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Real-time Reliability Analysis of Tunneling-induced Building Damage

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Abstract: During the construction of shield driven tunnels, the effects on the surrounding environment such as surface settlements and the risk of damages of existing buildings or infrastructures have to be assessed. Therefore, the evaluation of limit states of the system response, i.e. expected surface settlements or maximum strains in buildings, is necessary to select appropriate operational parameters for further construction steps. The evaluation is carried out by means of reliability analyses taking into account the uncertainties of the geotechnical parameters and the machine parameters. Here, machine operational parameters are considered as stochastic numbers in stochastic analyses. The reliability analyses with respect to settlement and building damage can be performed by using finite element (FE) simulations, as a deterministic solution. To obtain the analysis results in real-time, fast surrogate models are employed to substitute the time-consuming FE models. In prior works, a hybrid surrogate modeling strategy combining artificial neural networks and proper orthogonal decomposition approaches has been developed to predict high dimensional time variant surface settlement fields in just a few seconds with similar accuracy as the original FE model. In this work, the developed settlement prediction is combined with a building damage evaluation model to deliver the real-time reliability analysis of tunneling-induced damage of existing buildings. The reliability results can be used to support the selection of steering parameters during the advance of tunnel boring machines in mechanized tunneling.

Keywords: real-time, reliability analysis, building damage, surrogate models, artificial neural network, mechanized tunneling.

1. Introduction

During mechanized tunneling process, ground surface movements (settlement or heave), which might create possible damages on adjacent/nearby buildings, should be controlled. In practice tunnel engineering, empirical methods are widely used to estimate the magnitude and extent of a "green field" settlement curve. However, due to simplified assumptions the predicted results may not reflect appropriately the complex soil-structure interactions in mechanized tunneling, especially in urban areas with a lot of buildings.

Currently, a number of numerical models, in particular based on the finite element method (FEM), have been developed to investigate the complex soil-structure interactions in mechanized tunneling (Komiya 2009), (Kasper and Meschke 2004). In this work, the 3D numerical model in (Alsahly et al. 2016), which takes into account the most important components of tunneling process and their mutual interactions, has been adopted. Using this numerical model, the Gaussian curves obtained from empirical equations can be replaced by sets of vertical displacements of surface points from the numerical mesh for the building damage assessment.

Depending on the desired level of detail of the analysis, the building damage assessment is performed through analytical evaluations using a surrogate elastic beam, or 2D FE simulations of the facades or 3D simulations of complete structures. In case that the quality of analytical solutions is insufficient, using detailed FE models for real-time applications during tunnel construction requires to replace FE models by time efficient surrogate models.

To support the steering of Tunnel Boring Machines (TBM) directly at the construction site, the soil-structure simulation results are predicted in real-time to control the settlement trough, and consequently, the risk of damage in buildings located in the vicinity of the tunnel, within certain limits, by adjusting the operational parameters of TBMs, i.e. the face and the grouting pressure (Cao et al. 2019). Generally, the operational pressures are time dependent parameters, which vary over time due to the heterogeneity of geological conditions and uncertainty of machine driver’s operation. Considering the characteristic of uncertain data sources, uncertainty can be classified into two main groups: aleatoric and epistemic uncertainty (Möller and Beer 2008). The former should be considered in case of having enough data to construct a stochastic model, whereas the latter often deals with the case of lacking of information to have an adequate model. Here, the pressures are measured frequently during the tunneling process and therefore should be considered as stochastic processes. Reliability analyses taking into account the uncertainty of steering parameters require to perform the simulation model multiple times, e.g. to predict damage category probabilities of buildings. This is also a time consuming procedure within Monte Carlo simulations, hence surrogate models are necessary to substitute computational expensive FE models to maintain the prediction performance and to reduce the computation time significantly for real-time applications.

Different approaches have been developed for the generation of surrogate models, see e.g. (Simpson et al. 2001) for an overview. Each surrogate modeling approach has specific advantages for specific tasks. As an example, Artificial neural networks (ANNs), which are widely used in engineering (Adeli 2001), are advantageous for multiple input and single or low dimensional output mappings, Recurrent Neural Networks (RNN) for the prediction and extrapolation of time-variant processes and the Proper Orthogonal Decomposition (POD) method for the reduction of high dimensional data (Everson and Sirovich 1995). Benefits of RNNs and gappy POD (GPOD) approaches have been combined within a hybrid RNN-GPOD surrogate model with a low dimensional input and a high dimensional output (Cao et al. 2016). Considering the risk of building damages as the target to adjust the TBM process parameters, the hybrid surrogate model is coupled with a Feed-forward Neural Network (FFNN), which delivers the real-time assessment of the risk of damage on nearby buildings (Cao et al. 2019).

In this paper, the approach in (Cao et al. 2019) has been further extended by taking into account the uncertainty of process parameters as stochastic processes. The surface settlements are first predicted by the hybrid surrogate model RNN-POD. The subsequent assessment of the risk of damage on nearby buildings is then evaluated using a FFNN. The results from real-time reliability analysis of tunneling-induced damage of existing buildings are finally utilized as the target to adjust the operational parameters for the next construction steps of the tunneling process.

2. Uncertainty quantification by stochastic numbers

In practice tunnel engineering, a TBM driver usually adjusts the operational parameters (e.g. the face support pressure and the tail void grouting pressure) at the early construction stage of each ring. Simple and empirical methods based on local experiences are often used to determine the desired values of the parameters. During the advancement of the machine, the real applied values of parameters are recorded with a motion from 10 to 15 seconds. The recorded data usually fluctuate around the desired values. This is considered to be uncertain due to the dependence on the performance of equipment, machines and the skills of the workers. Therefore, the process parameters, e.g. the face support pressure or the grouting pressure, vary over time due to heterogeneity of soils, variability of stratum and uncertainty of driver's operation, and thus they should be considered as stochastic processes in the time domain.

To consider for the randomness of a process parameter, stochastic numbers (Phoon and Kulhawy 1999) can be used to describe the parameters. For each stochastic number, a stochastic model has to be selected, which is defined by its probability density function (pdf) and cumulative distribution function (cdf). Stochastic models can be used to consider spatial and time varying uncertainty. In general, an adequate database is required with a sufficient number of samples to identify the stochastic model and estimate the corresponding parameters. In mechanized tunneling, operational parameters describing the process, e.g. the support pressure at heading face or the tail void grouting pressure are typical examples where enough information is available to model time varying parameters by means of stochastic numbers. The desired values of the process parameters can be regarded as the mean value of the distribution, whereas the standard deviation of the distribution may be determined by considering their fluctuation behaviors.

3. Surface settlement field prediction

3.1 Finite element model

For the prediction of surface settlements during shield tunneling processes, the 3D numerical simulation proposed in (Alsahly et al, 2016) is employed. It is based upon the object-oriented finite element framework KRATOS and takes into consideration all relevant components of the mechanized shield tunneling and their mutual interactions. The components of the employed simulation model are illustrated in Fig. 1.

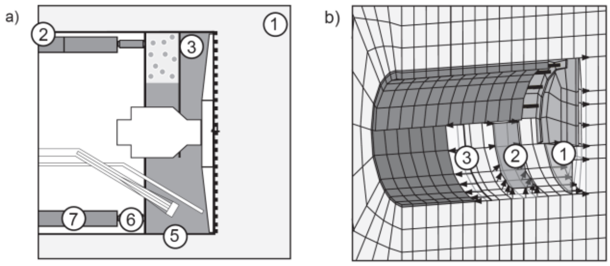

Figure 1. a) Main components in mechanized tunneling: (1) soil, (2) tail gap, (3) support medium, (4) cutting wheel, (5) shield, (6) hydraulic jacks and (7) lining; b) Interactions between soil and TBM in the simulation model: (1) face support, (2) frictional contact between shield and soil and (3) grouting of the tail gap.

The TBM is represented as a deformable body moving through the soil and interacting with the ground through frictional contact. Hence, a more realistic deformation of the surrounding soil due to the tapered geometry of the shield can be simulated. The excavation and the construction processes are modeled by means of the deactivation of soil elements and installation of tunnel lining and grouting elements. The soil is modeled as a two phase material, accounting for both the solid and the pore water according to the theory of mixtures.

3.2 Surrogate model

In the offline stage, a representative simulation model for a tunnel drive through a specific tunnel section is created with the numerical model in Section 3.1. By varying the deterministic values of the input parameters (process parameters), the corresponding deterministic outputs (surface settlements) are computed. These deterministic input-output data sets are utilized to train and test a deterministic surrogate model, which can be used directly to predict the complete time variant surface settlement field for a given set of user defined process parameters.

In the online stage, during the tunnel construction, adopting the actual recorded process parameters from previous time steps 1 to n, the surrogate model predicts the complete surface settlement field of time step n+1 depending on the chosen values of the steering parameters. The hybrid surrogate model consists of a RNN and the GPOD approach. The key idea is that an RNN is trained to predict the time variant settlements at selected monitoring points, while the GPOD is used to approximate the whole settlement field of each time step.

3.2.1 Recurrent Neural Network

For the prediction of dependencies between structural processes, RNN are often used due to the capability to learn dependencies between data series without considering time as additional input parameter. The layer network structure of RNNs is similar to the architecture of feed forward neural networks. But in addition to the neurons, so-called context neurons are used to consider the structure history. For each hidden and each output neuron, a context neuron is assigned. These context neurons send time delayed context signals to the hidden and output neurons. Figure 2 shows the structure of the RNN, which is used in the application example in Section 5. Different types of activation functions can be exploited to process the signals in the neurons.

$$\varphi^1(\mu) = \tanh(\mu) = \frac{\exp(\mu) - \exp(-\mu)}{\exp(\mu) + \exp(-\mu)} \tag{1}$$

$$\varphi^2(\mu) = \mu \tag{2}$$

Equations (1) and (2) show the hyperbolic tangent function and the linear activation function, which are used in the hidden neurons and the output neurons of the RNNs, respectively. The RNNs are trained using the Levenberg-Marquardt back propagation. During the training process, the synaptic weights, the context weights for each delayed time step and the bias values which are unknown network parameters are identified.

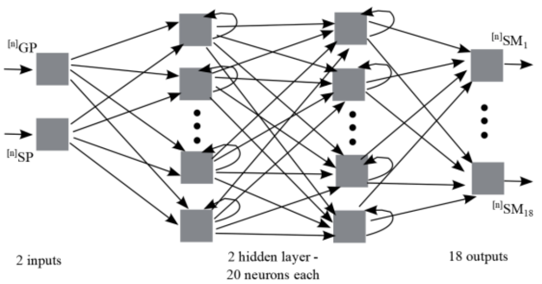

Figure 2. Structure of the employed RNN in Section 5 for the settlement prediction of selected monitoring points.

3.2.2 Gappy Proper Orthogonal Decomposition

The basic POD method is combined with a linear regression called GPOD. The POD technique is a widely used method in data analysis due to its efficiency in representing an original high-dimensional data set through a reduced order set of basic functions with a high level of accuracy. Without any missing data, an arbitrary snapshot $\boldsymbol{S}^j$, which belongs to a set of snapshots, can be approximated as a linear combination of the first K POD basis vectors and an amplitude vector $\boldsymbol{A}^j$. The amplitude vector is calculated by minimizing the error norm

$$\min . \left\| S^j - \Phi \cdot A^j \right\|_{L^2}^2 \tag{3}$$

The same least square approach can be effectively used to restore missing data of an incomplete data snapshot $\boldsymbol{S}$. However, due to missing elements, the gappy norm based on available data is utilized instead of the L^2 norm. The intermediate repaired vector $\boldsymbol{S}^*$ can be expressed in terms of truncated POD basis vectors Φ. The coefficient vector $\boldsymbol{A}^*$ can be computed by minimizing the error between $\boldsymbol{S}^*$ and $\boldsymbol{S}$. A solution to this so-called least squares problem is given by a linear system of equations

$$M \cdot A^* = R \tag{4}$$

$$M = \left(\Phi^{\mathrm{T}} \cdot \Phi\right);\ R = \left(\Phi^T \cdot S\right) \tag{5}$$

4. Assessment of building damage

Building damages are commonly referred to strains exceeding certain limits (Mark and Schnütgen 2001). Beams, shells or volumetric models are used as calculation models for the strain estimation, whereby simplified linear-elastic or non-linear material behavior can be assumed. Simple beam models do not capture soil-structure interactions and simply represent the real structural behavior in a very simplified way (Obel et al. 2018). For more detailed analyses, FE calculations of the building facades are usually used (Neuhausen et al. 2018). The maximum calculated strains are compared with limiting strains. Table 1 shows the assignment of limit tensile strains to corresponding category of damages.

Table 1. Damage categories and related tensile strains.

Category of damage	Degree of severity	Limiting tensile strain [%]
0	negligible	0 – 0.05
1	very slight	0.05 – 0.075
2	slight	0.075 – 0.15
3	moderate	0.15 – 0.3
4	severe	≥ 0.3

4.1 Finite Element Model of the facades

The facade is re-idealized by shell elements for the masonry and plate elements for the reinforced concrete foundation. The support type depends on the settlements determined beforehand. In case that the settlements were estimated using numerical models, the supports are idealized using hinged supports.

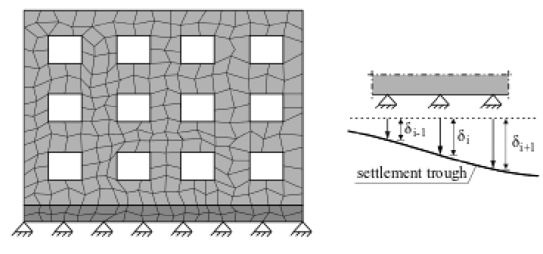

Figure 3. Building façade model.

With this idealization, the settlements δ_i affect the facade as forced quantities by displacing the support. To capture the nonlinear material behavior of masonry a simple isotropic damage model, parabolic-shaped in compression and linear in tension has been adopted. The tensile behavior of the masonry can be assumed to be linear-elastic and described by Hooke's law. Concrete's behavior in compression is approximated with an uniaxial material function defined in Eurocode II. Reinforced concrete can be modeled by a modified stress-strain relation of the reinforcement according to Model code.

4.2 Feed-forward Neural Network

Figure 4 shows the structure of the three-layer FFNN, which is used in the application example in Section 5. The inputs of the FFNN are eight settlements at the façade foundation SB_k (k = 1… 8), which are provided for each time step of the tunnel advance by the RNN-GPOD surrogate model, see Section 3.2. The hidden layer consists of 10 neurons (h = 1… 10) and the output layer has one neuron to predict the maximum strain ε_{max} anywhere in the facade. Compared to the RNN, the FFNN has no time delays context signals. The activation functions and the training algorithm used in the FFNN are similar as compared to the RNN.

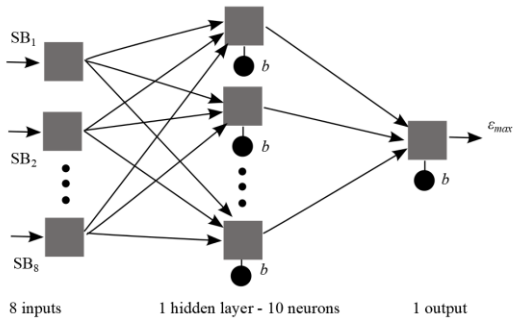

Figure 4. Structure of the employed FFNN in Section 5 for the prediction of maximum strains in buildings subjected to tunneling induced settlements.

5. Application example in mechanized tunneling

A simulation model of a tunnel section, which is assumed to be constructed by TBM method through an urban area, is generated using the FE-model described in Section 3.1. The tunnel is excavated directly underpass a multi-storey building as highlighted in Fig. 5(a). The surface settlement prediction and the corresponding building damage evaluation are performed to support the TBM driver selecting appropriate steering parameters to reduce the influence of the tunneling process to the investigated building. To obtain the predictions in real-time, surrogate models are employed.

5.1 Settlement prediction

In this example, a tunnel with an excavation diameter of D = 10.97m is assumed to be constructed by a TBM with a shallow overburden of 11m. The dimensions of the simulation model are 96m, 220m and 72m following X, Y, Z axis respectively. Existing buildings are considered by rectangular plate-like substitute models with corresponding equivalent thickness and stiffness at the top of the discretized soil body. It is assumed, that the TBM advances completely within the silty sand layer, i.e. the second top soil layer of the ground domain comprising four layers of soft soil as shown in Fig. 5(a). The soil behavior of all layers is assumed to be governed by an elastoplastic model using Drucker-Prager yield criterion with a linear isotropic hardening. The behavior of the lining, the grouting mortar and the TBM are assumed to be linear elastic.

Considering the location of the investigated building, a rectangular surface area with 165 points as illustrated in Fig. 5(b) is considered as the area of interest in this application example. The vertical displacements following Z-axis of these 165 points are defined as the outputs of a surrogate model using the RNN-POD approach. The two inputs of the surrogate model are the grouting pressure and the face support pressure applied at the tail void gap and the tunnel face respectively.

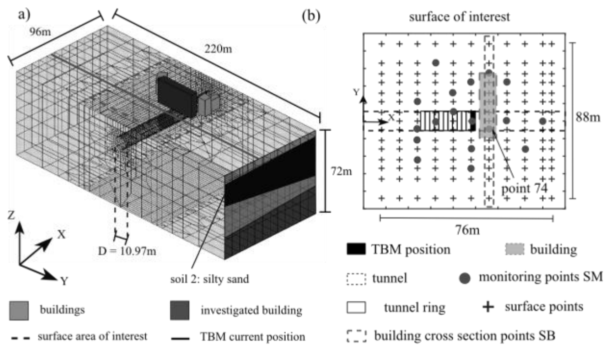

Figure 5. Simulation model of a tunnel section underpass a building: (a) Geometry; (b) Outputs of the RNN-POD surrogate model: settlements of 165 surface points.

It is assumed that the current state of the TBM advance corresponds to the 25rd step of the excavation process (directly in front of the investigated building) and the history of the process parameters from time step 1 to time step 25 is recorded. Here, the objective in this section is to predict the surface settlements of all 165 surface points at further time steps, e.g. the next 3 time steps (from time step 26 to time step 28) when the TBM passes under the building of interest, for arbitrary changes of the support and grouting pressures. In this example, 18 monitoring points are selected to be predicted by the RNN, which consists of 2 hidden layers with 20 neurons in each layer, see Fig. 2.

To set-up the surrogate model, a total number of 60 FE simulations corresponding to 60 combinations of input parameters is carried out. In each simulation, the input is a combination of a scenario of time varying levels of the grouting pressure GP and the face support pressure SP. The values of pressures in each time step are randomly initialized within possible ranges taken from practical tunneling processes, i.e. [60, 180] kPa for GP and [50, 150] kPa for SP. From the 60 FE simulations, two main data sets are split with ratios of 80% and 20% for the training and validation of the RNN-GPOD model. The quality of the surrogate model is then evaluated by comparing the prediction and "true" FE results of the validation set, i.e. 12 randomly selected simulation cases.

Figure 6 shows the prediction performance of the surrogate model RNN-POD as compared to the FE solution for the validation case 3 among the 12 validation cases. Regression plots representing for the agreement between predicted results from RNN-POD model and FE results at time step 26, 27 and 28 are depicted in Fig. 6(a). Figure 6(b) shows a comparison of the time evolution settlement of a surface point from FE and surrogate models. The average prediction error of all 12 validation cases using the RNN-POD surrogate model is around 7%. For this nonlinear problem, it is shown, that the surrogate model can produce good prediction results with similar accuracy comparing to the FE solutions. The computation time is significantly reduced from 12 hours for the FE analysis to less than 1 second with the surrogate model approach. Hence the RNN-POD model is employed for the next step of the TBM supported steering strategy by providing the predicted surface settlement field to the building damage assessment. As a result, the settlements of 8 surface points belonging to the building cross section points set SB see Fig. 5(b), are the inputs of the two-dimensional structural facade model.

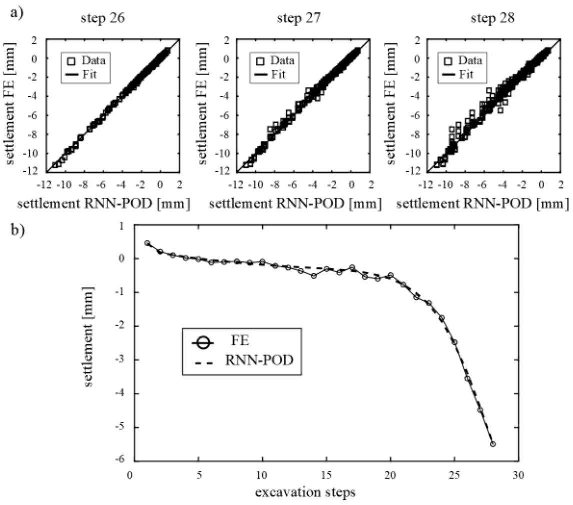

Figure 6. Prediction performance of the RNN-GPOD surrogate model for validation case 3: a) Comparison between predicted and FE settlements for all 165 surface points at time steps 26, 27 & 28; b) comparison between the predicted and FE settlement evolution (step 1 to step 28) at surface point 74 (see Fig. 5b).

5.2 Damage assessment of existing building

In the next step, the RNN-GPOD surrogate model is linked with a structural model for the building by providing the settlements SB_k at 8 points of the building foundation. A structural model of a façade, see Fig. 7(a), is established to compute the expected damage. The maximum expected strain at the facade is used as damage indicator for the classification of the building in terms of category of damage (cod). The facade is assumed to be made of calcium silicate masonry and a concrete type C30/37 according to Eurocode II is used for the foundation. The dead load of the masonry and concrete are 20 kN/m^3 and 25 kN/m^3, respectively. The distributed load p=10 kN/m corresponds to the contributions of the individual floors on the facade. In the facade model there are 180 nodes on this length (in total 15000 quadrilateral elements). The required intermediate values for the nodes of the facade model are linearly interpolated.

To train and test the FFNN damage assessment surrogate model, the 60 scenarios introduced in Subsection 5.1 are used. The 60 scenarios are randomly split into three data sub-sets for training, validation and testing with respective ratio of 70%, 15% and 15%. For each scenario, the 8 settlement values provided by the RNN-GPOD surrogate model are defined as inputs of the FFNN and the maximum strain in the facade ε_{max} is considered as output.

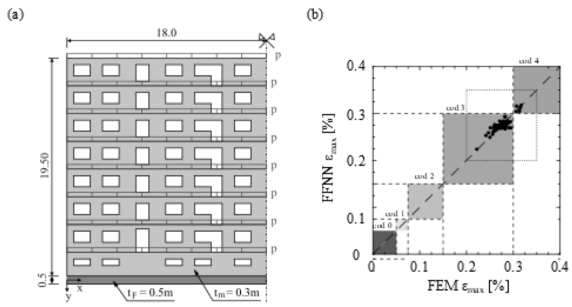

Figure 7. (a) Geometry of the facade; (b) Regression plot of the FFNN for all training cases.

Figure 7(b) compares the FE results with the FFNN predictions in a regression plot. Data points above and below the diagonal line indicate an FFNN overestimation and an underestimation of the strains, respectively. The square areas indicate the areas of the individual categories of damage (cod 0 to cod 4). The coefficient of determination values (R^2 = 0,82) indicates that the FFNN explains about 82% of all results. Since the exact level of strains is not required and only the category of damage is important, the FFNN provides satisfactory prediction accuracy. Neither over- nor underestimations lead to a change of the predicted damage category.

5.3 TBM steering supported

For sake of simplicity, in this example only the face support pressure is adopted as the operational parameter to be controlled. As mentioned above, the TBM has proceeded to the 25th step of the tunneling process and that the history of the face support pressure is assumed from time step 1 to time step 25 with a constant level of 120 kPa as shown in Fig. 8(a).

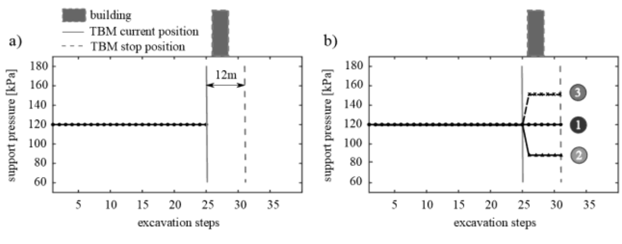

Figure 8. (a) Recorded data for face support pressure up to step 25; (b) three pressure changing scenarios (mean value).

In the next 6 excavation steps (i.e 12 meters), when the TBM advances underneath the building, 3 scenarios of applying face pressure (120 kPa, 90 kPa and 150 kPa) are investigated. The face pressure is considered as a stochastic number with a normal distribution. The mean values used for generating random input parameters SP corresponding to three scenarios are μ= 120 kPa, 90 kPa and 150 kPa. The standard deviation in the distribution is assumed to be constant in all 3 scenarios (σ = 10 kPa).

The objective in this reliability analysis is to calculate the probabilities of the building damage category in 3 investigated face pressure scenarios. A sample size of 10^3 is used in the Monte Carlo Simulation. As shown in Table 2, if the support pressure is applied around 90 kPa (scenario 2), 83% is the probability that the building damage category is in the group 4. If the support pressure remains unchanged (scenario 1), the probability of falling to the category 4 reduces to 62%. This value can be further reduced to 30% in case of applying a support pressure with the mean value of 150 kPa (scenario 3). In addition, as compared to a deterministic analysis with the support pressure of 120 kPa, which leads to the cod 4 of the building damage category, the scenario 1 provides more information about the possibility of the building damage. Therefore, the results are more helpful for the TBM driver to select appropriate operational parameters to advance the machine in the next construction steps. The computation time of the reliability analyses with 3 scenarios and 10^3 samples each (in total 3000 samples) is around 40 minutes without the help of parallelization, which is still in the range of necessary construction time of one ring in mechanized tunneling (typically 1 to 2 hours). These investigations can therefore provide a basis for a real-time application in mechanized tunneling.

Table 2. Probability of building damage category.

	Scenario 1 μ = 120 kPa	Scenario 2 μ = 90 kPa	Scenario 3 μ = 150 kPa
cod 3	0.38	0.17	0.70
cod 4	0.62	0.83	0.30

6. Conclusions

In the paper, a strategy using the predictions of soil-structure interactions to suggest the selection of process parameters during the advance of the TBM in mechanized tunneling has been presented. FE simulations are the basis for the surface settlement field prediction and the building damage assessment. ANNs are employed to replace the time-consuming FE simulations for the real-time predictions. A hybrid surrogate model RNN-POD and a FFNN are employed to quickly provide the surface settlements and consequently the associated damage risk categories. The efficiency of the proposed strategy has been illustrated in the application example, for which the FE simulations required around 12 hours while the proposed approach required only 1 second to compute the settlement field with 165 settlement components and the associated building damage category with a similar accuracy. Using the proposed strategy, a reliability analysis to investigate the probability of building damage category is performed by considering the process parameters as stochastic numbers. With a sample size of 10^3, the reliability results are delivered within 40 minutes which can be used to support the TBM driver to operate in the subsequent excavation steps.

One of future developments of the proposed approach includes the further consideration of uncertainties in mechanized tunneling. The uncertainties can arise from geotechnical parameters based on information from geotechnical reports and from geometrical parameters of the buildings. Sensitivity analysis will be performed to investigate the influence of each uncertainty source on the final distribution of maximum strain in building or the probability of building damage category.

Acknowledgement

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References

Adeli, H. 2001. Neural networks in Civil Engineering: 1989-2000. *Computer-Aided Civil and Infrastructure Engineering.* 16: 126-142.

Alsahly, A., Stascheit, J. and Meschke, G. 2016. Advanced finite element modeling of excavation and advancement processes in mechanized tunneling. *Advances in Engineering Software*, 100: 198-214.

Cao, B.T., Freitag, S. and Meschke, G. 2016. A Hybrid RNN-GPOD Surrogate Model for Real-time Settlement Predictions in Mechanised Tunnelling. *Adv. Mod. and Sim. in Eng. Sci.*, 3(5): 1-22.

Cao, B.T., Obel, M., Freitag, S., Meschke, G. and Mark, P. 2019. Artificial neural networks for real-time prediction of soil-structure interaction in mechanized tunnelling. In *5th Int. Conf. on Soft Comp. & Opt. in Civil, Struct. & Envi. Engineering*, Riva del Garda.

Everson, R. and Sirovich, L. 1995. Karhunen-Loeve Procedure for Gappy Data. *J. Opt. Soc. Am. A: Opt. Ima. Sci. Vis*., 12(8): 1657-1664.

Kasper, T. and Meschke, G. 2004. A 3D finite element model for TBM tunneling in soft Ground. *Int. Journal for Numerical and Analytical Methods in Geomechanics*, 28: 1441-1460.

Komiya, K. 2009. FE modelling of excavation and operation of a shield tunnelling machine. *Geomechanics and Tunneling*, 2(2): 199-208.

Mark, P. and Schnütgen, B. 2001. Limits of Elastic Material Behaviour of Concrete. *Beton- und Stahlbetonbau* , 96(5): 373-378.

Möller, B. and Beer, M. 2008. Engineering computation under uncertainty – Capabilities of non-traditional models. *Computers and Structures*, 86: 1024-1041.

Neuhausen, M., Obel, M. Martin, A., Mark, P. and König, M. 2018. Window detection in façade images for risk assessment in tunnelling. *Vis. in Eng 6(1):1-16*

Obel, M., Marwan, A., Alsahly, A., Freitag, S., Mark, P. and G. Meschke. 2018. Damage assessment concepts for urban structures during mechanized tunneling. *Bauingenieur*, 93(12): 482-490.

Phoon, K. and Kulhawy, F. 1999. Characterization of geotechnical variability. *Canadian Geotechnical Journal* 36: 612–624.

Simpson, T., Peplinski, J., Koch, P. and Allen, J. 2001. Metamodels for Computer-based Engineering Design: Survey and recommendations. *Engineering with Computers*, 17: 129–150.