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Real-Time Reliability Analysis in Mechanized Tunneling

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ABSTRACT: Real-time reliability analyses of mechanized tunneling processes can help to reduce the risk of tunneling induced damages and failures. In order to support the machine driver to steer the tunnel boring machine, fast simulation models are required. In this work, polymorphic uncertainty modeling approaches are combined with numerical surrogate models to provide reliability measures in real-time during tunnel construction. Based on a finite element simulation model of the mechanized tunneling process, deterministic and fuzzy surrogate models are created step by step to approximate the tunneling induced time variant settlement field and finally to compute fuzzy probability boxes of the settlements in a few minutes.

1. Introduction

Numerical simulations of mechanized tunneling processes can help to improve the reliability with respect to tunnel face collapse, tunnel lining damage and settlement induced damage of existing buildings and infrastructure. In the design stage of a tunnel project, finite element simulations of the tunneling process can be applied, see e.g. Swoboda and Abu-Krisha (1999); Komiya (2009); Do et al. (2014); Kasper and Meschke (2004), to evaluate the corresponding limit states by adequate reliability measures.

This requires to consider the uncertainties of the geotechnical parameters based on the information from geotechnical reports and expert experience. Also the variability of tunneling process parameters has to be considered for the reliability analyses to guarantee a safe construction workflow. In general, several uncertainty models such as intervals, fuzzy numbers and stochastic numbers have to be used to quantify the input parameters of the simulation model according to the available information taking into account both epistemic and aleatory sources of uncertainty, see e.g. Möller and Beer (2008). By combining Monte Carlo simulations with interval or fuzzy analyses in the framework of polymorphic uncertainty modeling, probability boxes or fuzzy probability boxes are obtained, respectively, to assess the reliability.

These reliability analyses of mechanized tunneling processes with high quality finite element simulation models needs prohibitively long computation times. For real-time reliability analysis, fast numerical surrogate models are required to approximate the tunneling process simulation. In prior works, a hybrid surrogate model has been developed combining artificial neural networks and proper orthogonal decomposition approaches, see Cao et al. (2016). This hybrid surrogate model allows to predict high dimensional time variant interval and fuzzy surface settlement fields in just a few seconds with similar accuracy as the original finite element model, see Freitag et al. (2018); Cao et al. (2018). These approaches are extended to compute high dimensional probability boxes of the tunneling induced surface settlements in a few minutes.

2. Uncertainty Quantification of Soil and Tunneling Process Parameters

Reliability analyses of mechanized tunneling processes, e.g. face stability analyses or settlement predictions, require to consider the unavoidable uncertainty associated with the geotechnical model parameters, e.g. the topology and the material properties of the soil layers. Adequate uncertainty models must deal with the fact, that in general only limited information of these parameters can be obtained from a few borehole data along the tunnel track, see Figure 1.

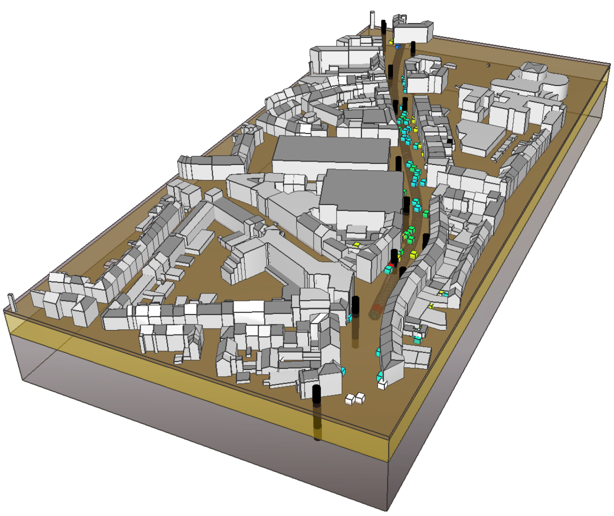

Figure 1: Digital tunneling information model with soil layers, existing buildings, tunnel alignment, boreholes and monitoring points for a tunnel project according to Schindler et al. (2014).

2.1. Intervals

In the geotechnical reports of a tunneling project, often ranges for the soil parameters are provided, see Table 1. In this case, it is not possible, to quantify the variability of the soil parameters by stochastic numbers, because no statistical information is provided.

The given range of a geotechnical parameter may directly be quantified as an interval

$$\bar{x} = [{}_l x, {}_u x] \ , \tag{1}$$

Table 1: Exemplified soil parameter ranges obtained from a geotechnical report.

Geotechnical parameter	Range
Young's modulus E_1 [MPa] of layer 1	10–30
Young's modulus E_2 [MPa] of layer 2	30–90
Friction angle ϕ_1 [°] of layer 1	25–35
Friction angle ϕ_2 [°] of layer 2	30–40
Cohesion c_1 [kPa] of layer 1	0–3
Cohesion c_2 [kPa] of layer 2	0–3

which is defined by its lower bound ${}_l x$ and its upper bound ${}_u x$. The midpoint of the interval $\bar{x}$ is obtained by

$${}_m x = \frac{{}_l x + {}_u x}{2} \tag{2}$$

and the radius of the interval $\bar{x}$ is given by

$${}_r x = \frac{{}_u x - {}_l x}{2} \ . \tag{3}$$

Reliability analyses with intervals requires to perform an interval analysis, which can be done by interval arithmetic operations or optimization based approaches, see e.g. Moens and Vandepitte (2005) for an overview. The reliability can be assessed by searching for the worst case scenario, i.e. by checking if the whole interval range of the results is on the safe side of the limit state.

2.2. Fuzzy Numbers

In order to investigate the sensitivity of the interval range to the results of the reliability analysis, the soil parameters may also be quantified as fuzzy numbers. A fuzzy number $\tilde{x}$ is an interval, which is assessed by a membership function $\mu(x)$ describing the possibility, that a realization x belongs to the fuzzy set $\tilde{x}$.

In the simplest case, a symmetric triangular membership function may be used, where the midpoint of support interval is assessed with a degree of membership $\mu({}_m x) = 1$ and the bounds of the support interval are assessed with a degree of membership $\mu({}_l x) = \mu({}_u x) = 0$.

For reliability analyses with fuzzy numbers, the membership functions of the fuzzy soil parameters are discretized into α-cuts resulting in nested intervals

$${}_\alpha \bar{x} = [{}_{\alpha_l} x, {}_{\alpha_u} x] \ . \tag{4}$$

This allows to represent a fuzzy number by a sorted sequence of the discretized lower and upper bounds, e.g. for three α-cuts

$$\tilde{x} = \langle {}_{1_l}x, {}_{2_l}x, {}_{3_l}x, {}_{3_u}x, {}_{2_u}x, {}_{1_u}x \rangle \ , \tag{5}$$

or by defining a reference point, e.g. ${}_{1_l}x$, and incremental differences Δ to all other bounds, see e.g. Möller and Reuter (2008), e.g. for three α-cuts

$$\tilde{x} = \langle {}_{1_l}x, {}_{1,2_l}\Delta x, {}_{2,3_l}\Delta x, {}_{3,3}\Delta x, {}_{3,2_u}\Delta x, {}_{2,1_u}\Delta x \rangle \ . \tag{6}$$

A reliability analysis with fuzzy numbers can be performed similar to an interval analysis, e.g. by means of fuzzy arithmetic Hanss (2005) or by α-level optimization Möller et al. (2000). The corresponding reliability can be assessed by possibility measures such as the credibility Liu (2006), which describes that the limit state is exceeded by a certain grade between 0 and 1.

2.3. *Stochastic Numbers*

Machine operational parameters may be quantified as stochastic numbers or stochastic processes, because tunnel boring machines are equipped with hundreds of sensors collecting data of the machine operational parameters during the tunnel excavation. In Figure 2, an example of collected data from a pressure sensor in the excavation chamber of a tunnel boring machine is shown. This data may be analyzed in real-time and can be fused with numerical prediction models to make prognoses of the tunneling process behavior for the subsequent excavation steps.

A stochastic number X is quantified by a cumulative distribution function (CDF),

$$F(x) = P(X \leq x) \ , \tag{7}$$

and its corresponding probability density function (PDF)

$$f(x) = \frac{\mathrm{d}F(x)}{\mathrm{d}x} \quad \text{or} \quad F(x) = \int_{-\infty}^{x} f(t)\mathrm{d}t \ . \tag{8}$$

The CDF and PDF has to be estimated from the statistical data base by selecting a suitable distribution type and determining the corresponding distribution parameters.

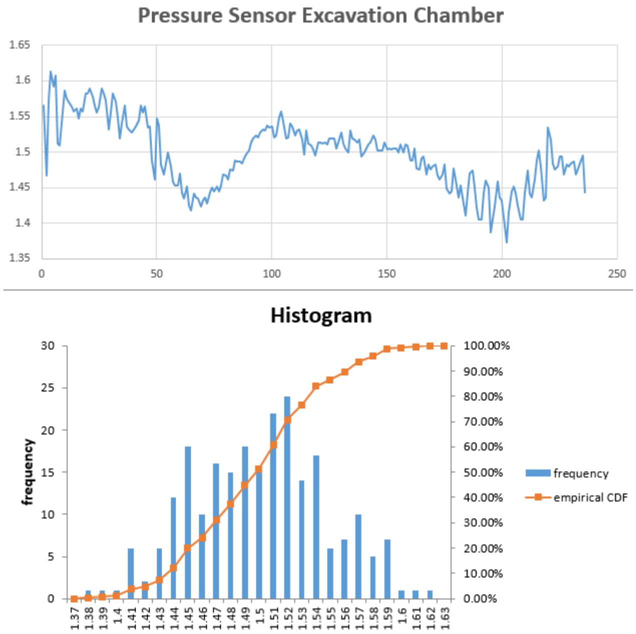

Figure 2: Example of a machine operational parameter of a tunnel boring machine, time series of the pressure in the excavation chamber measured during the excavation and the construction of one tunnel ring, and histogram with empirical cumulative distribution function (CDF).

Reliability analyses with stochastic numbers can be performed by numerical sampling approaches such as Monte Carlo simulation. This leads to probabilistic reliability measures, which describe that the limit state is exceeded by a probability between 0 and 1, i.e. the failure probability.

2.4. *Probability Boxes*

If stochastic and non-stochastic parameters have to be combined within a reliability analyses, imprecise probabilistic results are obtained. Probability boxes (p-boxes) can be created to quantify polymorphic uncertain data, which contain stochastic and interval information.

A p-box $\overline{X}$ is an imprecise stochastic number, which is quantified by its lower bound CDF ${}_lF(x)$ and its upper bound CDF ${}_uF(x)$, see e.g. Ferson et al. (2003). According to Schöbi and Sudret (2017), a free p-box allows to use different stochastic distribution functions, including empirical distributions, for the lower and upper bound CDFs and each distribution inside the p-box is a valid result.

In contrast to this, a parametric p-box (Schöbi and Sudret (2017)) is defined by a bunch of CDFs of the same type (shape), i.e. a CDF with interval distribution parameters, e.g. a Gaussian distribution with an interval mean value. A parametric p-box can also be denoted as interval stochastic number, see e.g. Freitag et al. (2013) and Freitag et al. (2015).

For reliability analyses with free p-boxes, a stochastic analysis with intervals (e.g. interval Monte Carlo simulation Zhang et al. (2010)) has to be performed, whereas for reliability analyses with parametric p-boxes an interval analysis with stochastic parameters is necessary. In both cases, an imprecise probability is obtained as reliability measure, e.g. lower and upper bounds of the failure probability, where the upper bound of this interval failure probability is related to the worst case scenario.

2.5. *Fuzzy Probability Boxes*

The p-box representation of polymorphic uncertain data can also be extended to combinations of stochastic and fuzzy numbers.

A fuzzy p-box $\tilde{X}$ is quantified by lower bound CDFs ${}_{\alpha_l}F(x)$ and upper bound CDFs ${}_{\alpha_u}F(x)$ at each α-cut, see Figure 3. For free fuzzy p-boxes, different stochastic distribution functions, including empirical distributions, can be used for the lower and upper bound CDFs of each α-cut. A parametric fuzzy p-box is a fuzzy stochastic number Möller and Beer (2004), which is represented by lower and upper bound CDFs at each α-cut obtained from a stochastic number with fuzzy bunch parameters, i.e. a CDF with fuzzy distribution parameters, e.g. a Gaussian distribution with a fuzzy mean value.

Reliability analyses with free fuzzy p-boxes require to perform an interval Monte Carlo simulation at each α-cut. Parametric fuzzy p-boxes can be computed by a fuzzy stochastic analysis Möller and Beer (2004). In both cases, the α-level optimization Möller et al. (2000) can be applied to solve the fuzzy analysis part of this combined stochastic and fuzzy analysis. This results in a fuzzy probabilistic reliability measure, e.g. a fuzzy failure probability, which may be assessed by adding a credibility grade to the pure probabilistic reliability measure.

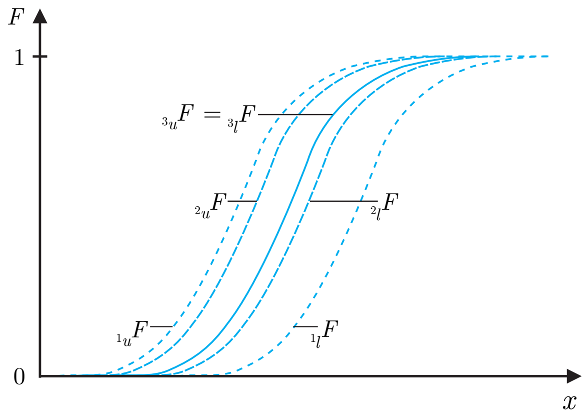

Figure 3: Fuzzy p-box $\tilde{X}$.

3. Surrogate Modeling for Real-Time Reliability Analyses in Mechanized Tunneling

In order to compute the settlement behavior induced by mechanized tunneling excavations, a process-oriented finite element model is applied, see e.g. Alsahly et al. (2016), which considers all relevant components of the tunnel construction process (e.g. the soil and groundwater conditions, the tunnel lining, the shield and the hydraulic jacks of the tunnel boring machine, the tail void grouting and the face support).

The presented reliability analyses approaches require multiple runs of this finite element model with varying uncertain input parameters to compute the corresponding reliability measures. The number of runs depends on the uncertainty model and the quantity of interest to be computed. It is in the range of a few hundred for simple worst case analyses of a single interval output value up to several millions for fuzzy failure probabilities or multiple fuzzy p-box output values.

For real-time reliability analyses during the tunnel excavation and construction, the finite element model has to be approximated by fast surrogate models. Here, it is focused on real-time analyses of time variant settlement fields as a result of interval and fuzzy geotechnical parameters and stochastic machine process parameters in the framework of a free fuzzy p-box approach, see Figure 4.

The surrogate modeling approach in Figure 4 has three levels. At the first level, a hybrid surrogate modeling approach for time varying settle-

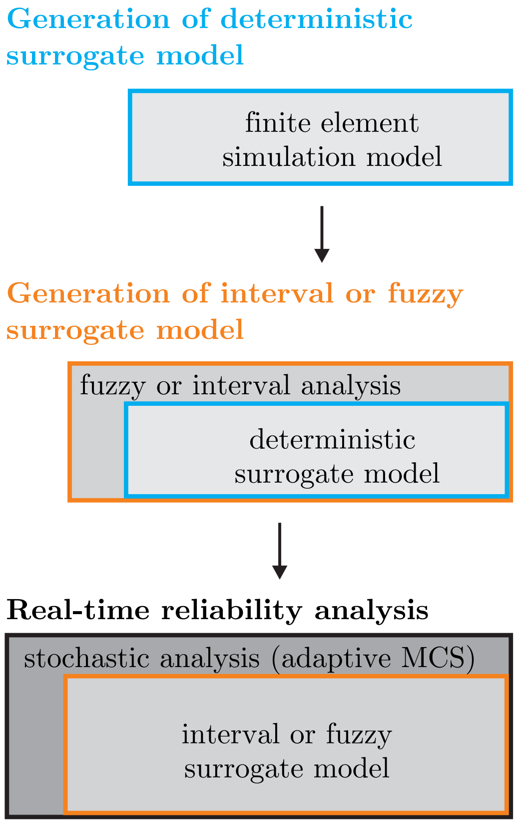

Figure 4: Surrogate modeling approach for real-time reliability analysis with free fuzzy p-boxes.

ment fields according to Cao et al. (2016) is applied to approximate the process-oriented finite element simulation. The hybrid surrogate model is based on a combination of a recurrent neural network to predict the time variant settlements at selected monitoring points and the gappy proper orthogonal decomposition approach to approximate the whole settlement field based on the recurrent neural network predictions and the proper orthogonal decomposition approximations. At the second level, this hybrid surrogate model is applied within an interval or fuzzy analysis to create an interval surrogate model Freitag et al. (2018) or a fuzzy surrogate model Cao et al. (2018), respectively.

Finally, these interval or fuzzy surrogate models can be applied for real-time reliability analyses within an adaptive Monte Carlo simulation (MCS) at the third level of Figure 4. Adaptive MCS means that after each MCS run, the free fuzzy p-box (empirical PDF of the lower and upper bounds of each α-cut) and the corresponding reliability measures are updated and displayed to the user. The MCS can be stopped as soon as enough information is available for making decisions. This allows to significantly reduce the computation time within the fuzzy p-box approach compared to approaches, where only the deterministic finite element simulation model is replaced.

4. Example and Assistance System for Mechanized Tunneling Processes

The fuzzy surrogate modeling strategy presented in Cao et al. (2018) is applied to predict the time variant fuzzy p-boxes of the settlement field induced by a mechanized tunneling process.

In Figure 5, the finite element simulation model of a 144 m $\times$ 220 m $\times$ 67 m tunnel section is shown. It can be seen, that the tunnel with a diameter of 10.97 m has a very low overburden of 6.5 m only. This may lead to critical settlements of a railway track, which is tunneled under by 72 excavation steps with a length of 2 m.

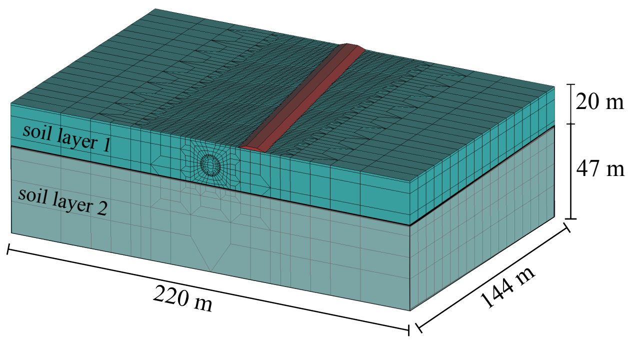

Figure 5: Finite element simulation model of a tunnel section.

The Young's modulus E_1 of soil layer 1 is quantified as fuzzy number with a trapezoidal membership function. It is discretized into two α-cuts, which leads to $\widetilde{E}_1 = \langle 52, 60, 70, 75 \rangle$ MPa. The time variant grouting pressure ${}^{[n]}GP$ and the time variant face support pressure ${}^{[n]}SP$ are quantified as stochastic processes with uncorrelated Gaussian distributions with mean values of 170 kPa and 150 kPa for ${}^{[n]}GP$ and ${}^{[n]}SP$, respectively, and the same standard deviation of 30 kPa.

After creating the deterministic and the fuzzy surrogate models based on finite element simulations, a real-time fuzzy analysis can be performed first by using realizations of the machine parameters ${}^{[n]}GP$ and ${}^{[n]}SP$ as steering parameters. This helps to get a first overview of the settlement behavior and to identify critical points and critical settlement scenarios. In Figure 6, the interval settlement field of an α-cut of excavation step 37 is visualized within the developed tunneling assistant system SMART.

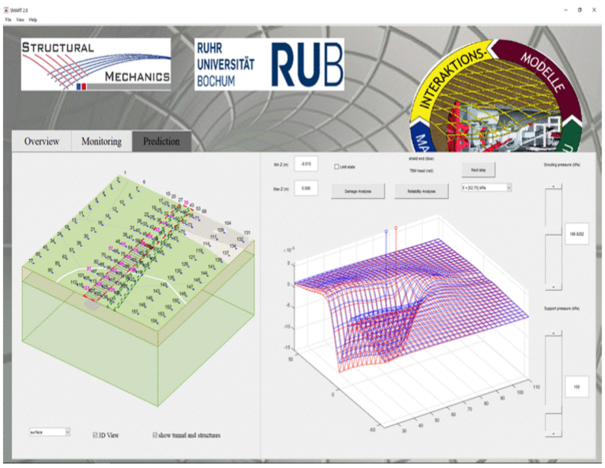

Figure 6: Visualization of an interval settlement field within the software SMART, an application for real-time reliability analyses to support the steering of tunnel boring machines.

It is also possible to track the time variant fuzzy settlement process of selected monitoring points. This is shown in Figure 7, where also the results of the fuzzy surrogate model (solid line) are compared with the reference solution (dashed line) obtained with an optimization-based fuzzy analysis. The relative error of the proposed method is 3.8% in average compared to the optimization based reference solution. The computation time of the fuzzy surrogate model is less than 3 seconds for one excavation step, where the optimization-based approach takes many hours in general.

Finally, free fuzzy p-boxes are computed with adaptive Monte Carlo simulations taking the stochastic distributed machine process parameters ${}^{[n]}GP$ and ${}^{[n]}SP$ and the fuzzy soil parameter $\widetilde{E}_1$ into account. In Figure 8, selected results of the growing fuzzy p-boxes computed with 5 to 1500 samples are presented. In the application SMART, the adaptive Monte Carlo simulation can be stopped at any time, i.e. as soon as enough information for the reliability assessment is available. It should be noted, that the evolution of the fuzzy p-box can be observed by the user for several monitoring points, but in each step of the adaptive Monte Carlo simulation, the free fuzzy p-boxes of the whole surface settlement field (i.e. the vertical displacement of all nodes of the finite element model, which have been selected to be approximated by the surrogate models) is computed and stored for further uncertainty quantification of the results and for the reliability assessment.

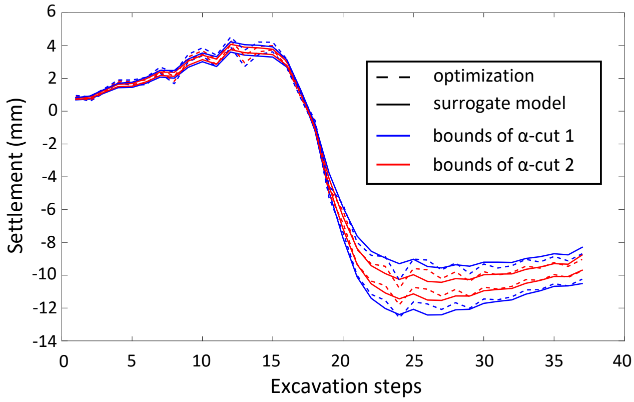

Figure 7: Fuzzy settlement process of a selected monitoring point at the surface.

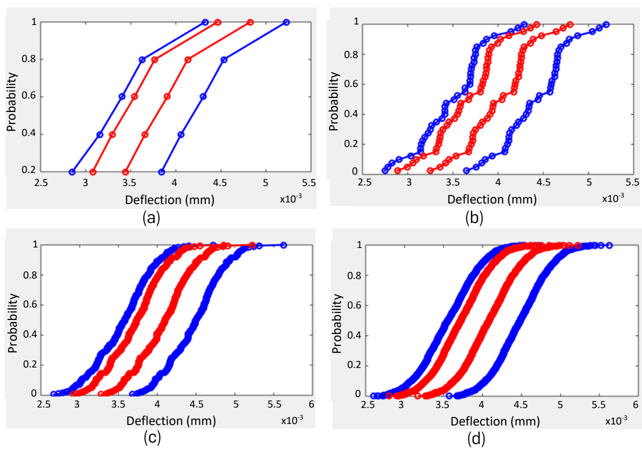

Figure 8: Adaptive Monte Carlo simulation to create free fuzzy p-boxes of the settlement at a critical monitoring point with a) 5 samples, b) 40 samples, c) 200 samples, and d) 1500 samples.

5. CONCLUSIONS

A surrogate modeling strategy for real-time reliability analyses in mechanized tunneling has been presented. Fuzzy probability boxes of time variant tunneling induced surface settlement fields are predicted by an adaptive Monte Carlo simulation in combination with a fuzzy surrogate model in a few minutes. This allows to assess the reliability during the tunnel construction process and to adjust the steering parameters for the subsequent excavation steps, and finally it helps to detect risky scenarios.

Currently, the settlement field prediction is extended with a real-time damage evaluation of existing buildings by linking the predicted settlement fields with building surrogate models to compute strain based damage indicators of structural members. In future works, the real-time assistance system SMART will be extended for additional objectives such as tunnel lining forces. It is also planed to fuse the simulation model with data based prediction models by analyzing the sensors of the tunnel boring machine in real-time.

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