\frac{2}{3}\overline{\varepsilon_{pl}} : \overline{\varepsilon_{pl}}}$, wherein $\overline{\varepsilon_{pl}}$ is the plastic strain tensor and: denotes the double contraction product, is used to quantify the damaged zone around the tunnel.

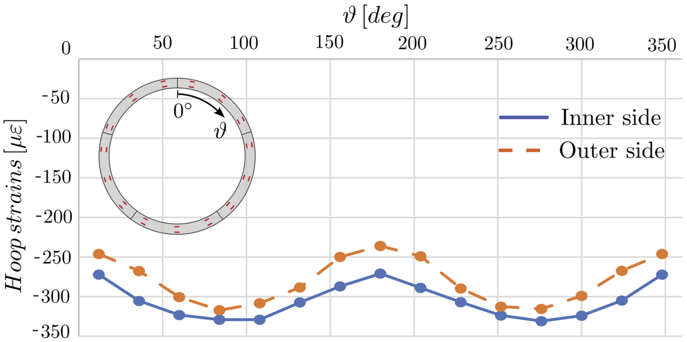


Figure 3. The hoop strains recorded in the lining at the positions where strain gauges are imagined to be placed are drawn. They refer to the last step of the excavation sequence of the first benchmark scenario.

resultants, i.e. maximum bending moment and axial force which are recorded in the lining, are stored. These data are eventually arranged into input quantities for the metamodel (strains), which represent the data that will be measured during the application of the method, and target quantities (maximum bending moment and corresponding axial force), which are the values that need to be predicted.

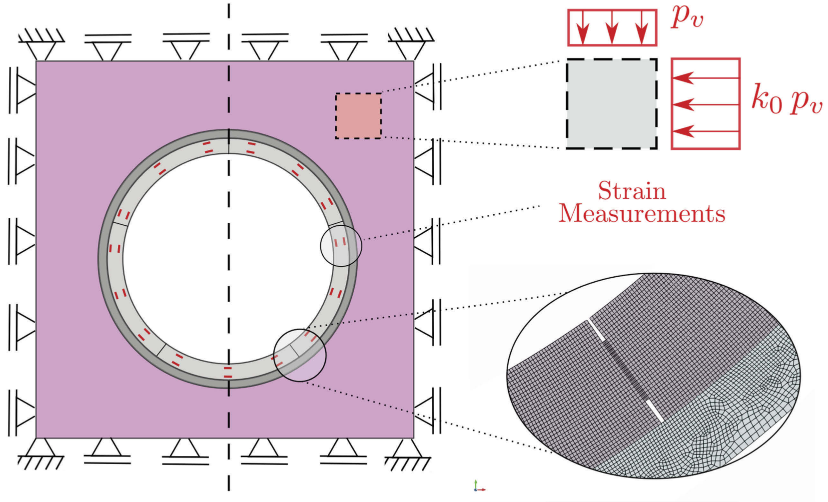


Figure 4. The FE model used for the generation of the synthetic data is depicted. The stress state is illustrated in detail in its vertical and horizontal component in a sampled portion of the domain. The segments of the lining are accurately modeled, along with the connecting joints and the grouting layer.

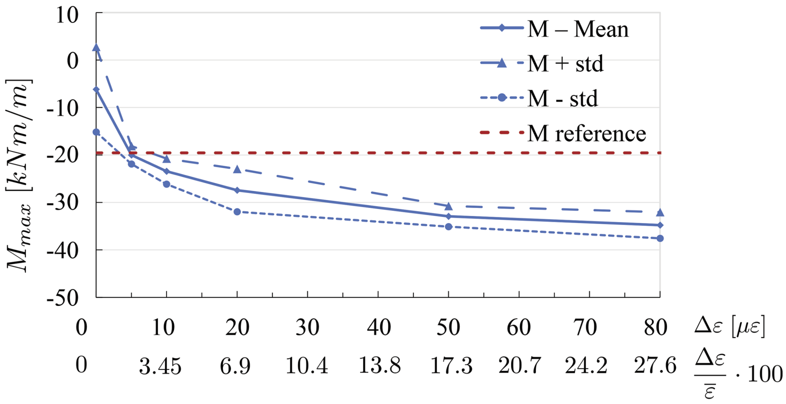
2.3 *Training of the ANN*

For the real-time prediction of the maximum stress resultants, feedforward neural networks (FFNNs) with multiple layers of perceptrons, which are trained on the synthetic data generated with the FE model explained in Section 2.2, are being deployed. For the first scenario, the input of the networks are the strains obtained at 16 locations in the lining segments (in the left half of the model in Figure 4), based on the assumption that the strain gauges are places at these locations in a potential monitoring section. Only the sensors in one half of the structure are taken into account, due to its symmetrical behaviour. However, for the scenario where a localized pressure is applied all the 32 strains are considered.

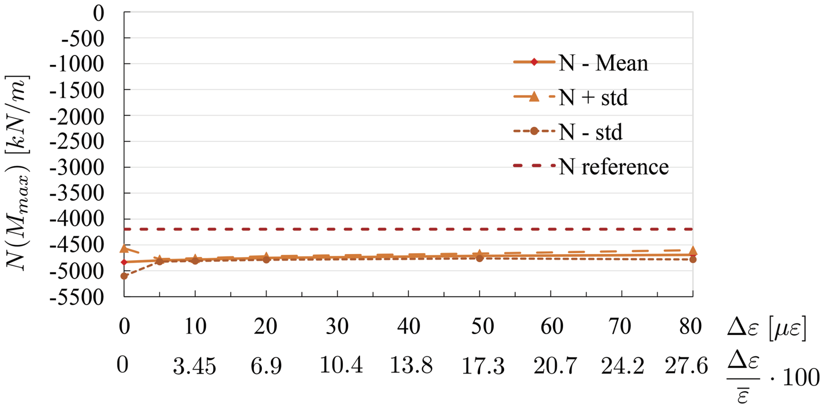
The normalized input signals are passed from the input to the hidden layers: the input signals of each neuron are scalarly multiplied by the synaptic weights, summed up together and a bias value is added. Finally, the resulting signal is multiplied by an activation function (here the hyperbolic tangent function) and passed to the next hidden layer. The generation of the metamodel occurs by tuning of its hyperparameters during training based on the minimization of the error between the network predictions and the training data.

3 APPLICATION AND RESULTS

For the application of a chosen metamodel to the test scenarios, it is necessary to guarantee that the network does not extrapolate when deployed in normal operational conditions. This is achieved by checking that the input space used during training encompasses, within a certain range, the input space where the network is going to be applied. Since the strain values in the lining are correlated with each other, it is important to verify that also the synthetic strains used for the network training present a similar correlation degree. However, since a perfect match between numerical model and reality for complex structures is difficult to accomplish (see (French, 1995)), a new method formulated on the addition of artificial noise in a controlled fashion to the input strains used for training is employed (Gottardi et al., 2022). This is based on the idea that by adding noise to the training data in the form of a small perturbation we assume that the physical model has a certain imprecision and deviation with respect to the reality. By doing so, the accuracy of a metamodel trained on such modified data decreases, yet it can help to overcome extrapolation if the network input values in the testing phase are nearby the synthetic data used during training.



(a)

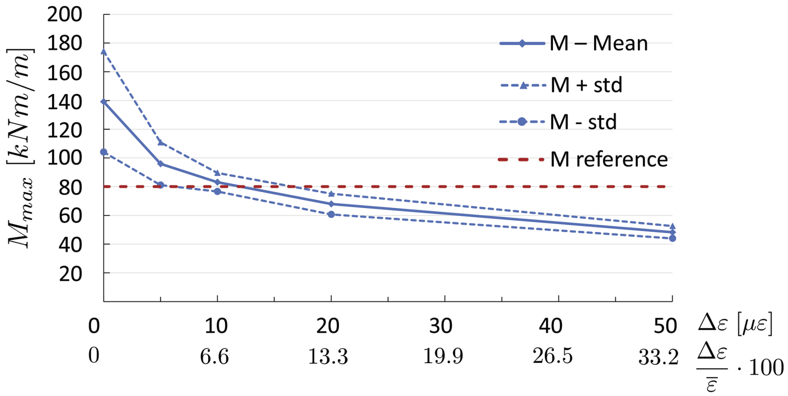


(b)

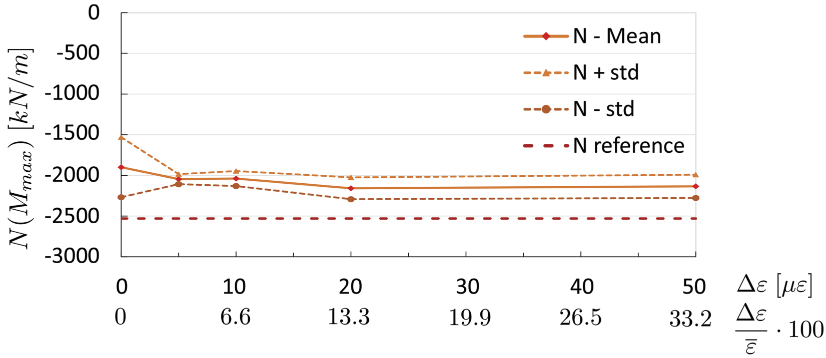
Figure 5. The predictions capabilities of the networks are here shown for the load scenario with $k_0 = 0.7$. In Figure a), the average and the standard deviations of the predicted maximum bending moments for several noise levels are drawn against the reference value. Underneath, in Figure b), the same statistics for the axial force are illustrated. In the abscissas, the noise added is expressed both in $[\mu\varepsilon]$ and in percentage with respect to the average measured strains in the benchmark $\bar{\varepsilon}$.

The performances of the networks are analyzed for multiple noise levels against the maximum stress resultants obtained in the benchmark scenarios. In order to verify the robustness of the method, a batch of 10 FFNNs is created for each of the noise levels defined. The mean value and the standard deviation of the predicted maximum bending moment M_{max} and corresponding axial force $N(M_{max})$ are computed for each batch. Selected results are summarized in Figure 5 for the load scenario with $k_0 = 0.7$ and in Figure 6 for the scenario where a localized pressure is applied.

By observing the statistics of the network predictions, a quite poor accuracy of the networks is recorded when no noise is applied. This stems from the different models used for the generation of the synthetic data and for the reference scenario, i.e. the use of an elastic continuum to model the surrounding ground mass in the former, in contrast to a plastic material in the latter. However, the addition of a minimal noise to the input data permits both to substantially increase the prediction capabilities of the networks, since the predicted stress resultants approach the ones in the benchmark scenarios, and to reduce the variation of the network predictions. When the amount of noise applied raises beyond a certain threshold, a worsening of the metamodel predictions occurs along with an increase of their scattering. In addition to this, even though the maximum bending moment reveals to be sensitive to the noise level considered, it is not the same for the related axial force which shows a steady tendency, although a reduction in its standard deviation is visible.



(a)



(b)

Figure 6. The predictions capabilities of the networks are here shown for the load scenario where a local load on the lining is simulated. In Figure a), the statistics of the predicted bending moments are drawn over the noise levels while in Figure b) the same statistics for the axial force are illustrated.

3.1 *An estimation of the safety level*

The prediction of the maximum stress resultants recorded in the lining permits to obtain a quantitative estimate of the utilization of the structure, from which a definition of the safety level of the lining can be introduced. By defining threshold values for the stress resultants that can be reached in the lining, the safety of the lining might be defined in the form of a domain encompassing admissible stress states:

$$\begin{cases} M_{predicted} \leq M_{threshold} \\ N(M_{predicted}) \leq N_{threshold} \end{cases}$$

Where the predicted values are the results obtained from the metamodel, while the threshold values ($M_{threshold}$ and $N_{threshold}$) are limits for the bending moment and the axial force that can be defined based on the cross section resistance or other project requirements.

4 CONCLUSIONS

A method for the prediction of the utilization level, and in turn the safety level in segmental linings, was described. The concept is based on the use of strains at certain locations in the lining to assess the overall maximum stress state in the structure by means of machine learning tools. The great advantage of these tools is the possibility of enabling real-time predictions of the target quantities, after a training process was carried out on synthetic data generated with a FE model. The results obtained, in terms of predicted maximum bending moments and axial forces, showed satisfactory performances of the networks when applied to the benchmark. Whilst the accuracy of the networks trained on the original synthetic data was quite poor when applied to the benchmark scenarios, the accuracy in the bending moment prediction improved significantly with the addition of slight perturbations to the training data, obtaining the best performance for noise levels between 3 to 6% in the two reference scenarios considered. The axial force appeared to be insensitive to the application of noise and for the highest noise levels a worsening in the prediction accuracy was observed. The introduction of artificial noise to the training data could boost the predictive capabilities of the metamodels, along with their range of applicability, offering a workaround for extrapolation. The predicted stress resultants could be eventually employed for the assessment of a safety measurement of the lining, defined in terms of a domain containing admissible stress states based on prescribed threshold values.

ACKNOWLEDGEMENTS

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