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

TunAID - Interactive simulation-based tunnel track design tool for mechanized tunneling in urban areas

Y. Zendaki, B.T. Cao & A. Alsahly
Ruhr University Bochum, Bochum, Germany

S. Freitag
Karlsruhe Institute of Technology, Karlsruhe, Germany

G. Meschke
Ruhr University Bochum, Bochum, Germany

ABSTRACT: Alignment design in urban tunneling aims at selecting an optimal tunnel track satisfying various design specifications and safety constraints as well as considering the environmental and socio-economic impact. In this work, an interactive tunnel track design tool is proposed, which enables finding optimized tunnel alignments by considering the impact of the tunnel advancement on existing infrastructure as a design criterion. An advanced numerical simulation model based on the Finite Cell Method (FCM) is utilized to predict the damage to existing buildings, during the tunneling process. To enable interactive applications in real-time, the FCM simulation model is substituted by a model reduction technique based on Proper Orthogonal Decomposition and Radial Basis Functions (POD-RBF). The fitness function to be minimized in the optimization problem is the maximum principal strains in all existing buildings. The Particle Swarm Optimization (PSO) algorithm is used to solve the minimization task. Finally, the alignment optimization is demonstrated in a real-time manner within a software environment. In each optimization step, the current optimum tunnel alignment and the associated risks of damage to all existing buildings are visualized in the developed software package. The proposed and developed strategy can be used to improve the tunnel alignment decision-making as well as can be extended by incorporating multi-objective functions for the optimization of tunnel alignment design.

1 INTRODUCTION

The choice of an optimal tunnel alignment in urban tunnel projects is a complex task, in which a number of constraints and design criteria need to be fulfilled simultaneously. One of the design criteria is to minimize the risk of damage to sensitive existing buildings and existing infrastructure. The assessment of the potential damage for a large number of design variants is highly demanding and often involves highly simplified models in this initial stage of a project. Currently, in case more realistic computational models are used, a new finite element model needs to be generated for each of the investigated variants, connected with an enormous effort in manpower. Classical finite element methods based on boundary-fitted discretization are commonly used to simulate the soil-structure interactions during mechanized tunneling processes (Alsahly et al., 2016; Marwan et al., 2021). However, situations involving complicated geometries such as curved tunnel alignments require a lot of manual work and effort in order to generate the numerical mesh for the simulation (Alsahly et al., 2016).

DOI: 10.1201/9781003348030-355

Recently, to efficiently establish numerical models in such situations, and to enable a seamless transition from BIM models to computational models, an advanced tunnel simulation model based on the Finite Cell Method (FCM) (Elhaddad et al., 2017) has been developed in (Bui et al., 2022). One of the distinctive features of the FCM is to allow for independent meshing of structural components, i.e. the ground, the lining, and the TBM. This leads to a simplification of the mesh generation procedure due to the possibility of structured meshing for individual components. This technique enables directly incorporating information on soil layers, and existing underground as well as surface infrastructure generated in BIM models into the computational model, without the need for generating a new finite element mesh for each design variant.

Generally, a possible application of the FCM technology is to efficiently investigate different tunnel alignments with respect to surface settlements and associated risks of damage to existing buildings induced by the tunneling process in urban areas. Using directly the FCM model in the context of tunnel track design to find a reasonable alignment satisfying all engineering criteria is not preferable since each simulation can require many hours.

Following the vision of an interactive tool allowing to investigate different alignments in real-time on a laptop or a tablet, or even to find an optimal track design considering prescribed constraints, requires efficient machine learning techniques to generate a faster surrogate model substituting the FCM model such that the computation time can be reduced by orders of magnitude, while the prediction capability is still maintained. Artificial neural networks (ANN) (Freitag et al., 2018; Cao et al., 2020) and Proper Orthogonal Decomposition (POD) (Ostrowski et al., 2008) are machine learning techniques that are successfully adopted as surrogate models in a wide range of application fields. In mechanized tunneling, the POD has been combined with Radial Basis Functions (POD-RBF) as surrogate models for the prediction ranging from hundreds of settlement points (Cao et al., 2016) to thousands of tunnel lining displacements and structural forces (Zendaki et al., 2022).

In this paper, considering the minimization of damage to existing buildings as a criterion, a tool denoted as TunAID is proposed, which allows to interactively determine (in real-time) optimized tunnel alignments resulting in minimal settlement-induced damage within a predefined section of a tunnel project. The maximum principal strain is used as a damage criterion for concrete structures. However, it should be noted that different damage criteria could be used for different types of structures i.e. masonary or wood structures. The prediction model employed within the optimization process is a surrogate model based on the POD-RBF method, which can quickly predict maximum principal strains in all buildings during the tunneling process. The surrogate model and the optimization strategy based on the Particle Swarm Optimization (PSO) (Shi and Eberhart, 1998) are integrated into the interactive tunnel alignment design software TunAID as a simulation-based assistant tool to support the decision-making in the early stages of urban tunnel projects. Using this tool, the tunneling-induced building damage risks can be visualized immediately with respect to each tunnel alignment not only in each iteration of the optimization process, but also corresponding to the manual user-defined interactive adjustment of the alignment.

2 COMPUTATIONAL SCHEME FOR TUNNEL ALIGNMENT OPTIMIZATION

A schematic illustration of the tunnel alignment optimization concept is presented in Figure 1. In the first step of the procedure, a number of possible tunnel alignments is generated. The process-oriented FCM model is then used to simulate the mechanized tunneling processes with various tunnel alignments. The coordinates of a set of points representing the tunnel alignment are regarded as the input parameters to perform each simulation. Afterwards, these coordinates of points together with the strains in buildings in all alignment scenarios are collected to construct the POD-RBF surrogate model. For the training and testing of the surrogate model, tunnel alignments are kept as the inputs and building damage are considered as the outputs. In the last step, the PSO algorithm will search for the optimum alignment which can minimize the damage in all involved buildings. The components of the computational scheme will be described briefly in the following subsections.

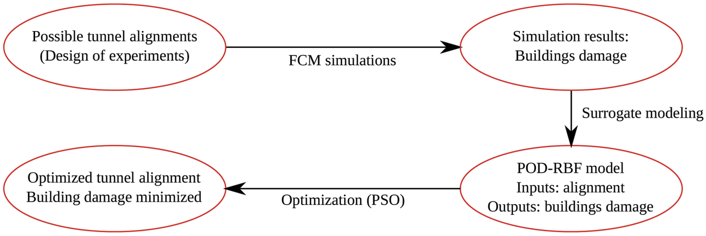

Figure 1. Concept of the simulation-based real-time tunnel alignment design optimization.

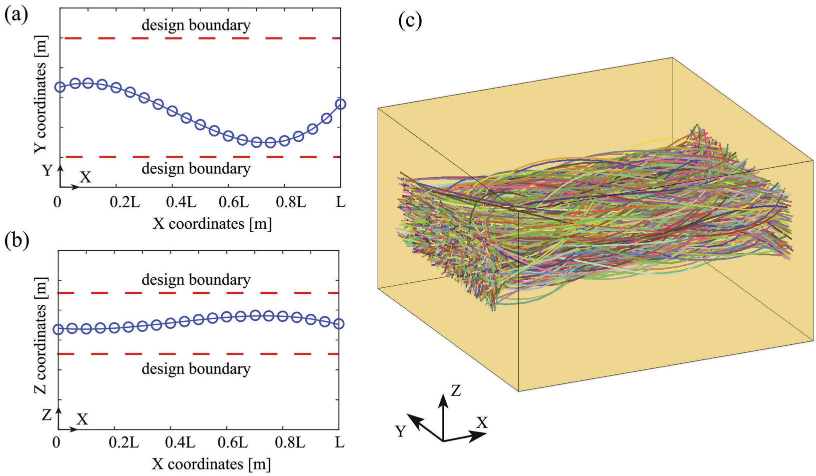

Figure 2. (a) Design constraints for the width of tunnel alignments; (b) Design constraints for the depth of tunnel alignments; (c) Possible three-dimensional tunnel alignments.

2.1 *Design of experiments for tunnel alignments*

Following the predefined design requirements in a tunnel project and considering constraints with respect to tunnel serviceability, e.g. fixed positions of stations, and curvature constraints with respect to the design speed of the train, a tunnel alignment can have many possible shapes. In this work, the alignment is assumed to be represented by a set of control points following a cubic function to have a parametric representation, see Figure 2. It is worth mentioning that the proposed strategy is also valid for a general case, where a different function is used to represent the alignment. Considering a three-dimensional design problem, the X coordinates of the control points are fixed, and only the Y and Z coordinates of the alignment are created using the Latin Hypercube sampling. Figure 2 illustrates the alignment design in 3D space with a 2D top view design in Figure 2(a) and a 2D side view design in Figure 2(b). A collection of possible tunnel alignments within a predefined section is visualized in Figure 2(c). These collected Y and Z coordinates of all alignments scenarios, which are regarded as inputs of the surrogate model, are then sent to the FCM model to execute the simulations.

2.2 *Finite cell method*

Unlike boundary-fitted methods, FCM is an immersed boundary method where the discretization extends beyond the boundaries of the physical domain to the so-called fictitious domain. The boundary is resolved by penalizing the weights of the integration points that lie in the fictitious domain. The error stemming from this boundary resolution is reduced by adding more integration points in a tree-based integration point refinement scheme. FCM allows for the use of one structured background mesh for all simulations, which removes the need to create a custom mesh for each track alignment in every simulation. This is particularly important for the generation of synthetic data where thousands of simulations are needed. The accuracy of the solution and the computational requirements of the simulation are enhanced by using adaptive mesh refinement (AMR). This automatically refines the structured background mesh around tunnel components and underground structures (Zendaki and Meschke, 2022).

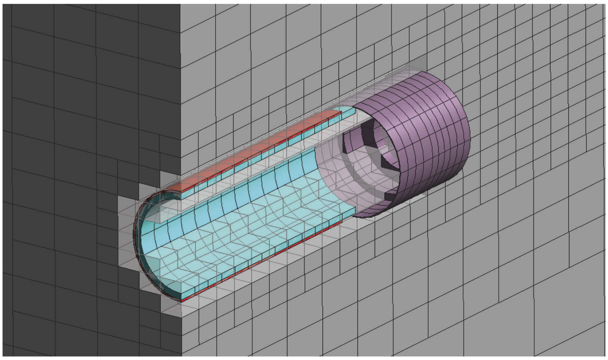

Figure 3. Components of the Finite Cell tunnel modeler.

The soil domain is discretized using the structured background mesh, whereas the other tunnel components like grouting and lining are discretized with a boundary-fitted mesh and tied to the background mesh. The components of the FCM tunnel modeler are shown in Figure 3. Different soil layers are modeled using a boundary representation that completely cuts through the background mesh. The material properties are then assigned to integration points depending on their position with respect to each of the soil layers' boundary representations. Face support pressure is modeled as a force and a prescribed pressure on the face of the excavation as well as outside of the shield to account for the transfer of pressure of the slurry around the TBM. The effect of the advancement speed of the TBM on the consolidation of the soil is also modeled. More details about the FCM in tunneling can be found in (Bui et al., 2022).

2.3 *Proper orthogonal decomposition and radial basis functions*

The collection of M snapshots of possible building damage with respect to tunnel alignments is arranged into a matrix S (N rows x M columns), where each column consists of N output values (maximum principal strains in all buildings) corresponding to a specific set of input parameters (coordinates of alignment points). The Proper Orthogonal Decomposition (POD) basis vectors Φ, which characterize the matrix $\mathbf{S}$, can be obtained by a Single Value Decomposition of $\mathbf{S}$ or by solving the eigenvalue problem of the sample covariance matrix $\mathbf{C} = \mathbf{S}^T \cdot \mathbf{S}$. For the approximation of $\mathbf{S}$, only $K \ll M$ basis functions are kept instead of a full order of M dimensions. The resulting matrix consisting of the first K POD modes is denoted as truncated POD basis matrix $\hat{\Phi}$. The original snapshots matrix S is approximated by

$$\mathbf{S} \approx \hat{\Phi} \cdot \hat{\mathbf{A}}, \tag{1}$$

where the truncated amplitude matrix, $\hat{\mathbf{A}}$, contains constant values associated with the given matrix $\mathbf{S}$. As a result, only an approximation for snapshots, which were included in the original high-dimensional snapshots, is possible. To obtain a rather continuous approximation, the matrix $\hat{\mathbf{A}}$ is formulated as a nonlinear interpolation function of input parameters on which the system depends. Therefore, the truncated amplitude matrix $\hat{\mathbf{A}}$ is expressed via interpolation functions $\mathbf{F}$ of input parameters and an unknown matrix of constant coefficient $\mathbf{B}$ as

$$\hat{\mathbf{A}} = \mathbf{B} \cdot \mathbf{F}. \tag{2}$$

In this work, the inverse multi-quadric radial function, a type of Radial Basis Functions (RBF) (Hardy, 1990), has been selected as the interpolation function. Finally, an approximation of damage in all buildings corresponding to an arbitrary alignment is obtained by

$$S^a \approx \hat{\Phi} \cdot \mathbf{B} \cdot \mathbf{F}^a. \tag{3}$$

More details about the POD-RBF algorithm can be found in (Cao et al., 2016).

2.4 *Particle swarm optimization*

The Particle Swarm Optimization (PSO) method optimizes a problem by iteratively trying to improve a solution candidate (a particle) of a population (swarm) with respect to a given criterion. In the first step, a population with a number of possible particles is initialized randomly within the search space. The particles are then moved around the search space considering information of all other particles in the swarm and their own particle search history to reach optima following the predefined criterion. The position and velocity of the particles are updated continuously in each iteration of the search process. Considering two successive iterations t and t+1, the position $\mathbf{u}_z$ of the particle z is updated as

$$\mathbf{u}_z(t+1) = \mathbf{u}_z(t) + \mathbf{v}_z(t+1), \tag{4}$$

With $\mathbf{v}_z$ representing the velocity of the particle z. The local best position of each particle among all past iterations is thus extracted and stored. In a similar way, the global best position of the whole population is also updated in each iteration following the best position found by all of the particles in the iteration. The movement of each particle is thus governed not only by its local best-known position but is also guided globally toward the best-known positions in the search space. Therefore, the velocity $\mathbf{v}_z$ at the iteration t+1 is expressed as

$$\mathbf{v}_z(t+1) = \mathbf{v}_z(t) + c_1(\mathbf{l}_z - \mathbf{u}_z(t))r_1 + c_2(\mathbf{g} - \mathbf{u}_z(t))r_2, \tag{5}$$

where c_1 and c_2 are acceleration coefficients governing the magnitude of the moving step of the particle z towards the local best position $\mathbf{l}_z$ and the global best position $\mathbf{g}$ of the swarm; r_1 and r_2 are random numbers uniformly distributed in [0, 1] accounting for the stochastic influence on the velocity update rule. The algorithm is repeated until a stopping criterion, e.g. a maximum number of iterations or a tolerated minimal value of the objective function, is met. The PSO is considered a global optimization algorithm since the search process guides the swarm to converge to the best solutions in the global search space.

3 APPLICATION EXAMPLE

This section is devoted to the application of the proposed approach in a scenario of design optimization for tunnel alignment in an urban area. A section of 400 x 300 meters inspired by the tunnel project Wehrhahn Line Metro in Düsseldorf, Germany is generated. The shield tunneling method is assumed to be used to construct a tunnel in soft, fully saturated soil with an excavation diameter of D = 9.5 meters, see Figure 4. The length of the computational model is 400 meters, which represents 200 excavation steps of 2 meters length. The bottom surface of the model is fixed in both horizontal and vertical directions since it is assumed that deformations in deeper soil layers can be neglected. In this study, the geological condition is assumed to be made up of only one homogeneous soil layer of soft silty clay. Buildings located at the ground surface are modeled as 3D solid blocks with a homogeneous elastic surrogate stiffness of 2.1 MPa, see (Schindler and Mark, 2013), and the Poisson ratio is 0.3. It should be noted that also more detailed building models can be used if structural details are available. In addition, each building should be assigned a stiffness value depending on the structural type, the material, and the usage status of the building. However, in this paper, the main focus is on the general applicability of real-time alignment optimization to minimize the risks of damage to existing buildings.

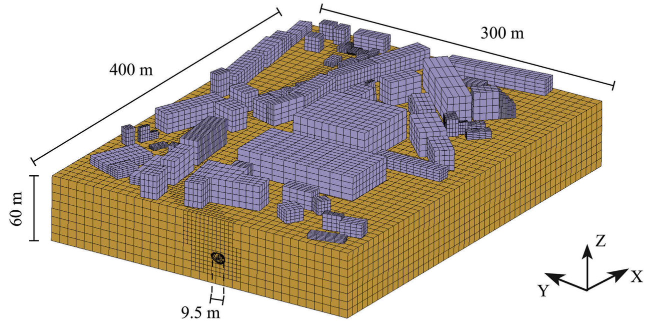

Figure 4. Computational model of a tunnel section with buildings.

Figure 4(a) shows an overview of the computational model with 85 buildings at the top surface used in this application example. The design task is to find an optimum tunnel alignment that can minimize the total possible damage to all buildings. The damage assessment of the buildings is performed in a way similar to (Cao et al., 2022) by estimating the maximum principal tensile strain (ε_1, $\varepsilon_1 \geq 0$) in each building individually. A POD-RBF surrogate model, which considers the Y and Z coordinates of the alignment control points as the inputs as introduced in Section 2.1, is established to predict the maximum tensile strains in 85 buildings.

A total number of 2000 three-dimensional tunnel alignments are simulated to generate the necessary data and the 10-fold cross validation is employed to evaluate the quality of the POD-RBF model. In this example, the 2000 samples are generated with a constraint such that in each alignment the Y coordinates of the control points are within the range from 50 to 250 meters, i.e. $Y = [50, 250]$. Additionally, the variation of the alignment Z coordinates is constrained between 16 meters and 36 meters, i.e. the cover depth in the range of $1.2D$ to $3.3D$ with D as the excavation diameter, to maintain the purpose of designing a shallow tunnel. Table 1 summarizes the mean L_2 norm errors of all validation cases in each fold of the 10-fold cross validation for the prediction of maximum tensile strains in buildings as compared to the reference solutions from FCM simulations. With an average error of only 2.7% and similar prediction accuracy in all 10 folds, it is shown that the POD-RBF surrogate model can efficiently predict the maximum tensile strain in the buildings with respect to different tunnel alignment scenarios instead of using the FCM simulation model.

Table 1. Prediction performance of the POD-RBF surrogate model: L_2 norm error (in [%]).

10-fold cross validation	1	2	3	4	5	6	7	8	9	10	Avg.
Building strain error %	5.2	2.3	2.2	1.7	4.9	1.9	2.3	2.2	1.9	2.0	**2.7**

The POD-RBF is then used within the search process of the PSO optimization algorithm to find the optimum tunnel alignment. In this paper, to account for total damage in all buildings as the fitness function of the optimization, a simple criterion based on the sum of all absolute maximum strains in all buildings is defined. It should be noted, that also a weighting of the individual building damages would be possible, e.g. with respect to the building size or the importance of a building. The optimized alignment in the XY plane (top view design) is shown in Figure 5(a), which suggests that the alignment should follow the existing street and not cross under any buildings. To some extent, the suggestion agrees with the engineering experience and guidelines when designing a tunnel alignment, which proves the reliability of the proposed approach. Similarly, to have less settlement and therefore to reduce the possible damage to buildings, a deeper tunnel is favorable, see Figure 5(b).

Based on the proposed computational strategy, an interactive real-time simulation software is developed to support the decision-making of tunnel alignment selection during the design phase of a tunnel project. This software focuses on predicting in real-time the system responses resulting from TBM-soil interactions, i.e. the surface settlements and the associated risk of damage to buildings, corresponding to an arbitrary tunnel alignment. Figure 6 shows screenshots of the developed software, named "TunAID" (Tunnel Alignment Interactive Design). In addition, the software can also suggest the optimized alignment following a predefined criterion as shown in the application example. In each optimization step, the current optimum tunnel alignment and the associated risks of damage to all existing buildings are visualized in the developed software package.

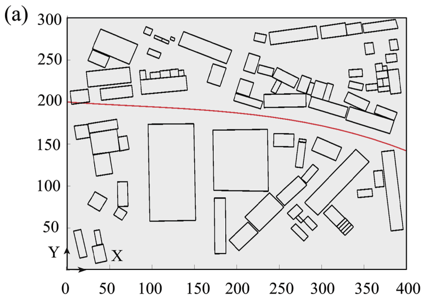

Figure 5. Optimization results (continuous red line) (a) The optimized tunnel alignment in top view design; (b) The optimized depth of the alignment.

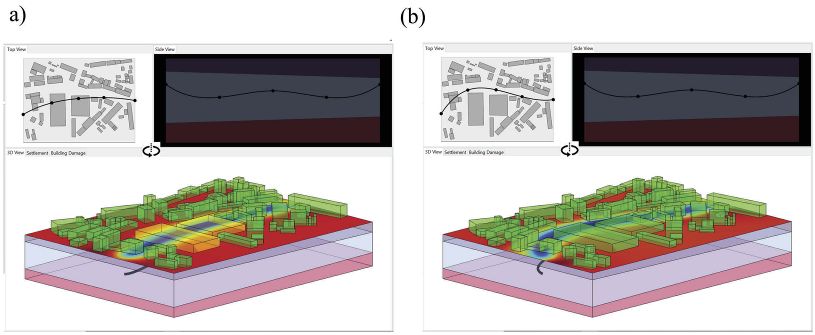

Figure 6. Screenshots of TunAID software (Tunnel Alignment Interactive Design). (a) Tunnel alignment underpassing several buildings, (b) Tunnel alignment following the street.

4 CONCLUSION

A simulation-based track design tool for urban tunneling projects denoted as TunAID has been presented, which allows to interactively determine (in real-time) optimized tunnel alignments resulting in minimal settlement-induced damage within a predefined section of a tunnel project. For the analysis of soil-structure interactions a finite cell (FC) simulation model is employed, which, in contrast to standard finite element models, enables smooth integration of BIM models without the need for re-generating a separate finite element model for each of the investigated design variants. To enable a real-time performance of the track design tool, machine learning procedures (denoted as POD-RBF), based on synthetic data generated by the FCM model, have been applied to generate surrogate models to substitute the (time-consuming) FCM model. Predictions from the POD-RBF model show very good agreement with the reference results obtained from the original FCM model, which qualifies the application for the optimization task to determine the optimal alignment. Considering the damage risks on buildings as a target to optimize the alignment, the suggested solution agrees with engineering interpretation and expectations which shows the promising capability for future applications of the proposed design tool. To assist engineers in decision-making, an interactive platform for tunnel alignment design in urban areas is developed, which can quickly provide the settlements and damage risks of buildings for different alignments. A current limitation of the proposed design tool is, that not all relevant criteria and boundary conditions are yet considered. Future extensions will consider additional constraints, such as fixed locations of stations, weighted importance of buildings, maximum track radii, and vertical inclinations, which will be included in the fitness function to optimize the tunnel alignment.

ACKNOWLEDGEMENTS

This research is funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – Project number: 77309832 within Subproject C1 of the Collaborative Research Center SFB 837 “Interaction Modeling in Mechanised Tunnelling”.

REFERENCES

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

Bui, H.-G., D. Schillinger, Y. Zendaki, and G. Meschke (2022). A cutfem based framework for numerical simulations of machine driven tunnels with arbitrary alignments. *Computers and Geotechnics 144*, 104637.

Cao, B., M. Obel, S. Freitag, P. Mark, and G. Meschke (2020). Artificial neural network surrogate modelling for real-time predictions and control of building damage during mechanised tunnelling. *Advances in Engineering Software 149*, 102869.

Cao, B.-T., S. Freitag, and G. Meschke (2016). A hybrid rnn-gpod surrogate model for real-time settlement predictions in mechanised tunnelling. *Advanced Modeling and Simulation in Engineering Sciences 3*(1), 1–22.

Cao, B. T., M. Obel, S. Freitag, L. Heußner, G. Meschke, and P. Mark (2022). Real-time risk assessment of tunneling-induced building damage considering polymorphic uncertainty. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering 8*(1).

Elhaddad, M., N. Zander, T. Bog, L. Kudela, S. Kollmannsberger, J. Kirschke, T. Baum, M. Ruess, and E. Rank (2017, 12). Multi-level hp-finite cell method for embedded interface problems with application in biomechanics. *International Journal for Numerical Methods in Biomedical Engineering* 34.

Freitag, S., B. Cao, J. Ninić, and G. Meschke (2018). Recurrent neural networks and proper orthogonal decomposition with interval data for real-time predictions of mechanised tunnelling processes. *Computers & Structures 207*, 258–273. CIVIL-COMP 2017.

Hardy, R. L. (1990). Theory and applications of the multiquadric-biharmonic method: 20 years of discovery 1968-1988. *Computers & Mathematics With Applications 19*, 163–208.

Marwan, A., V. E. Gall, A. Alsahly, and G. Meschke (2021). Structural forces in segmental linings: process-oriented tunnel advance simulations vs. conventional structural analysis. *Tunnelling and Underground Space Technology 111*, 103836.

Ostrowski, Z., R. Bialecki, and A. Kassab (2008, 01). Solving inverse heat conduction problems using trained pod-rbf network. *Inverse Problems in Science and Engineering 16*, 39–54.

Schindler, S. and P. Mark (2013). Evaluation of building stiffness in the risk-assessment of structures affected by settlements.

Shi, Y. and R. C. Eberhart (1998). Parameter selection in particle swarm optimization. In V. W. Porto, N. Saravanan, D. Waagen, and A. E. Eiben (Eds.), *Evolutionary Programming VII*, Berlin, Heidelberg, pp. 591–600. Springer Berlin Heidelberg.

Zendaki, Y., B. T. Cao, S. Freitag, and G. Meschke (2022). Simulation-based surrogate models for real-time tunnel lining behavior predictions. In *International Conference on Computational Methods and Information Models in Tunneling (EURO:TUN)*.

Zendaki, Y. and G. Meschke (2022). Adaptive mesh refinement using octree for finite cell simulation and its application for tunneling in saturated soils. *PAMM 22*(S4).