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A Hybrid Finite Element and Surrogate Modelling Approach for Simulation and Monitoring Supported TBM Steering

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Abstract

The paper proposes a novel computational method for real-time simulation and monitoring-based predictions during the construction of machine-driven tunnels to support decisions concerning the steering of tunnel boring machines (TBMs). The proposed technique combines the capacity of a process-oriented 3D simulation model for mechanized tunnelling to accurately describe the complex geological and mechanical interactions of the tunnelling process with the computational efficiency of surrogate (or meta) models based on artificial neural networks. The process-oriented 3D simulation model with updated model parameters based on acquired monitoring data during the advancement process is used in combination with surrogate models to determine optimal tunnel machine-related parameters such that tunnelling-induced settlements are kept below a tolerated level within the forthcoming process steps. The performance of the proposed strategy is applied to the Wehrhahn-line metro project in Düsseldorf, Germany and compared with a recently developed approach for real-time steering of TBMs, in which only surrogate models are used.

Keywords: Mechanized tunnelling; finite element method; parameter identification; surrogate model; recurrent neural network; computational steering; tunnel boring machine; monitoring; settlements; real-time prediction

1. Introduction

Mechanized tunnelling is a flexible and efficient technology for the construction of underground infrastructure, which is characterized by a dynamic technological progress of tunnel boring machines (TBMs) and an increasing range of applicability to various ground conditions [1]. During TBM-driven tunnelling in urban environments, in particular in the presence of sensitive buildings, the risk of damage caused by construction-induced settlements needs to be limited. To this end, computational models are required to efficiently and reliably predict the expected response of the ground and existing infrastructure to the tunnel drive.

Engineering decisions during the construction process are based, besides the (often limited) a priori knowledge from analyses made in the design stage of the project, mainly on the interpretation of data from on site monitoring including data related to soil deformations, pore pressure and machine performance. However, the capacity of computational models to quantify the effect of engineering decisions on stability and safety at the construction site during the tunnel drive is not exploited.

The mechanized tunnelling process involves complex spatio-temporal interactions between the TBM, the tunnel structure, the surrounding soil and the existing infrastructure. In addition to empirical and analytical relations for the

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description of surface and subsurface settlements induced by tunnelling [2, 3, 4], 2D and 3D numerical analyses have been applied (see [5, 6, 7, 8] and references therein) to model the tunnelling process and the physics behind it more accurately.

Numerical analyses of geotechnical problems are characterized by a large number of problem-dependent model parameters related, among others, to the geotechnical specifications of the ground. In case of tunnelling, these parameters may have a significant spatial variability [9]. Furthermore, in the design stage, only limited information on the specific soil parameters is available from distinct boreholes, which limits the quality of the model parameters based upon these data. Therefore, in geotechnical analysis, to reduce the uncertainty of model parameters, back analysis based on in situ measurements is often used for the calibration of numerical models to determine more reliable updated model parameters. Several authors have addressed inverse analysis for geotechnical processes, see e.g. [10, 11, 12]. If optimization algorithms such as Particle Swarm Optimization (PSO) [13] are used for inverse analyses, often a large number of realizations is required. Since this is connected with a prohibitively large effort if large-scale 3D finite element models are used, often surrogate models (alternatively also denoted as meta models) are employed for the evaluation of the objective functions [14, 15]. In [16], this approach is used for back analysis of material parameters and steering of the mechanized tunnelling process.

Surrogate models are a compact representation for the simulation model, and can be generated based on different methods, e.g. regression models, Artificial Neural Networks (ANNs), Proper Orthogonal Decomposition (POD), etc. (see [16, 17] and references therein). In geotechnical problems, ANNs have been applied as surrogate models trained by means of numerical simulations and used e.g. for the prediction of the deformations induced by geotechnical interventions [15] or for the prediction of tunnelling-induced settlements [18, 19, 20, 21, 22]. Hybrid surrogate modelling approaches in mechanized tunnelling combining POD and ANNs are presented in [23] and [24].

For computational prognoses during construction, (almost) real-time predictions are required. If numerical simulation models would be employed, the required continuous model update during the tunnel drive would only be possible using massive parallelization. This is not feasible for most practical applications. To overcome this obstacle, an approach to support the TBM steering based upon surrogate models has been proposed in a recent paper by the authors [16]. Feedforward neural networks have been used to substitute the computationally demanding 3D finite element simulation models. Evidently, this approach only provides an approximation of the tunnelling-induced settlements, which relies on the a priori parameterization of the surrogate model. It is not able to provide detailed information on the tunnel-ground interaction with a resolution comparable to an advanced numerical simulation model. Therefore, in this paper, a novel hybrid FE-surrogate modelling strategy is proposed for the support of the TBM steering during construction with model parameters updated according to monitoring data in association with adequately designed surrogate models used to determine optimized steering parameters. In contrast to [16], Recurrent Neural Networks (RNNs) [25] are employed, which are able to account for history-dependent processes. This approach combines the advantage of surrogate models to provide fast computations needed for the numerous realizations involved in the parameter identification and the iterative determination of optimal steering parameters with the accuracy provided by a process-oriented finite element model in regards to the consequences of the tunnel drive on ground deformations, buildings, lining stresses etc.

The proposed strategy is demonstrated by means of real project data from the Tunnelling Information Model (TIM) [26] of the Wehrhahn-line (WHL) metro project in Düsseldorf. Based on the project data, sensitivity analysis are conducted first to preselect a set of relevant material and machine-operational parameters, which are then used to set up numerical simulations using a process-oriented 3D Finite Element (FE) simulation model for mechanized tunnelling [7, 27] in order to generate the surrogate model. In this work, an RNN surrogate model [25] is applied, which is trained using an optimized back-propagation algorithm [16].

The remainder of the paper is organized as follows: Section 2 introduces the overall concept for simulation-supported steering in mechanized tunnelling, the RNN and the hybrid FE-surrogate modelling approach. In Section 3, the 3D FE model for a selected section of the Wehrhahn-line metro project in Düsseldorf is presented. Using a complete data set of the selected project section, the generation of the surrogate model, the parameter identification and the model-supported steering is demonstrated in Section 4. In this section, also a comparison with a recently proposed approach for real-time steering based on surrogate models only is provided.

2. TBM steering concept combining surrogate models and finite element simulations

Prior to the construction of a TBM-driven tunnel, the parameters of the tunnel boring process to be used in the project are determined in the design stage according to geological explorations to satisfy design objectives such as tolerated surface settlements, safety against loss of face stability and other specific construction requirements. However, during tunnel construction, due to on site ground conditions, which differ from the original assumptions, the settlements often exceed tolerated values. This is of particular importance in tunnelling in urban areas, where the existing infrastructure may be affected by damage caused by tunnelling-induced ground settlements. Controlling the TBM process parameters, denoted in the following also as steering parameters (i.e. the support pressure, grouting pressure, advance rate, etc.), it is possible to control the surface settlements and to reduce or even prevent damage of existing infrastructure.

The conceptual outline of simulation-supported process control in mechanized tunnelling is illustrated in Fig. 1. It contains the generation of surrogate models in the design phase, the model update based on monitoring data and the determination of optimal steering parameters to keep the ground settlements below tolerated values.

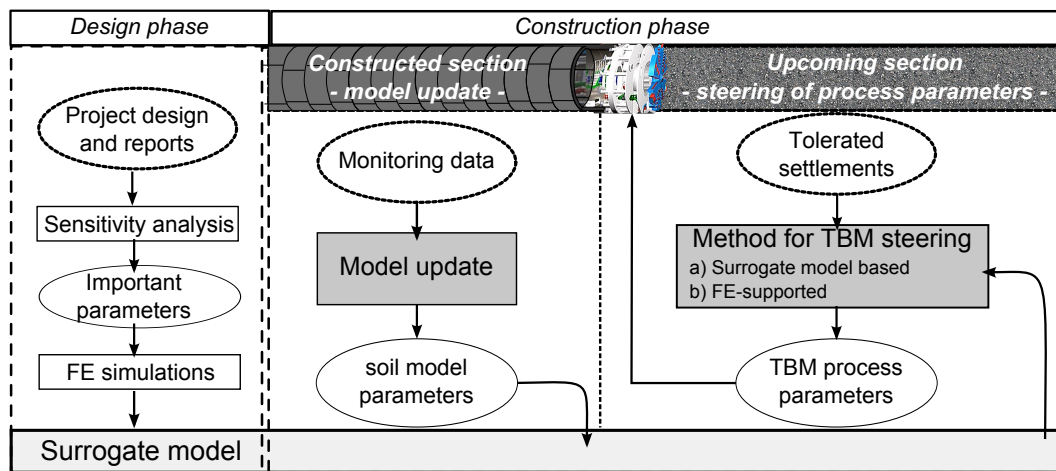


Figure 1. Concept of the simulation-supported process control in mechanized tunnelling.

After the selection of the relevant project sections, in which the steering support will be needed, surrogate models are generated in the design phase of the project especially for these sections.

A 3D numerical model of a tunnelling project characterized by a complex geotechnical situation generally requires a large number (from around ten to more than 100) parameters to characterize the geotechnical model, the alignment, the TBM and the lining shell, including a number of operational parameters and parameters related to the existing infrastructure. Some of the model parameters are well determined (geometry of TBM and lining), while geotechnical parameters such as the topology of soil layers and material parameters of the soil are usually associated with uncertainties and hence are provided in general only as a set of admissible ranges.

If all uncertain parameters are taken into account, it would be extremely time consuming to reach a good quality of the surrogate model. Therefore, prior to the generation of the surrogate model, a sensitivity analysis has to be conducted to determine a set of important parameters sensitive to the output of the model [16]. Based on pre-selected important parameters, a reliable surrogate model is generated in the design phase as shown in Fig. 1. The algorithm for the generation of reliable surrogate models for tunnel sections is summarized in the Appendix (Table 3). In this paper, an RNN is used for the generation of the surrogate model. RNNs (in contrast to feedforward ANNs) are able to represent space-time dependencies, which is essential to consider time-dependent processes occurring during the mechanized tunnelling. The RNN model is described in the following Section 2.1.

The surrogate model is used for the update of geotechnical parameters according to monitoring data acquired on site during tunnel construction. For the model update, back analysis is performed using the Particle Swarm Optimization (PSO), an evolutionary algorithm, which is able to provide global optima. The realizations needed for the evaluation of the objective function are performed by means of the RNN surrogate model.

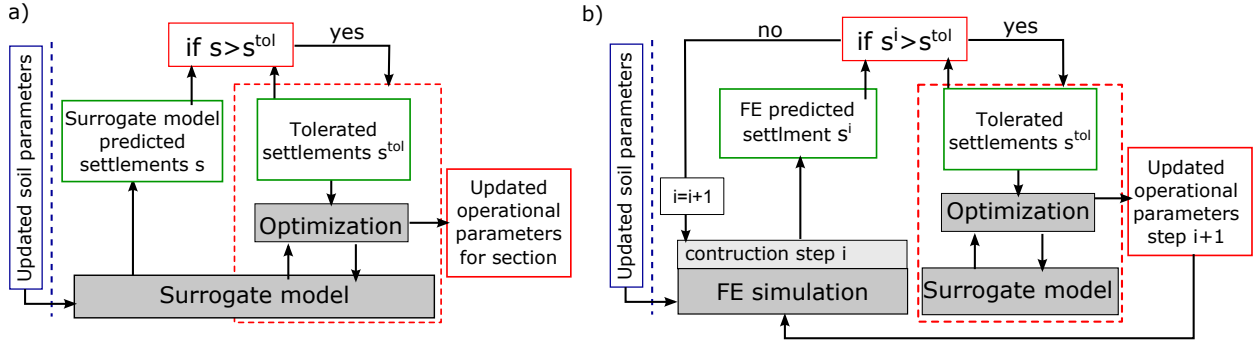


Figure 2. Strategies for the steering support of TBMs: a) Surrogate model-based steering [16]; b) Hybrid FE and surrogate model-based steering.

During the tunnel construction, the process parameters, such as the face and the grouting pressure, are adjusted to control the tunnelling process to satisfy various requirements for safety and stability of the system (e.g. tolerated surface settlements, tunnel face stability, damage induced in buildings). Since the surface deformations are in general relevant for the risk assessment during the construction process, in the following, the tolerated maximum surface settlement s^{tol} is chosen as a control criteria in this study. In [16], the surrogate model with updated model parameters has been directly used for settlement predictions, which provides an almost instantaneous response. Therefore, if the tolerated limits s^{tol} are exceeded, the process (steering) parameters are optimized, such that the predicted settlements s for all excavation steps within the section remain below the given tolerance. This surrogate model-based approach for real-time steering of TBMs is illustrated in Fig. 2a.

However, the excavation process affects the behaviour of all model components involved in mechanized tunnelling and their mutual interactions, which cannot be quantified by the surrogate models. Therefore, a new hybrid approach combining surrogate model-based steering and process-oriented finite element simulation is introduced in Subsection 2.2. Using surrogate models, the process parameters are optimized in each construction step i , if the simulated settlements s_i exceed the tolerated settlements s^{tol} . The final system response based on optimized parameters is evaluated by means of the FE model (see Fig. 2b).

2.1. RNN-based surrogate model

In order to be used in real-time, the computationally expensive FE simulation model is substituted by a surrogate model generated offline for a pre-selected section of the tunnel project. The training of the surrogate model is performed in the design stage of a project, and therefore is not time-critical. In [16], a procedure for the automated generation of an input set for 3D FE simulations of a straight tunnel, the data processing and the generation of a feed-forward neural network-based surrogate model have been proposed. In this paper, this method is extended to account for time-dependent processes by using RNN architectures [25]. RNNs are able to learn dependencies between data series without considering time as an additional input parameter. They allow to capture time-dependent phenomena in data series and to predict (extrapolate) the future structural responses.

Figure 3 illustrates the structure of the Extended Elman's network as proposed in [28]. As an extension to feed-forward neural networks, a context layer is added to each hidden layer and to the output layer. The processing units of those layers are so-called context neurons, which are activated by the output of their corresponding hidden/output neurons. In this type of neural networks, the input \mathbf{x}^t is processed from the input nodes through the hidden layers of the network to compute the output y_j^t of a hidden neuron:

$$y_j^t = f \left(\sum_{i=1}^n w_{ji} x_i^t + \sum_{i=1}^m c_{ji} z_i^{t-1} + \theta_j \right) \quad \text{where} \quad z_i^t = f \left(y_j^t \alpha_i + z_i^{t-1} \lambda_i \right). \quad (1)$$

In Eq. (1), z_i^t is the output of the context neuron at time t , w_{ji} and c_{ji} are weighting coefficients of the input and context neurons, respectively, θ_j is a bias, α_i is a memory factor and λ_i represents the feedback factor of the i th context neuron. Both α_i and λ_i are deterministic values in the interval $[0, 1]$ and are randomly chosen at the beginning of the training

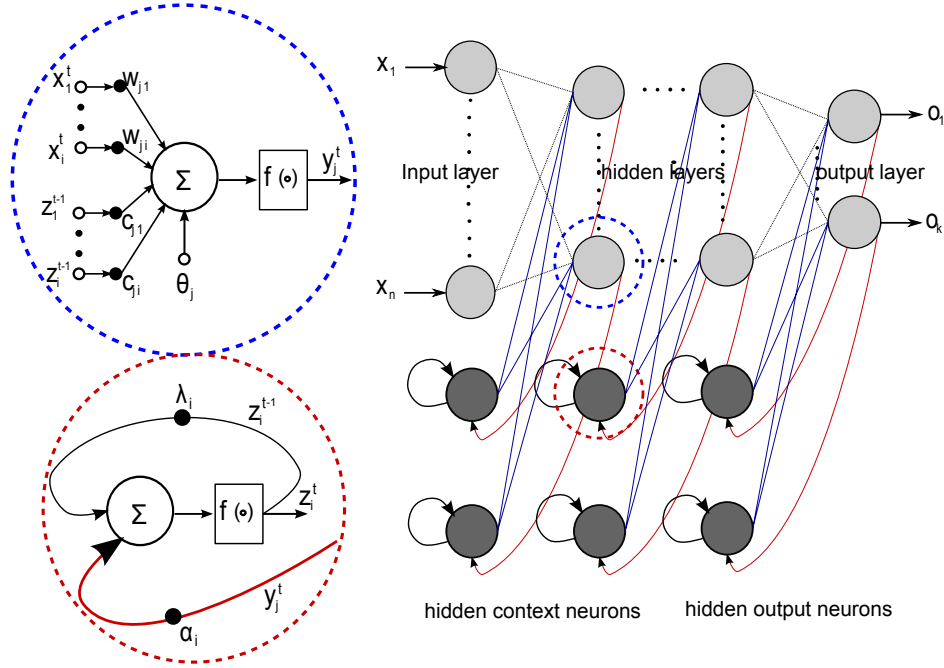


Figure 3. Schematic illustration of the structure of an RNN according to [28].

process and then kept fixed. The information is similarly processed in all hidden layers by the sigmoid activation function $f(\bullet)$ and finally passed to the output of the network, taking the output of the nodes of the previous layer as the input of the current layer.

The goal of the learning process is to adjust the synaptic weights of hidden and context neurons such that the output of the network for the given input matches the expected (target) values t_k^t . In the proposed model, so-called “batch mode” learning is used, where the error E^{tot} between predicted and target values of the output nodes m is calculated after processing the set of all input patterns $p = [1, \dots, P]$ within the time step $t = [1, \dots, T]$:

$$E^t = \frac{1}{2} \sum_{k=1}^m (o_k^t - t_k^t)^2 \quad E^{tot} = \sum_{p=1}^P \sum_{t=1}^T E^t . \quad (2)$$

The learning process is accomplished by minimizing the error in Eq. (2), where the gradient of E^{tot} with respect to the input quantities is calculated and the weights are adjusted incrementally for both hidden and context neurons:

$$\Delta w_{ij} = -\gamma \frac{\partial E^{tot}}{\partial w_{ij}} \quad \text{and} \quad \Delta c_{ij} = -\beta \frac{\partial E^{tot}}{\partial c_{ij}} . \quad (3)$$

γ and β are learning rates. In this study, the architecture and the learning coefficients are optimized using PSO similar to the approach recently presented in [16]. In comparison to feedforward ANNs, RNNs show better learning properties for the same number of training cycles.

2.2. Hybrid finite element and surrogate model-based steering of TBMs

In order to perform a back analysis of the parameters of the computational model based on monitoring data in real-time, the computing time should be in the order of seconds to few minutes. In [16], PSO is used in conjunction with computationally cheap surrogate models, which replace the original finite element model, to enable almost instantaneous back analysis of the model parameters. The solution space is initialized with particles described with their position p_{ij} and velocity v_{ij} . The position of the particles is updated in each iteration step based on local and global best positions ($p_{best,i}^{local}, p_{best}^{global}$) according to Eq. (4), moving towards the optimal solution by maximizing the

objective function F in Eq. (5), which is evaluated by means of the RNN surrogate model (Eq. (2)). In Eq. (4), r_1 and r_2 are random numbers uniformly distributed in $[0, 1]$, and ϕ_1 and ϕ_2 are cognition and social learning factors. In Eq. (5), TOL is the tolerance added to avoid singularity of the solution.

$$v_{i,j+1} = w_{ij} + \phi_1 r_1 (p_{best,i}^{local} - p_{ij}) + \phi_2 r_2 (p_{best}^{global} - p_{ij}) \quad \text{and} \quad p_{i,j+1} = p_{ij} + v_{i,j+1} \cdot \quad (4)$$

$$F = \frac{1}{\sum_0^{p_n} E^{tot} + TOL} \quad (5)$$

The complete procedure is described in [16]. The algorithm summarizing the steps for the surrogate model based inverse identification of soil material parameters (mp_0) according to measured settlements $s^{n,mes}$ in the monitoring point n is given in the Appendix (Table 4).

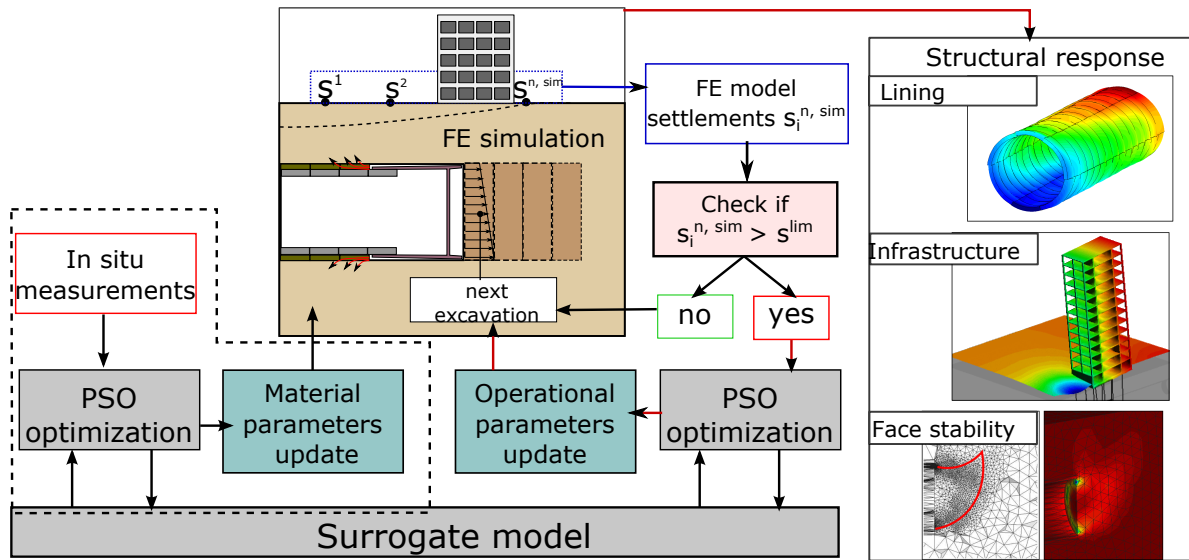


Figure 4. Hybrid FE and surrogate model-supported steering of the mechanized tunnelling process.

Having a surrogate model trained to predict settlements with sufficient accuracy after identification of the soil material parameters (mp^{ident}) at the current stage of TBM advancement, it is possible to control the advancement process for the forthcoming section, such that the settlements (or other target parameters) are reduced to a desired value by optimizing the values of the TBM process parameters (such as support and grouting pressure, advance rate, etc.).

The proposed computational strategy illustrated in Fig. 4 is characterized by combining the full-scale 3D finite element model and the previously described surrogate models during the construction process. In this hybrid concept, the process-oriented simulation model **ekate**, described in Subsection 3.2, is invoked during the construction process using parameters, which have been updated according to monitoring data by means of back analysis using the computationally much cheaper RNN-PSO surrogate model for the investigated tunnelling section. After each TBM advance step i , the surface settlements obtained from the 3D FE simulation ($s_i^{n, sim}$) are checked. In case that prescribed limits s^{lim} are exceeded, the parameters for the steering of the TBM (i.e. the face pressure and the grouting pressure) are optimized, again by using surrogate models according to the procedure described above. These prescribed limits are set as a certain percentage of the tolerated settlements s^{tol} : $s^{lim} = \nu s^{tol}$. The next advancement step is then simulated by means of the FE model adopting the updated (optimized) steering parameters (sp_i^{optim}). During each step, the full response of all components (soil, linings, TBM) involved in the tunnelling process can be directly accessed from the post processing of the numerical simulation. This hybrid strategy assigns computationally intensive tasks, such as the repetitive analysis of the model for different input parameters involved in the back analysis procedure and in the optimization procedure to determine the optimal steering parameters, respectively, to the computationally efficient

surrogate model. The 3D FE simulation model is employed to provide predictions for the current excavation step considering the previously optimized set of model parameters. Since the computation follows the construction step by step, the computational effort is restricted to only simulating these construction steps. By using efficient implementations [29] these computational analyses can be performed in a fraction of the time needed for the real tunnelling process.

The hybrid FE and surrogate model-supported steering procedure is enabled by implementing the previously described RNN-PSO algorithm as a so-called *OptimizationUtility* in the framework of the **ekate** simulation model. Based upon the simulation results, it is now possible to define criteria for calling the surrogate model-based optimization utility and for adapting TBM operational parameters directly within the simulation. The algorithm for performing the FE analysis, checking the correlation of predicted data s_i^{sim} with tolerated limits s_i^{lim} and calling the RNN-PSO model to determine optimized levels for the steering parameters (face pressure and grouting pressure) is described in Table 1.

Initialize FE model and surrogate model	
$mp_i = mp^{ident}$	
$sp_0 = designprocessparameters$	
Calculate ring construction step	
for construction step i	
<i>FESimulation.SetBoundaryConditions</i> (mp^{ident}, sp_i)	
<i>FESimulation.ExcavationStep</i> (time)	
<i>FESimulation.StandStill</i> (time)	
<i>FESimulation.WriteOutput</i> ($s_i^{n,sim}, time$)	
$s_i^{n,sim} < s_i^{n,lim}$	
Yes	No
$sp_i = sp_0$	Optimization of process parameters using RNN-PSO
	<i>PSO.InitializeParticles</i> (p_{jk}, v_{jk})
	<i>j < num_of_iterations</i>
	for each particle(k)
	$s_i^n(time) = RNN.CalculateRNNOutput$ ($mp^{ident}, p_{k,j}$) - Eq. (1)
	<i>PSO.EvaluateObjectiveFunction</i> ($s_i^n(time), s^{tol}$) - Eq. (5)
	Update particle positions and velocity: $v_{k,j+1}, p_{k,j+1}$ - Eq. (4)
	$sp_i = sp_i^{optim} = p_{best}^{global}$
construction step i+1	

Table 1. Algorithm for the hybrid FE and surrogate model-supported steering in mechanized tunnelling

The added value of this hybrid approach is firstly to obtain more accurate results from the 3D simulation model for the optimized set of parameters and secondly to obtain additional insight into the physical behavior of the soil-structure interaction during the machine advance, i.e., how the chosen process parameters affect the interacting system constituted by the tunnelling process, the surrounding soil and existing buildings. Another advantage is that it enables the user to set multiple criteria (multiple objectives and constraints) for the optimization of the process such as the residual safety against loss of face stability in addition to surface settlements. Based on the results acquired from the simulation model during the tunnel drive, new constraints can be set. Each time the optimization procedure is invoked, the design space can be adjusted accordingly to satisfy all prescribed criteria.

3. Simulation model for the Wehrhahn-line project

In this section, a simulation model for mechanized tunnelling is generated according to project data of the Wehrhahn-line (WHL) metro project in Düsseldorf, Germany. For this project, a tunnelling information model has

been established, which is directly interlinked with the numerical simulation model **ekate** via an interaction platform, which enables automated exchange of data and flexible generation of numerical models for selected sections of the tunnel project.

3.1. Tunnelling Information Model

To store all relevant information related to the tunnelling process, to enable seamless integration of this data into the numerical simulation model, and to automate the large number of parametric analyses required for the generation of the surrogate model, a flexible information platform is required. In order to manage the huge amount of time-dependent, dispersed and heterogeneous project data, a holistic spatio-temporal Tunnelling Information Model (TIM) for mechanized tunnelling developed in [26] is used for the present project. All relevant design and construction information of the WHL project in Düsseldorf has been collected, classified, structured and linked within the proposed TIM to support unified access. This model is designed using the concept of Building Information Modeling (BIM) and contains four essential sub-models: the ground data model, the tunnel boring machine model, the tunnel lining model and the built environment model. These models are inherently linked and provide the basis to automatically derive numerical simulation models [30]. The visualization of the information contained in the TIM of a WHL section is shown in Fig. 5.

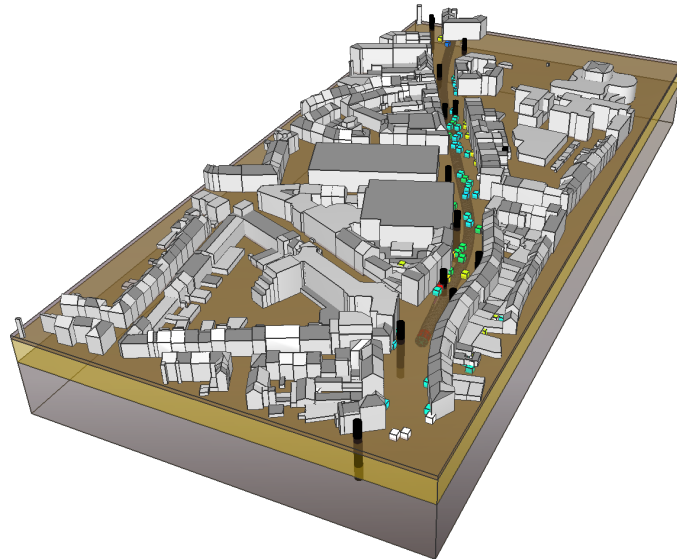


Figure 5. Tunnelling Information Model for the Wehrhahn-line in Düsseldorf: Visualization of soil layers, existing buildings, tunnel alignment, boreholes and measurement points.

The investigated section of the WHL contains a single-tube double-track tunnel excavated with a 9.47 m slurry shield. The ground along the alignment consists of almost homogeneous, horizontally layered soil specified below. For the numerical analysis, a section of the tunnel advance between two stations, namely the Schadowstraße station and Pempelforter Straße station on the eastern section of the project has been selected. This section has been both equipped with a sensor field and observed with radar survey to monitor the settlements during the construction phase of the tunnel [31, 32].

The ground model has been generated from 18 geo-referenced boreholes and groundwater measuring points along the tunnel route [32]. The subsoil consists of four soil layers: surface layer filling (2–3 m to max. 8 m thickness locally); alluvial layer with silt and clay deposits (thickness 0.5–1.5 m to max. 3.5 m locally); low terrace of the river Rhine with sand and gravel of the quaternary (15–25 m thickness); tertiary with slightly silty and medium sandy to silty fine sand (23–25 m below the ground surface level). The selected section for the TIM does not contain the alluvial soil layers. Based on this data, a subsoil section of approximately 730 m × 340 m is defined (see Fig. 5). The overburden varies between 12 m and 16 m, while the ground water table is approximately 8 m to 12 m below the ground surface with temporal fluctuations in the range of 2–5 m.

The size of the simulation domain has been chosen such that disturbing effects on the solution caused by boundary and initial conditions are not affecting the results in the vicinity of the monitoring field. Considering that the soil consists of sandy layers, the soil model used for representation of the soil behavior in this study is Drucker-Prager with non-associative flow rule [33]. Table 2 contains the geotechnical data used in the numerical simulation.

Parameter	Range
Young's Modulus of layer 1 — E_1 [MPa]	10–30
Young's Modulus of layer 2 — E_2 [MPa]	30–150
Young's Modulus of layer 3 — E_3 [MPa]	60–150
Weight of layer 1 — γ'_1 [kg/m ³]	900–1100
Weight of layer 2 — γ'_2 [kg/m³]	1000–1300
Friction angle of layer 1 — ϕ_1 [°]	25–35
Friction angle of layer 2 — ϕ_2 [°]	30–40
Cohesion of layer 1 — c_1 [kPa]	0–3
Cohesion of layer 2 — c_2 [kPa]	0–3
Grouting pressure scaling factor — gp [-]	0.9–1.1
Support pressure scaling factor — sp [-]	0.8–1.2

Table 2. Range of geomechanical and process parameters used for the analysis of the Wehrhahn-line project (in bold face: parameters used for the generation of the surrogate model).

3.2. Numerical simulation model for mechanized tunnelling

The simulation model for mechanized tunnelling **ekate** is generated using the object-oriented FE framework KRATOS [34]. All relevant components of the mechanized tunnelling process (see Fig. 6) are properly modelled in this 3D FE process-oriented simulation model [27, 7] as shown in Fig. 6.

3.2.1. Modelling of the ground

The soft soil is modelled as a two-phase fully saturated material, accounting for the soil matrix and the pore water as distinct phases according to the theory of porous media (see [35] for details). Depending on the type of the soil and available material parameters, two elastoplastic constitutive models are available in **ekate**: the Drucker-Prager model, which is preferably used for sandy soils, and the more general Clay and Sand model, characterized by non-associative plasticity and Lode-angle dependent yield surfaces [36], which is well suited for clayey soil. For the WHL project, Drucker-Prager was used to describe the sandy soil.

Having a fully coupled formulation, it is possible to follow the dissipation of the pore water in time. To accurately model the consolidation process, the actual time required for the excavation steps, the installation of the linings and stand still steps is considered in the set up of the simulation model for the WHL metro. The temporal discretization (i.e. the number and length of the increments) within each of these construction stages is adapted according to the consolidation characteristics of the soil.

In order to allow for a user-friendly input of the soil layers and their material properties, a routine denoted as *MaterialPropertiesUtility* is implemented. Through the simulation script, the material properties are assigned directly to the finite element mesh, storing the respective values at the element Gauss points inside of the polygon defining the respective soil layer, as illustrated in part (1) of Fig. 6.

3.2.2. Shield machine, hydraulic jacks, lining and backup trailer

In the simulation model **ekate**, the shield machine, the hydraulic jacks and the segmented lining are considered as separate components (see parts (2), (3) and (5) of Fig. 6). The TBM is modelled as a deformable body moving through the soil and interacting with the ground through surface-to-surface contact. By virtue of this modelling approach, the volume loss due to the excavation process naturally follows the real, tapered geometry and the over-cutting of the shield machine. For the WHL project the hydro shield machine with a cutting wheel of 9.49 m diameter and a length

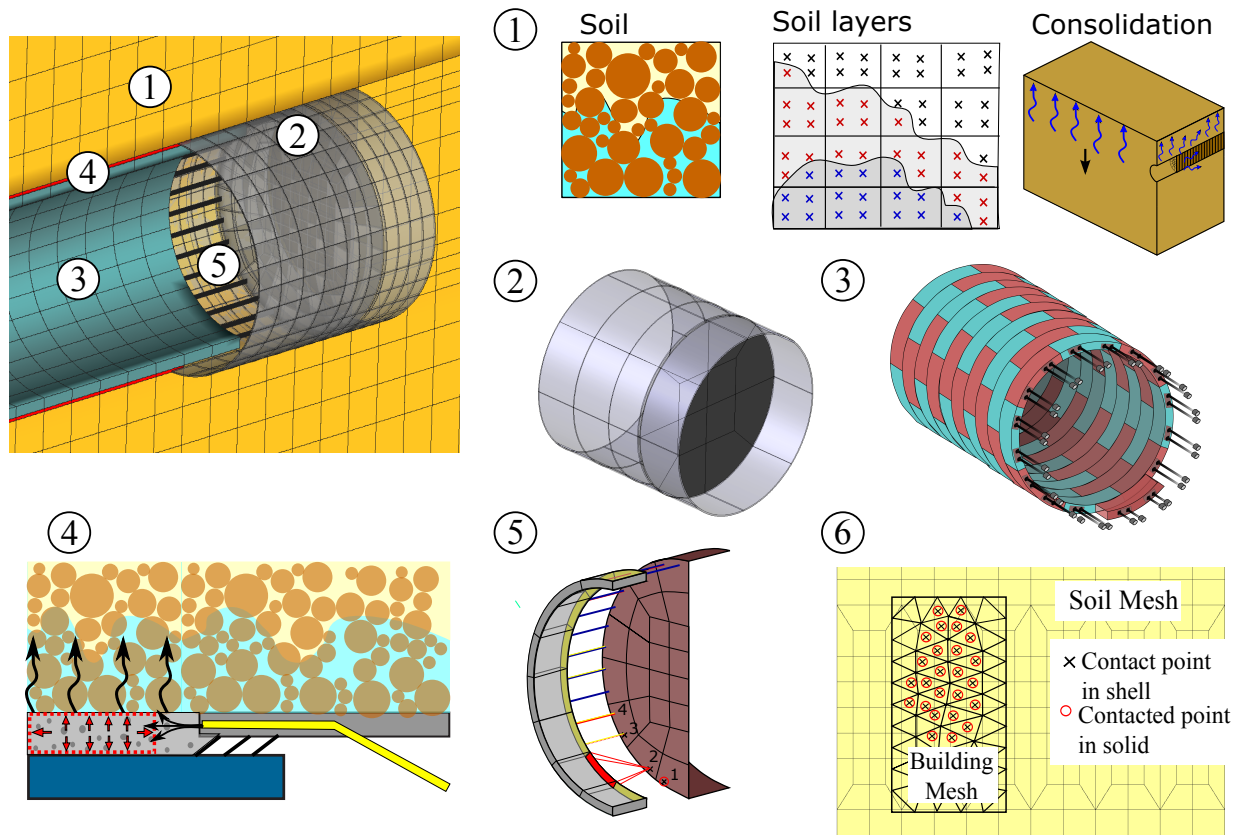


Figure 6. Process-oriented FE model for shield tunnelling **ekate** with relevant components: (1) Surrounding soil, definition of soil layers, consolidation; (2) TBM and frictional contact between shield skin and soil and; (3) segmented lining; (4) tail gap; (5) steering with hydraulic jacks; (6) existing infrastructure.

of 9.42 m with slightly tapered geometry is modelled with linear hexahedral finite elements. The loading from the engine, the lining erector and the backup trailer are applied as surface loads.

The TBM is pushed forward by elongation of the hydraulic jacks, excavating in a step by step procedure. The hydraulic jacks are represented by truss elements tied between the lining and the shield machine.

3.2.3. Modelling of support measures

The annular gap between the segmented lining tube and the excavation boundary is assumed to be refilled with cement-based grouting material, modelled as a fully saturated two-phase material with a hydrating matrix phase, considering the evolution of stiffness and permeability of the cementitious grout [37] (see part (4) of Fig. 6). To provide the stability of the tunnel face due to distortions caused by the excavation process and to reduce ground loss behind the tapered shield, the face support pressure and the grouting pressure are applied at the tunnel face and in the steering gap, respectively (see Fig. 6). In this simulation model, both support and grouting pressure are applied according to data measured during the construction phase. Although for this project about 200 to 300 values from about 250 data sources are collected for each ring, for the simulation model, only averaged values per ring are applied.

3.2.4. Modelling of existing infrastructure

Buildings are considered in the tunnelling model **ekate** by means of reduced models with a substitute elastic stiffness E , height H and weight ρ computed according to an approach proposed in [38]. In the presented FE formulation, isotropic shell elements are adopted with respective structural properties, interacting with the soil through a mesh-independent surface-to-surface contact algorithm, which prevents the penetration of the foundation of the

building into the soil (see part (6) of Fig. 6). It also takes different mechanisms of the soil-structure interaction corresponding to “sagging” and “hogging” modes into account. The geometry of the buildings is imported from the TIM as described in the following subsection and illustrated in Fig. 7.

3.3. Data exchange between the Tunnelling Information Model and the simulation model

Using the TIM for the Wehrhahn-line, the data for the selected section of the tunnel construction site was extracted to create a simulation model. The selected simulation box contains the data of the topology of the subsoil including the geomechanical properties of the soil layers, existing infrastructure with material properties of substitute models for buildings [38], advance rates of the machine and the measured support and grouting pressures (see Fig. 7). All measured data is utilized in the stepwise simulation of the tunnelling process. For instance, the advance rate, which is described with excavation time, ring construction time and stop time is implemented in the simulation of stepwise tunnel advance. Time-dependent effects, such as the consolidation process, are of a great importance for the pressure distribution around the tunnel lining and for the total surface settlements, particularly in the case of large intervals of stop time between two construction steps, which was often the case in this tunnel project.

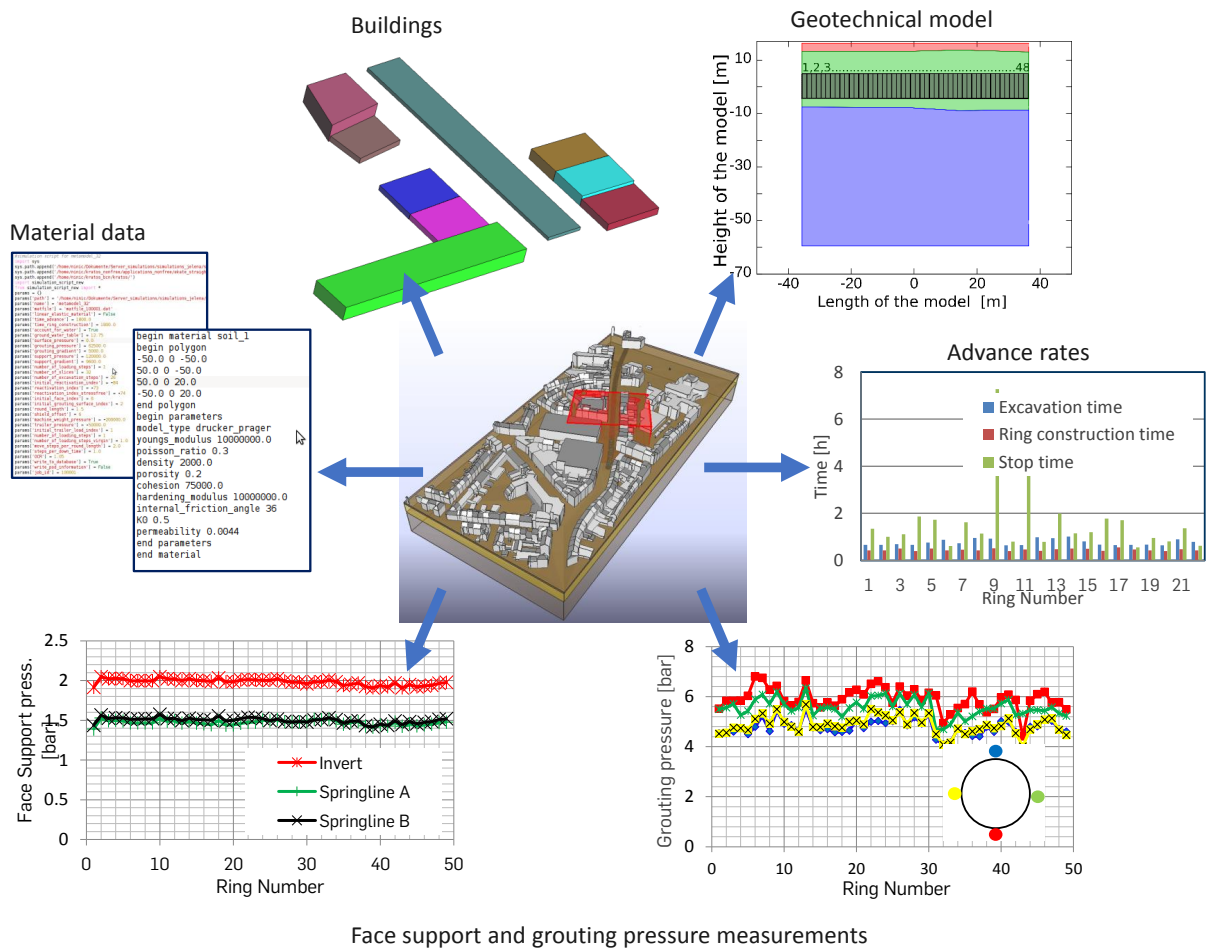


Figure 7. Data exchange between the TIM and the FE simulation model **ekate**.

For the generation of the surrogate model, a series of numerical simulations was performed, extracting the data from the TIM and using an automated *data generator* (see [16]) together with the automatic modeller **ekate** [39] to set up the simulation script for each individual realization. This approach allows for automated and flexible access to tunnel project data, generation and execution of shield tunnelling simulations as well as processing of simulation data

in a form that can directly be used for the generation of the surrogate model. In this context, the following tasks have to be performed:

- Definition of the section of the project to be simulated and the spatial extent of the analysis model in the TIM and acquisition of geometrical and geotechnical information to define the model size, the number of constructed rings and the model boundaries.
- Acquisition of input parameters (e.g. related to the existing infrastructure, machine type, material parameters for soil layers, grout and linings, advancement rate, soil water conditions, etc.).
- Generation of the FE simulation model controlled by a simulation script that is evaluated by a Python interpreter.
- Application of the *data generator* for setting up the numerical experiments based on admissible ranges of geotechnical and process parameters for generation of the surrogate model.
- Execution of the numerical simulations on the available computing resources in parallel using a shared memory system based on OpenMP.
- Postprocessing of the simulation output.
- Training and testing of the RNN-PSO based surrogate model.

4. Simulation and monitoring-supported steering of TBM for the Wehrhahn-line project

This section describes a prototype application of the computational concept for simulation and monitoring-supported steering of TBMs using data from the WHL project together with the simulation model and the surrogate model set up as presented in the previous section.

4.1. Pre-selection of relevant parameters

For the given range of model parameters of the investigated section of the WHL project, a sensitivity analysis has been performed to identify the most relevant model parameters needed to be updated during the TBM advancement. The sensitivity of model parameters strongly depends on the range of the chosen parameters and the target of evaluation. In geotechnical reports available for mechanized tunnelling projects, a range of suitable geotechnical parameters describing the soil properties, water-soil conditions, topology, etc. is generally provided, which can be used to conduct such a sensitivity analysis. In this study, the elementary effect of nine soil and two machine operational parameters on the settlement of a chosen monitoring point is investigated: Young's modulus E_1 , E_2 , E_3 for all three layers, the weight γ'_1 , γ'_2 of layers 1 and 2, the friction angle ϕ_1 , ϕ_2 of layers 1 and 2; the soil cohesion c_1 , c_2 of layers 1 and 2, scaling factors of measured grouting pressure gp and the face support pressure sp) in the range given in Table 2.

Figure 8 contains the results of a sensitivity analysis using the project data of the WHL. As already mentioned, the subsoil consists of three soil layers, see also Fig. 8a. The TBM is passing only through the second layer, a low terrace layer of the Rhine characterized by sand and gravel of the quaternary of approximately 15–25 m thickness.

In Fig. 8b, the normalised absolute mean of the elementary effect $|\mu_j^*|$ of the change of the input parameters on the surface settlement in a monitoring point (\times) (see Fig. 8a) is plotted for different positions of the TBM w.r.t. the measurement section. From this graph, it can be concluded that the grouting pressure and the soil stiffness of the second layer E_2 have the largest relative influence on the surface settlements. The parameters γ'_1 , ϕ_2 , c_1 and c_2 show an almost negligible effect on the surface settlements for the chosen range of parameters. It is also interesting to note the change of the sensitivity of the parameters when the shield machine is approaching (step 17) and passing the monitoring section (step 23). While in the first case, the support pressure plays an important role, in the second case, the grouting pressure becomes dominant.

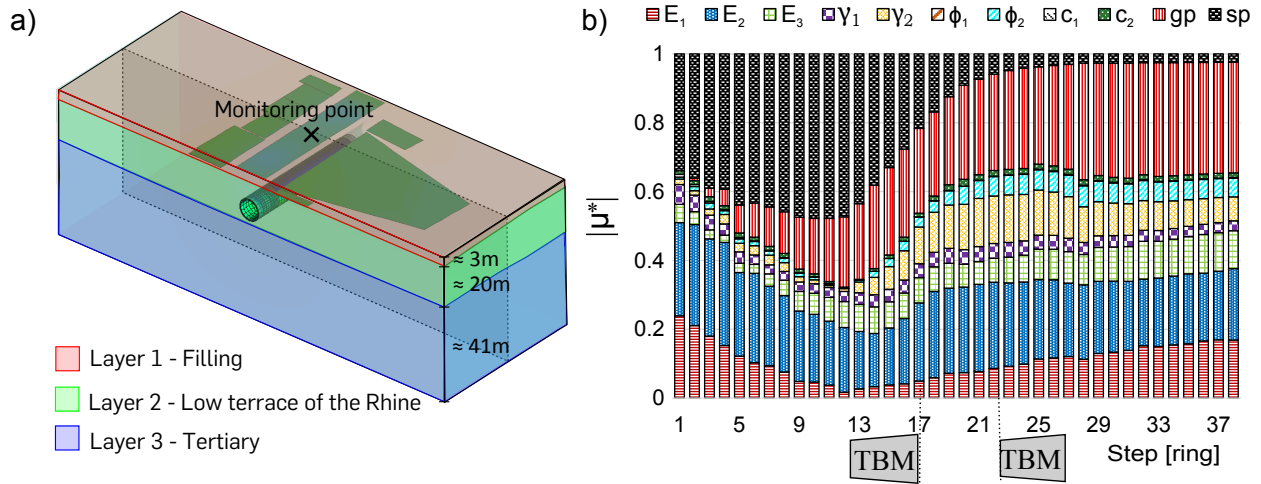


Figure 8. Sensitivity analysis using project data of the Wehrhahn-line. a) Schematic geotechnical section of the model; b) Sensitivity measures of the model parameters w.r.t the settlements in the monitoring point in terms of $|\mu^*|$ for the model parameters ($E_1, E_2, E_3, \gamma'_1, \gamma'_2, \phi_1, \phi_2, c_1, c_2, gp, sp$).

4.2. Surrogate model for the metro project Wehrhahn-line

Using the results of the sensitivity analysis, the surrogate model was created based on a reduced set of the most relevant model parameters ($E_1, E_2, E_3, \gamma'_2, \phi_2$ and gp). Since the accuracy of a surrogate model strongly depends on the number of sampling points and their distribution inside the input parameter space, for this example, a Latin Hypercube Sampling (LHS) strategy has been chosen [17]. The LHS method has a random nature and the generated samples are uniform, if each dimension is viewed separately. For the relevant parameters obtained from the sensitivity analysis, using the LHS method, 100 samples for the training set and 50 samples for the validation set are used, varying the parameters in the ranges described in Table 2.

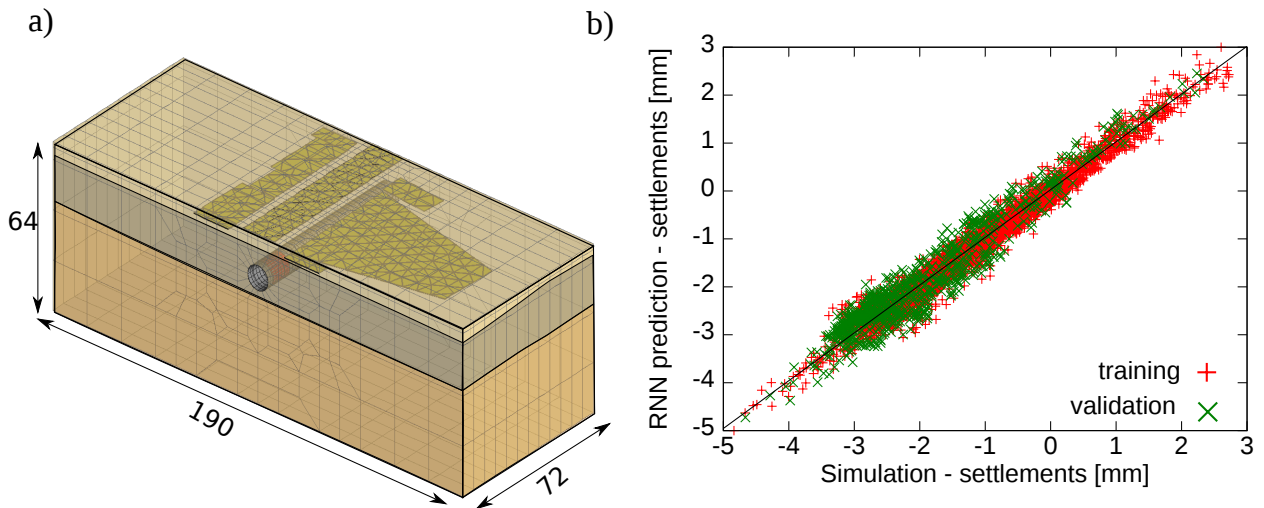


Figure 9. a) Geometry and finite element mesh used for the generation of the surrogate model for a specific section of the WHL project; b) Comparison between settlements obtained from the FE simulation and predictions of the trained surrogate model for the training and validation sets.

The simulation model is concerned with a tunnel of diameter $D = 9.49$ m excavated in 48 steps of 1.5 m length each. The simulation model is shown in Fig. 9a. It has 72 m length, 190 m width and an overburden of 16 m. For

each excavation step and each stage within one advancement step, the real time (advance rate) was properly modelled, accounting for time-dependent effects such as consolidation, water pressure distribution on the tunnel face and grout inflow. In the simulation, the measured support and grouting pressure (per ring) have been used. For the grouting pressure, the values measured at the grouting pipes were adopted with a scaling factor and applied as boundary conditions at the nodes related to the corresponding injection positions of the grouting elements. For each input parameter set with six independent input parameters (six input nodes), the recorded output is the temporal evolution of the surface settlement at a monitoring point, see Fig. 8a. The RNN surrogate model described in Section 2.1 has been trained with optimized architecture and learning rate. The optimized architecture leads to one hidden layer with 20 hidden and respective context (history) neurons. Figure 9b shows the agreement between the settlements at the chosen monitoring point predicted by the surrogate model and the target settlements obtained from the numerical simulations for both training and validation sets. This figure shows that the surrogate model provides good prediction capabilities with a Relative Root Mean Square Error (rRMSE) of 3.1% for the training and 3.5% for the validation set.

Once the surrogate model is set up, it is used for model updating according to the monitoring data. For the surface settlements at the selected monitoring point “+” in Fig. 10, back analyses are conducted to determine precise values of the material parameters summarized in Table 2 within the range given in the geotechnical report. For the back analysis, the surrogate model-based PSO algorithm was used as described in Table 4 in the Appendix. The PSO is initialized with 50 particles and a maximum of 100 iterations.

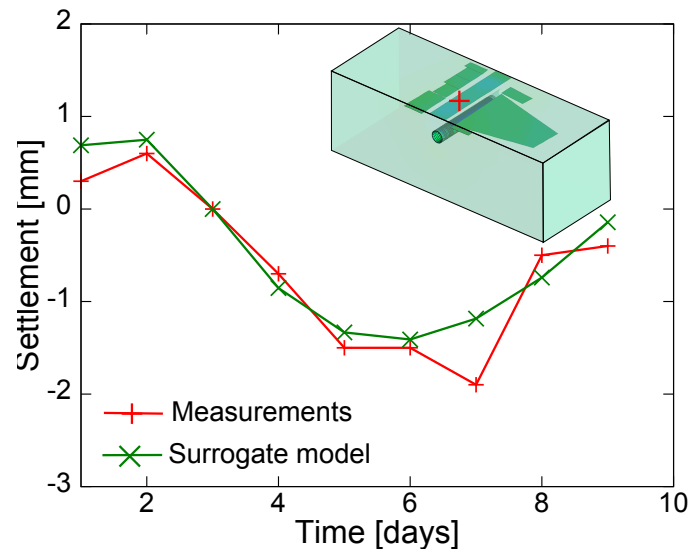


Figure 10. Comparison of the settlements at the monitoring point “+” obtained from monitoring and from predictions of the surrogate model after parameter identification.

Figure 10 shows a comparison between the measurements and the prediction of the surrogate model for the settlements at the monitoring point “+” after the model parameters have been identified from the back analysis. The model parameters from Table 2 have been identified as $E_1 = 30$ MPa, $E_2 = 46$ MPa, $E_3 = 124$ MPa, $\gamma'_2 = 1000$ kg/m³, $\phi_2 = 32.5^\circ$ and averaged $gp \approx 220$ kPa. The predictions of the surrogate model match the in situ measurements for the identified set of parameters very well. Due to the fact that a surrogate model is used for the forward analysis in the PSO algorithm, the back analysis was performed in approximately 5 seconds on a standard PC, converging within the first 20 iterations.

4.3. Model-supported steering of TBM to minimize settlements

If surface settlements were above the critical value, the next step would be an optimization of the TBM-related parameters in order to minimize surface settlements. However, in the WHL project, surface settlements were almost negligible. Therefore, in the following subsection, a “worst case scenario” for the geotechnical parameters, taking the lower bounds of the ranges in Table 2 into account, is assumed to demonstrate the capabilities of the hybrid FE

and surrogate model-based iterative steering of TBM parameters with the goal of minimizing the surface settlements during the TBM advance. To this end, a new surrogate model has been constructed with fixed values of the material parameters (lower bound of given ranges in Table 2), taking into account the variation of the support and grouting pressures scaling factors in the ranges of 0.8–1.2 and 0.6–1.2, respectively. The surface settlement was measured in five points along the tunnel alignment in each TBM advance step. The RNN surrogate model was constructed based on this data using the same procedure as described in the previous subsection, with a prediction accuracy of 98%.

4.3.1. Surrogate model-based steering

In this example, the previously developed surrogate model-based steering strategy, similar to the approach in [16], is applied for minimization of tunnelling-induced settlements. The RNN-PSO algorithm, outlined in Fig. 2a and summarized in the Appendix (Table 5), is applied to optimize TBM-related parameters to reduce tunnel-induced settlements such that the tolerated limit value of 1 cm is not exceeded. Figure 11 shows the surface settlements predicted by the surrogate model for the initial values of the support and grouting pressures and the settlements after optimization of the support and grouting pressures with the objective that the maximum settlements do not exceed the limit value of 10 mm in five selected monitoring points.

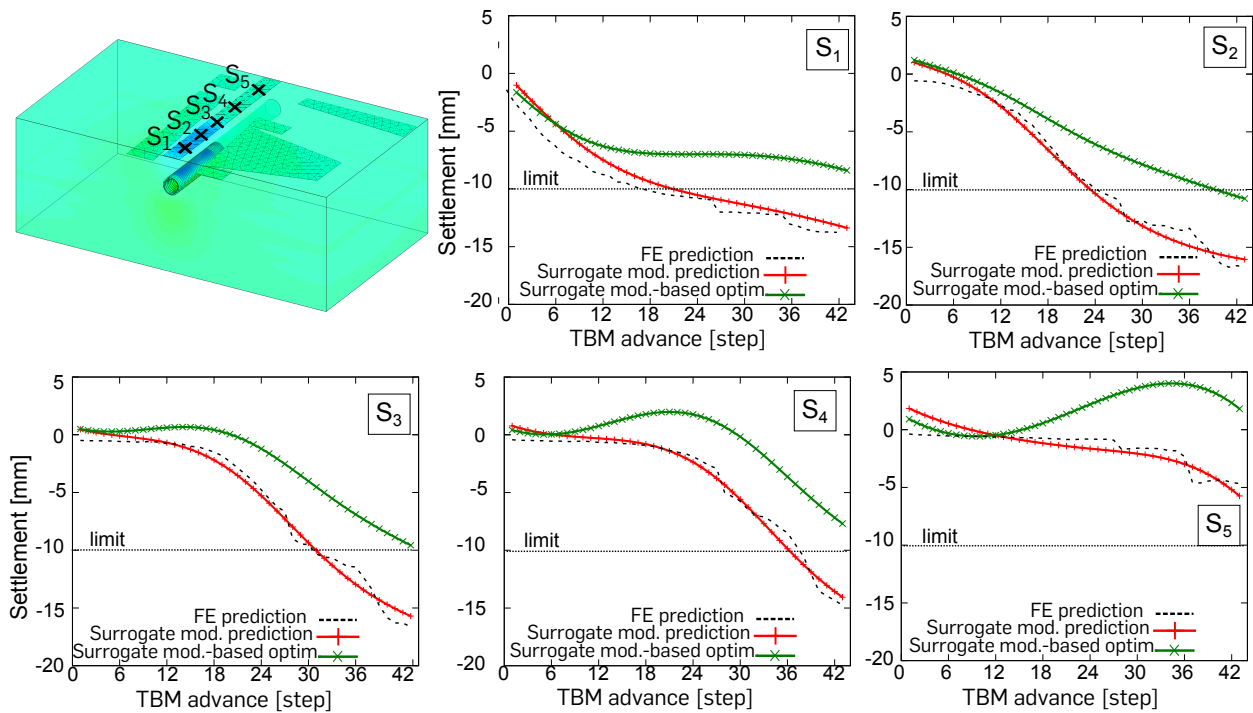


Figure 11. Model-based optimization of TBM-steering parameters: Settlements at five measurement points with and without optimized steering parameters.

The results in Fig. 11 demonstrate the good agreement between the predictions of tunnelling-induced settlements (red line with + mark) from the RNN-PSO surrogate model and the predicted settlements (dashed line) from the 3D FE simulation model. The curves show that the tolerated settlements are exceeded in all monitoring points except the fifth monitoring point. Figure 11 also contains the settlements computed by the surrogate model after optimizing the TBM steering parameters (green line with × mark). The fact that now the maximum settlement of 10 mm is not exceeded in any of the control points demonstrates the efficiency of the surrogate model-based process control of TBMs. However, it has to be noted that although the optimization target has been fulfilled and the maximum settlements for the first four points are kept below the limit, this has a negative effect to the ground displacement of the fifth point, where significant heaving is induced. This is a consequence of the fact that the surrogate model-based steering is conducted

for the complete tunnel section with a time-constant grouting and support pressure. It can be avoided by defining also heaving limit states and optimizing the settlements with time-variant pressures.

4.3.2. Hybrid finite element and surrogate model-supported TBM steering

The new hybrid finite element and surrogate model-supported steering strategy proposed in Section 2.2 is applied to the same section of the WHL project as used in the previous subsection. Starting from the lowest values of the

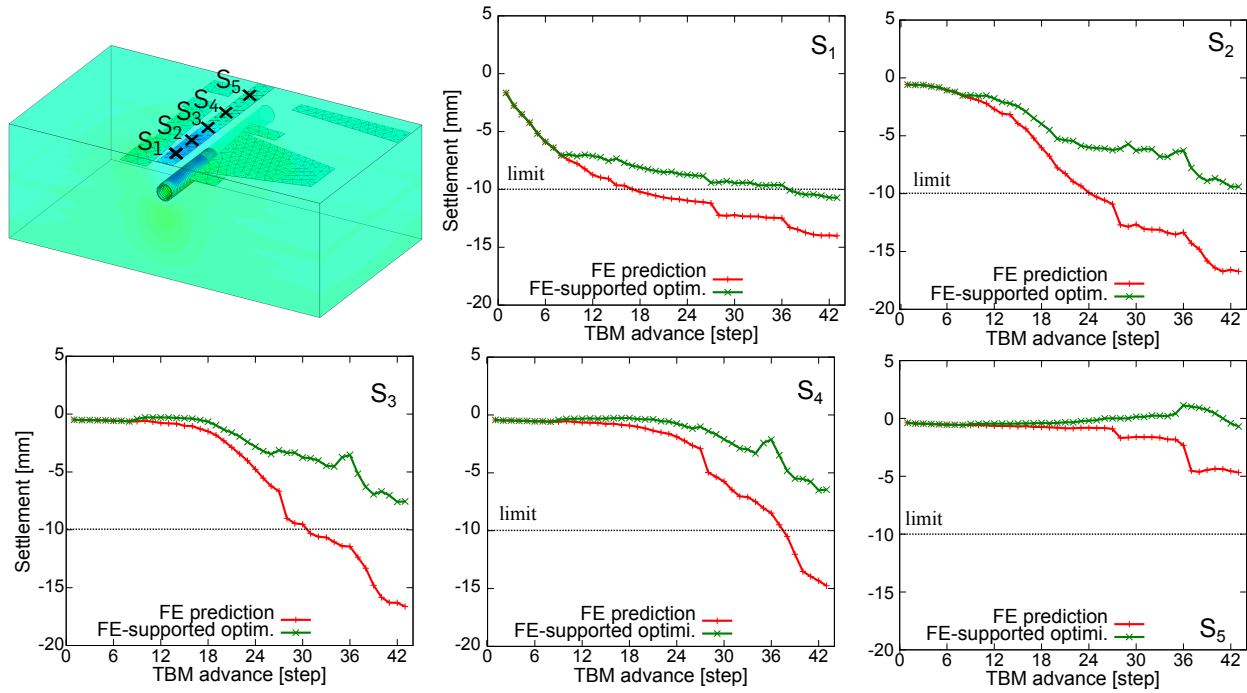


Figure 12. Hybrid FE and surrogate model-supported optimization of TBM steering parameters: Settlements at five measurement points with and without optimized steering parameters.

support and grouting pressure, the iterative steering procedure described in Section 2.2 is applied to minimize the settlements assuming a tolerated limit settlement value of 10 mm. According to Fig. 4, in each excavation step the FE simulation model for the selected section of the WHL project is supplied with continuously updated process parameters obtained from the surrogate model-based optimization algorithm to compute the tunnelling-induced settlement trough. After each TBM advancement step, the surface settlements are checked in all five monitoring points depicted in the upper left part of Fig. 12. If the surface settlements reach 80% of the limit value, the RNN-PSO algorithm is invoked with the objective to optimize support and grouting pressure such that tunnelling-induced settlements do not exceed the tolerated limit. Figure 12 shows the settlements at the selected control points before (red line with + mark) and after (green line with × mark) stepwise optimization of the TBM steering parameters. In this figure, it can be observed that the optimization procedure is first activated in the 9th excavation step, continuing with an updated value of the face and grouting pressure in each step until the end of the tunnel section.

Figure 13 shows the optimized values of the face support (Fig. 13a) and the grouting pressure (Fig. 13b), respectively, in comparison with the initial design parameters. In this figure, it can be seen that the face pressure is almost constantly increased from ≈ 160 kPa to ≈ 175 kPa, while the grouting pressure has a considerably larger variation during the TBM advance due to the high sensitivity of this process parameter w.r.t. the surface settlements as shown in Fig. 8. Furthermore, it is observed from Fig. 13b that a significant drop of the optimized grouting pressure occurs after the 30th TBM advance step. This drop is a consequence of the tendency of the settlements at the measurement point (S_5) to become positive.

Comparing the results of this hybrid FE and surrogate model-based optimization strategy with the surrogate model-based steering control presented in the previous subsection, it is concluded that both strategies satisfy the objective of

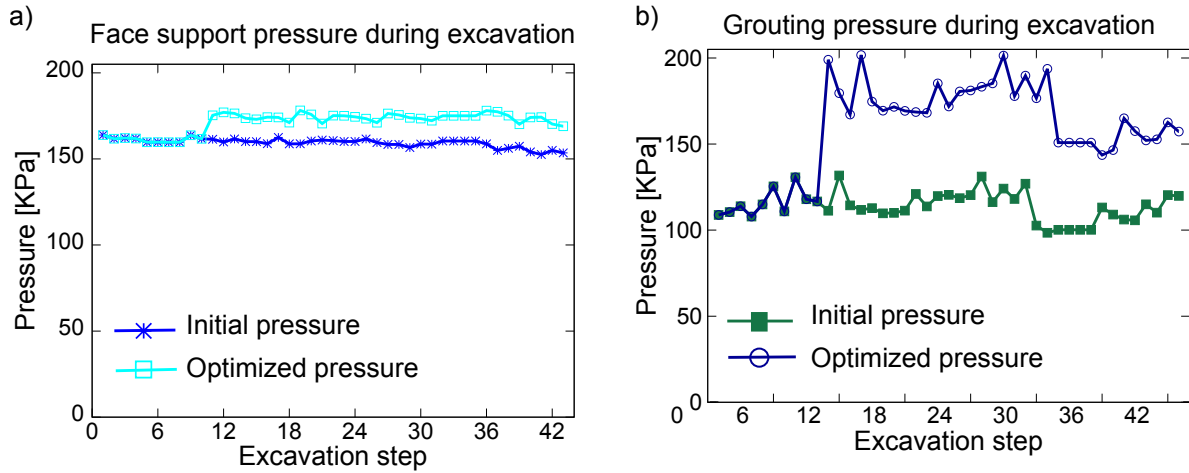


Figure 13. Temporal development of the support and grouting pressure during the hybrid finite element and surrogate model-based optimization of the TBM steering parameters.

keeping the surface settlements below the tolerated limit. However, the FE and surrogate model-supported steering shows an advantage due to the fact that the optimization is continuously supplied with the physical model response and that the steering parameters are iteratively determined based on this response.

In Section 4.3.1, the support and grouting pressures are optimized for the complete tunnel section such that the maximum settlements do not exceed tolerated values. Note that this results in positive displacements (heaving) in the last monitoring point. In the hybrid FE and surrogate model-supported steering, the iterative optimization provides an optimal solution for each TBM advancement step based on the computed settlements, which results in reduced grouting pressures in the last steps (Fig. 13b) satisfying the control objective and avoiding the heaving at the same time. The disadvantage of the new approach as compared to surrogate model-based steering is that it requires the computation of the full 3D finite element model in each advancement step, which is connected with larger computational costs as compared to the surrogate model technique. However, since the TBM process parameters are calculated from numerical simulations of individual advancement steps, depending on the size of the model, this requires computation times in the range of 5–30 minutes, depending on the used hardware. This response time is still acceptable to allow the incorporation of the optimized steering parameters and the computational results into the decision making process at the construction site.

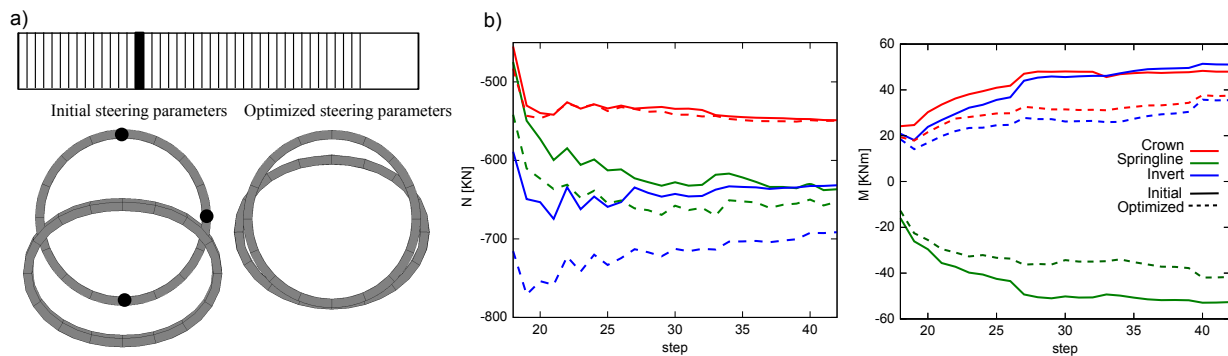


Figure 14. a) Deformed lining ring for initial and optimized steering parameters obtained for the simulation model; b) Normal forces (N) and bending moments (M) for the selected ring in the crown, springline and invert.

One of the major advantages of the FE supported steering is its ability to directly access the effect of steering on all structural components of the system. In Fig. 14, the deformation of a lining ring (Fig. 14a) as well as the evolution of

structural forces during construction (Fig. 14b) for initial (solid lines) and optimized (dashed lines) process parameters are presented. The deformed configuration of the ring, scaled with factor 500 in Fig. 14a, shows that the optimization of process parameters results in a smaller deformation of the lining. This is a consequence of the larger grouting pressure (Fig. 13b), which has a nearly hydrostatic distribution and leads to a dominantly convergence deformation mode and a reduced ovalization as compared to the lower initial grouting pressure. This is directly reflected in the temporal evolution of bending moments (M) in the lining, plotted in Fig. 14b for the crown, the springline and the invert, which are all reduced when using the optimized grouting pressure. On the contrary, the significantly larger grouting pressures after optimization lead to larger normal forces (N).

5. Conclusions

In this paper, a computational strategy for a simulation and monitoring-supported steering of TBMs in real-time has been proposed, which is characterized by combining a process-oriented 3D finite element model and accompanying surrogate models to update the model parameters according to monitoring data and to provide continuously optimized steering parameters such as the grouting or the face pressure to keep the tunnelling induced settlements below a tolerated limit. This procedure was compared to a strategy recently proposed by the authors, which was completely based on surrogate models, restricting the use of the original 3D FE model to a tool for the (offline) training of the surrogate model in the design stage of the project.

The proposed new method consists of three major steps: Firstly, an efficient method for the update of the geotechnical parameters of the computational model for mechanized tunnelling according to monitoring data acquired during the construction process is presented. For this purpose, which involves a large number of realizations, surrogate models based on RNNs are trained in an offline mode in the design stage of a project. The use of RNNs allows to account for the time dependency of the tunnelling process. The relevant geotechnical parameters subject to an update have been selected a priori for the tunnelling section by a sensitivity analysis for parameter ranges obtained from the geotechnical report to preselect the most influencing parameters before creating the surrogate model. Secondly, TBM process parameters used for the stepwise analysis of the tunnelling process are optimized in each excavation step according to prescribed limits for the target settlements. The computation of the optimized process parameters is again accomplished by means of the surrogate model according to the proposed strategy. For the forward analyses during the tunnel advancement, a process-oriented finite element model is used to predict the settlements in the forthcoming steps and, after having optimized process parameters, to predict the complete system response, i.e. the settlements, pore pressures or lining forces.

This method was applied using data of the Wehrhahn-line metro project in Düsseldorf, Germany. The finite element simulation model was created based on data obtained from the TIM for a chosen tunnel section. The actual advance rates of the TBM used in the project have been properly implemented in the simulation model within all excavation steps. In the presented examples, the support and grouting pressures have been updated during the advance of the TBM to keep the tunnelling-induced settlements below tolerated limits during all excavation steps.

It was demonstrated that the surrogate model-based TBM steering support allows for the determination of optimized steering parameters in a few seconds. Although the accuracy of the predictions may be satisfactory for most practical purposes, it was also shown that evidently, the response obtained from the surrogate model relies on a certain prescribed range of values for the parameters and does not provide the complete insight into the physics behind the interactions between the tunnel advancement process, the surrounding soil and the existing buildings. As was shown by a comparative analysis, this disadvantage of the surrogate model technique is compensated by the proposed novel hybrid FE and surrogate model-based approach, since in this procedure, the actual model response is predicted by the 3D process-oriented finite element model, in which all interactions are incorporated independent of the range of parameters. Here, the surrogate model takes the role of determining the updated geotechnical parameters and the optimized steering parameters, respectively. Another advantage of this hybrid method is that in contrast to the surrogate model-based strategy, one can follow the influence of the selected steering parameters through all components of the tunnelling project, which are represented in the numerical simulation model, e.g. the pore pressure distribution in the soil or the level of stresses in the lining shell. This is not possible when using surrogate models only.

Evidently, compared to the surrogate model-based approach, the required computation time is higher. However, since the model is used stepwise simultaneously with the actual tunnel advance, the required response time (in the range of ~5–30 minutes even for large models as used in the presented Wehrhahn-line project) is acceptable to allow

the incorporation of the computational results and the optimized steering parameters into the decision making process at the construction site.

It should be emphasized that this method can be extended by adding multiple criteria for triggering and controlling the process optimization, including target parameters such as the residual safety against loss of face stability in addition to surface settlements or settlement inclinations. Furthermore, a priori information on parameter sensitivity available from the design stage may also be used in the parameter identification process performed during the advancement process to govern the choice and/or magnitude of the optimized TBM parameters.

Evidently, an important ingredient for the model-based determination of process parameters is the consideration of the uncertainty of the geotechnical parameters in front of the tunnel face. This was not addressed in the paper. Uncertainty models such as fuzzy or combined fuzzy stochastic approaches can be incorporated in the proposed concept and may also be performed in real-time. Results from current research on fuzzy stochastic approaches for real time steering of the TBM advancement process in mechanized tunnelling will be presented in a follow-up publication.

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References

- [1] B. Maidl, M. Herrenknecht, U. Maidl, G. Wehrmeyer, *Mechanised Shield Tunnelling*, Ernst und Sohn, 2012.
- [2] R. Peck, Deep excavations and tunnelling in soft ground, in: 7th International Conference on Soil Mechanics and Foundation Engineering Mexico City, 1969, pp. 225–290.
- [3] R. Rowe, K. Lo, G. Kack, A method of estimating surface settlement above tunnels constructed in soft ground, *Canadian Geotechnical Journal* 20 (1983) 11–22.
- [4] F. Pinto, A. Whittle, Ground movements due to shallow tunnels in soft ground: 1. analytical solutions, *ASCE Journal of Geotechnical and Geoenvironmental Engineering*, 140 (4) (2014).
- [5] G. Swoboda, Abu-Krishna, Three-dimensional numerical modelling for TBM tunnelling in consolidated clay, *Tunnelling and Underground Space Technology* 14 (1999) 327–333.
- [6] K. Komiya, Finite element modelling of excavation and operation of a shield tunnelling machine, *Geomechanics and Tunneling* 2 (2) (2009) 199–208.
- [7] G. Meschke, J. Ninić, J. Stascheit, A. Alsahly, Parallelized computational modeling of pile-soil interactions in mechanized tunneling, *Engineering Structures* 47 (2013) 35 – 44.
- [8] N. Do, D. Dias, P. Oreste, I. Djeran-Maigre, Three-dimensional numerical simulation for mechanized tunnelling in soft ground: the influence of the joint pattern, *Acta Geotechnica* 9 (4) (2014) 673–694.
- [9] K. Phoon, F. Kulhawy, Characterization of geotechnical variability, *Canadian Geotechnical Journal* 36 (1999) 612–624.
- [10] M. Calvello, R. J. Finno, Selecting parameters to optimize in model calibration by inverse analysis, *Computers and Geotechnics* 31 (5) (2004) 410 – 424.
- [11] T. Schanz, M. Zimmerer, M. Datcheva, J. Meier, Identification of constitutive parameters for numerical models via inverse approach, *Felsbau, Rock and Soil Engineering* 24 (2) (2006) 11–21.
- [12] J. Meier, Parameterbestimmung mittels inverser Verfahren für geotechnische Problemstellungen, Ph.D. thesis, Bauhaus-Universität Weimar (2008).
- [13] J. Kennedy, R. C. Eberhart, Particle swarm optimization, in: I. Press (Ed.), *Proceedings of the IEEE International Conference on Neural Networks*, Piscataway, NJ, USA, 1995, pp. 1942 – 1948.
- [14] J. Deng, C. Lee, Displacement back analysis for a steep slope at the Three Gorges Project site, *International Journal of Rock Mechanics and Mining Sciences* 38 (2) (2001) 259 – 268.
- [15] B. Pichler, R. Lackner, H. Mang, Back analysis of model parameters in geotechnical engineering by means of soft computing, *International Journal for Numerical Methods in Engineering* 57 (14) (2003) 1943–1978.
- [16] J. Ninić, G. Meschke, Model update and real-time steering of tunnel boring machines using simulation-based meta models, *Tunnelling and Underground Space Technology* 45 (2015) 138 – 152.
- [17] K. Khaledi, S. Miro, M. König, T. Schanz, Robust and reliable metamodells for mechanized tunnel simulations, *Computers and Geotechnics* 61 (2014) 1–12.
- [18] C. Kim, G. Bae, S. Hong, C. Park, H. Moon, H. Shin, Neural network based prediction of ground surface settlements due to tunnelling, *Computers and Geotechnics* 28 (6-7) (2001) 517–547.
- [19] S. Suwansawat, H. Einstein, Artificial neural networks for predicting the maximum surface settlement caused by EPB shield tunneling, *Tunnelling and Underground Space Technology* 21 (2) (2006) 133–150.

- [20] J. Ninić, J. Stascheit, G. Meschke, Simulation-based steering for mechanized tunneling using an ANN-PSO-based meta-model, in: *The Third International Conference on Soft Computing Technology in Civil, Structural and Environmental Engineering*, Civil-Comp Press, 2013, p. paper 5.
- [21] J. Ninić, Computational strategies for predictions of the soil-structure interaction during mechanized tunneling, Ph.D. thesis, Institute for Structural Mechanics Ruhr University Bochum (2015).
- [22] J. Stascheit, S. Freitag, M. Beer, K. Phoon, J. Ninić, B. Cao, G. Meschke, Concepts for reliability analyses in mechanised tunnelling – part 2: Application, in: *Proceedings of the Third International Conference on Computational Methods in Tunnelling and Subsurface Engineering (EURO:TUN 2013)*, Aedificatio Publishers, Bochum, 2013, pp. 801–811.
- [23] B.T. Cao, S. Freitag, G. Meschke, A hybrid RNN-GPOD surrogate model for real-time settlement predictions in mechanised tunnelling, *Advanced Modeling and Simulation in Engineering Sciences*, 3 (5) (2016), 1–22.
- [24] S. Freitag, B. T. Cao, J. Ninić, G. Meschke, Hybrid surrogate modelling for mechanised tunnelling simulations with uncertain data, *International Journal of Reliability and Safety* 9 (2/3) (2015) 154–173. doi:10.1504/IJRS.2015.072717.
- [25] S. Freitag, W. Graf, M. Kaliske, Recurrent neural networks for fuzzy data, *Integrated Computer-Aided Engineering* 18 (3) (2011) 265–280.
- [26] J. Amann, A. Borrmann, F. Hegemann, J. Jubierre, M. Flurl, C. Koch, M. König, A refined product model for shield tunnels based on a generalized approach for alignment representation, in: *Proc. of the 1st ICCBEI 2013*, 2013.
- [27] F. Nagel, J. Stascheit, G. Meschke, Process-oriented numerical simulation of shield tunneling in soft soils, *Geomechanics and Tunnelling* 3 (3) (2010) 268–282.
- [28] A. Zell, *Simulation neuronaler Netze*, Addison-Wesley, Bonn, Paris, 1994.
- [29] G. Bui, J. Stascheit, G. Meschke, A parallel block preconditioner for coupled simulations of partially saturated soils in finite element analyses, in: *The Third International Conference on Parallel, Distributed, Grid and Cloud Computing for Engineering*, Civil-Comp, 2013, p. paper 24.
- [30] J. Stascheit, C. Koch, F. Hegemann, M. König, G. Meschke, Process-oriented numerical simulation of mechanized tunneling using an IFC based tunnel product model, in: *Proceedings of the 13th International Conference on Construction Applications of Virtual Reality (CONVR)*, London, 2013.
- [31] P. Mark, W. Niemeier, S. Schindler, A. Blome, P. Heek, A. Krivenko, E. Ziem, Radarinterferometrie zum Setzungsmonitoring beim Tunnelbau, *Bautechnik* 89 (2012) 764–776.
- [32] S. Schindler, F. Hegemann, A. Alsahly, T. Barciaga, M. Galli, C. Koch, K. Lehner, An interaction platform for mechanized tunnelling. Application on the Wehrhahn-line in Düsseldorf (Germany), *Geomechanics and Tunnelling*, 7 (2014) 72–86.
- [33] D. Drucker, W. Prager, Soil mechanics and plastic analysis or limit design, *Quarterly of Applied Mathematics* 10 (2) (1952) 157–162.
- [34] P. Dadvand, R. Rossi, E. Oñate, An object-oriented environment for developing finite element codes for multi-disciplinary applications, *Archives of Computational Methods in Engineering* 17 (2010) 253–297.
- [35] F. Nagel, G. Meschke, An elasto-plastic three phase model for partially saturated soil for the finite element simulation of compressed air support in tunnelling, *International Journal for Numerical and Analytical Methods in Geomechanics* 34 (2010) 605–625.
- [36] H. Yu, CASM: a unified state parameter model for clay and sand, *International Journal for Numerical and Analytical Methods in Geomechanics* 48 (1998) 773–778.
- [37] T. Kasper, G. Meschke, On the influence of face pressure, grouting pressure and TBM design in soft ground tunnelling, *Tunnelling and Underground Space Technology* 21 (2) (2006) 160–171.
- [38] S. Schindler, P. Mark, Evaluation of building stiffness in the risk-assessment of structures affected by settlements., in: *Proc. 3rd Int. Conf. on Comp. Meth. in Tunneling and Subsurface Engineering - EURO:TUN 2013*, RUB, Bochum, Germany, 2013, pp. 477–486.
- [39] J. Stascheit, F. Nagel, G. Meschke, M. Stavropoulou, G. Exadaktylos, An automatic modeller for finite element simulations of shield tunnelling, in: *Computational Modelling in Tunnelling (EURO:TUN 2007)*, Vienna, Austria, 2007, CD-ROM.

Appendix

Algorithms for surrogate model generation, model update and steering of TBM

The simulation and monitoring supported steering is implemented as a collection of Python scripts, which is used in a highly automated manner to generate surrogate models for selected tunnel sections and to perform inverse analysis of material and process parameters based on measured and tolerated settlements. The steering support tool consists of six main components (“classes”): The FE simulation, the data generator, sensitivity analysis, the RNN surrogate model, the PSO used as the optimization tool and data connected with the construction process. Each class is provided with the list of respective objects and parameters which are summarized in Fig. 15.

FE simulation -geometry -material parameters (mp_i) -process parameters (sp_i) <hr/> +Set boundary conditions (support grouting pressure) +Excavation step +Ring construction step +Stand still (consolidation) +Write output for measured point	Data Generator -FE simulation model (FESim) -design parameters -ranges of parameters -sampling method -computational resources <hr/> +Generate simulations +Compute in parallel +Write the input-output files +Filter the noise	Sensitivity analysis -number of input parameters -input x_{ij} -output y_{ij} <hr/> +Calculate Elementary effect E^j +Calculate absolute mean of E^j
RNN -architecture -synaptic weights: w_{ij}, c_{ij} -input parameters (x_i) -output parameters (o_k) -target output (t_k) <hr/> +Calculate output (Eq. (1)) + Train (Eq. (2)) + Optimize architecture [21]	PSO -number of particles (n^{part}) -position and velocity (p_{ij}, v_{ij}) -input parameters -objective function (F) -trained surrogate model (RNN) <hr/> + Initialize solutions + Evaluate objective function + Update parameters	Construction process -measurements (s_n^{mes}) -tolerated settlements (s_n^{tol}) -material parameters (mp_i) -steering parameters (sp_i) <hr/> +Initialize first step for given section +update parameters

Figure 15. Main classes of the steering support tool including main objects and functions.

Initialize First Construction Step	
$mp_0 = designmaterialparameters$	
$sp_0 = designprocessparameters$	
Predict settlements using RNN for monitoring point n	
$s^n = RNN.CalculateRNNOutput (mp_0, sp_0) - Eq. (1)$	
Yes	$s_n = s_n^{mes}$
No	Back analysis of material parameters using RNN-PSO
$mp_i = mp_0$	$PSO.InitializeParticles (p_{ij}, v_{ij})$
	$i < num_of_iterations$
	for each particle (j)
	$s^n = RNN.CalculateRNNOutput (p_{j,i+1}, sp_0) - Eq. (1)$
	$PSO.EvaluateObjectiveFunction (s^n, s^{tol}) - Eq. (5)$
	Update particle positions and velocity: $v_{j,i+1}, p_{j,i+1} - Eq. (4)$
	$mp^{ident} = p_{best}^{global}$

Table 4. Algorithm for model update: Identification of the soil parameters based on in situ measurements.

Sensitivity analysis for selection of important parameters																	
$i < \text{num_of_params}$																	
<table border="1" style="width: 100%;"> <tr> <td colspan="2" style="text-align: center;">$j < \text{num_of_params}$</td> </tr> <tr> <td colspan="2" style="text-align: center;">$k < \text{num_of_intervals}$</td> </tr> <tr> <td colspan="2" style="text-align: center;">$\text{DataGenerator.GenerateSimulations}(x_j, x_i + \Delta)$</td> </tr> <tr> <td colspan="2" style="text-align: center;">$\text{DataGenerator.ComputeInParallel}()$</td> </tr> <tr> <td colspan="2" style="text-align: center;">$IO = \text{DataGenerator.WriteInputOutputForSelectedPoints}(s^n)$</td> </tr> <tr> <td colspan="2" style="text-align: center;">$\Delta+ = \Delta$</td> </tr> <tr> <td colspan="2" style="text-align: center;">$E_j^i = \text{SensitivityAnalysis.CalculateElementaryEffect}(io)$</td> </tr> <tr> <td colspan="2" style="text-align: center;">$\mu_j^* = \text{SensitivityAnalysis.CalculateSensitivityMeasures}(E_j^i)$</td> </tr> </table>		$j < \text{num_of_params}$		$k < \text{num_of_intervals}$		$\text{DataGenerator.GenerateSimulations}(x_j, x_i + \Delta)$		$\text{DataGenerator.ComputeInParallel}()$		$IO = \text{DataGenerator.WriteInputOutputForSelectedPoints}(s^n)$		$\Delta+ = \Delta$		$E_j^i = \text{SensitivityAnalysis.CalculateElementaryEffect}(io)$		$\mu_j^* = \text{SensitivityAnalysis.CalculateSensitivityMeasures}(E_j^i)$	
$j < \text{num_of_params}$																	
$k < \text{num_of_intervals}$																	
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$\Delta+ = \Delta$																	
$E_j^i = \text{SensitivityAnalysis.CalculateElementaryEffect}(io)$																	
$\mu_j^* = \text{SensitivityAnalysis.CalculateSensitivityMeasures}(E_j^i)$																	
$x_m^* = \text{SensitivityAnalysis.SelectImportantParameters}()$																	
Generation of surrogate model																	
$\text{DataGenerator.HypercubeSampling}(x_m^*)$																	
$i < \text{num_of_samples}$																	
<table border="1" style="width: 100%;"> <tr> <td colspan="2" style="text-align: center;">$\text{DataGenerator.GenerateSimulations}()$</td> </tr> <tr> <td colspan="2" style="text-align: center;">$\text{DataGenerator.ComputeInParallel}()$</td> </tr> <tr> <td colspan="2" style="text-align: center;">$\text{DataGenerator.WriteInputOutputForSelectedPoints}(io)$</td> </tr> <tr> <td colspan="2" style="text-align: center;">$\text{DataGenerator.FilterNoise}()$</td> </tr> </table>		$\text{DataGenerator.GenerateSimulations}()$		$\text{DataGenerator.ComputeInParallel}()$		$\text{DataGenerator.WriteInputOutputForSelectedPoints}(io)$		$\text{DataGenerator.FilterNoise}()$									
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$\text{DataGenerator.WriteInputOutputForSelectedPoints}(io)$																	
$\text{DataGenerator.FilterNoise}()$																	
$\text{RNN.OptimizeArchitecture().Train}(IO)$																	
Return : architecture, wij, cij																	

Table 3. Algorithm for the generation of reliable surrogate models

Initialize surrogate model	
$mp_i = mp^{ident}$	
$sp_0 = \text{designprocessparameters}$	
Predict settlements with trained RNN	
$s_n = \text{RNN.CalculateRNNOutput}(mp^{ident}, sp_0) - \text{Eq. (1)}$	
$s^n < s^{tol}$	
Yes	No
$sp_i = sp_0$	Back analysis of process parameters using RNN-PSO
	$\text{PSO.InitializeParticles}(p_{ij}, v_{ij})$
	$i < \text{num_of_iterations}$
	for each particle (j)
	$s^n = \text{RNN.CalculateRNNOutput}(mp^{ident}, p_{j,i}) - \text{Eq. (1)}$
	$\text{PSO.EvaluateObjectiveFunction}(s^n, s^{tol}) - \text{Eq. (5)}$
Update particle positions and velocity: $v_{j,i+1}, p_{j,i+1} - \text{Eq. (4)}$	
$sp^{optim} = p_{best}^{global}$	

Table 5. Algorithm for surrogate model-based steering