Meta models for real-time design assessment within an integrated information and numerical modelling framework

Jelena Ninic[1], Christian Koch[2] and Walid Tizani[1]

[1] University of Nottingham, NG7 2RD, UK
[2] Bauhaus-Universität Weimar, 99423 Weimar, Germany
jelena.ninic@nottingham.ac.uk

Abstract. In situations where rapid decisions are required or a large number of design alternatives is to be explored, numerical predictions of construction processes have to be performed in near real-time. For the design assessment of complex engineering problems such as mechanised tunnelling, simple numerical and analytical models are not able to reproduce all complex 3D interactions. To overcome this problem, in this paper a novel concept for on-demand design assessment for mechanized tunnelling using simulation-based meta models is proposed. This concept includes: i) the generation of enhanced simulation-based meta models; ii) real-time meta model-based design assessment in the design tool, and; iii) the implementation within a unified numerical and information modelling platform called SATBIM. The capabilities of this concept are demonstrated through an example for the evaluation of tunnel alignment design and the assessment of the impact of tunnelling on existing infrastructure. Moreover, meta models are used for fast forward calculation in sensitivity analyses for the evaluation of the importance of model parameters. The concept proved its efficiency by assessing the design alternatives in real-time with the prediction error of less than 3% compared to complex numerical simulation in presented example.

Keywords: Building Information Modelling, Numerical analysis, Meta models, Level of Detail, Soil-structure interaction, Real-time prediction.

1 Introduction

Complex engineering problems, such as mechanized tunnelling, require reliable design assessment from early design over to construction and operation phases. In situations where quick decisions are required, or when a large number of alternatives has to be tested, the predictions have to be performed in near real-time. This can be achieved using analytical and empirical solutions. However, these introduce a number of assumptions and simplifications associated with them. For example, analytical and empirical solutions do not take three-dimensional effects and complex interactions between individual components into account, and they are usually characterized with a simple linear elastic response [1]. On the other hand, complex 3D numerical simulations are able to reproduce all complex soil-structure interaction effects induced by the tunnelling process, however, they are often characterised by high computational cost, and are difficult to operate in real-time [2]. This can be overcome using computationally efficient meta models instead of the original, detailed numerical models [3].

Meta modelling is understood differently in different domains. In model-driven software engineering, for example, a meta model specifies the structure, the semantics, and the constraints for a family of models in a certain domain, e.g. in cyber-physical systems modelling [4]. While a model is, simply speaking, an abstraction of phenomena in the real world, a meta model is a further abstraction that specifies the properties of the model itself [5], In other domains, meta models have also been developed to serve as "surrogate models" for expensive simulation processes in order to improve the overall computational efficiency. In that sense, they have been applied to solve a number of practical engineering problems in the last years. Meta models are extensively used for prediction, sensitivity analysis, pattern recognition, and design optimization [6]. In tunnelling applications, meta models trained using field monitoring data collected during the tunnel construction process [7] or complex simulation models [8] have been applied for predicting the surface settlements induced by tunnelling. Apart from the prediction speed, the advantage of using meta models is their ability to learn from the different types and large amount data and therefore interpret and summarise existing knowledge in different forms compared to physical models.

Simulation models, on the other hand, are complex and require a large amount of project-specific information that is often available in the form of dispersed resources usually either given in some Computer Aided Design (CAD) format, or, more recently, stored in a Building Information Model (BIM) together with other relevant data about design and construction [9, 10]. One of the challenges during the optimisation of a project design is to preserve the consistency between design alternatives and the corresponding design assessment across different sub-models and throughout different phases. Currently, this is usually an error-prone process, involving manual conversion of data from a BIM or similar storage to a format accepted by numerical design tools. An efficient solution to solve this problem is an integrated design-analysis-assessment framework where the numerical simulations are automatically generated based on the geometry and semantics stored in BIM design tools such as Revit [11]. Therefore, we proposed a unified platform for information, numerical modelling and visualisation of simulation results called "SATBIM" (Simulations for multi-level Analysis of interactions in Tunnelling based on the Building Information Modelling technology) [12]. In this paper, this platform is extended with a tool for meta model-based design assessment.

In the unified design-analysis-visualisation platform SATBIM, we developed a novel concept for on-demand design assessment at the design phase using simulation-based meta models, as "surrogate models", for real-time prediction. To this end, Section 2 presents: i) a brief description of the unified design-analysis-assessment platform; ii) the concept for on-demand real-time design assessment using simulation-based meta models; iii) the meta modelling techniques and requirements for generation of enhanced meta models, and iv) the importance of sensitivity analysis in this concept. The implementation of this concept within the unified numerical and information modelling platform SATBIM is given in Section 3. Finally, in Section 4, we present a numerical example for the evaluation of tunnel alignment design and the assessment of the impact of tunnelling on existing infrastructure. Moreover, the importance of model parameters is evaluated by means of sensitivity analysis.

2 Methodology

In order to enable on-demand design assessment in engineering design environments, a unified platform for information and numerical modelling considering a multi-level representation, extended with a tool for real-time prediction is proposed in this paper.

2.1 On-demand design assessment in information models

Unified platform for information and numerical modelling. SATBIM is an integrated, open-source platform for information modelling, structural analysis and visualisation of the mechanised tunnelling process. Based on a parametric BIM for tunnelling [13], a multi-level simulation model is developed to support engineering decisions during the project life cycle and to allow for the evaluation and minimisation of risks on existing infrastructure (see Fig. 1). Within this platform, industry-standard tools (Autodesk Revit) are employed for the design of the tunnel structure and the surrounding infrastructure with consideration of different Levels of Detail (LoDs) for all system components (soil, tunnel structure, tunnel boring machine, existing buildings). Based on the multi-level, parametric BIM, multi-level numerical models for each component are developed, considering proper geometric as well as material representation, interfaces and the representation of the construction process. The numerical models are then fully automatically instantiated and executed based on the geometry and semantic exported from BIM using newly developed software SatBimModeller [12]. Finally, the simulation outputs are read back and visualised within Revit.

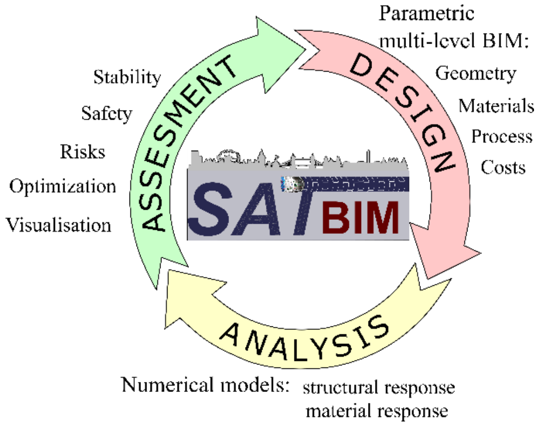


Fig. 1. Concept for integrated SATBIM platform for design, numerical analysis and assessment on different LoDs.

In the SATBIM framework, a multi-scale modelling concept is applied to the shield tunnelling components (soil, TBM, lining, buildings) to enable efficient representation of the tunnelling process with different LoDs as the calling process requires. For example, on the kilometre scale, a low LoD is applied to represent the general alignment of the track and surrounding infrastructure, while on the centimetre scale, all details are captured with the highest LoD of each component. The multi-level approach is also useful over different project stages due to the availability of the information and details at the different design phases. At early design stages only basic requirements are known, and therefore lower LoDs can be represented, while towards the final design and over the construction phase the highest LoDs are represented within information and numerical models. Such an integrated multi-scale design-numerical approach contributes to modelling efficiency by minimising the time needed for model generation as well as computation.
This model is used as a basis for i) information modelling, ii) numerical modelling for the generation of the data set for meta model training and iii) visualisation of numerical assessment results.

Real time-design assessment. To enable real-time assessment, meta models are trained a priori using a process-oriented simulation model generated from a multi-level tunnelling information model (TIM) using the SatBimModeller [12]. Apart from settlements, output parameters include the lining stresses, pore pressures, and damage estimates for existing buildings. Figure 2 illustrates the use of simulation-based meta models for real-time predictions. For different design alternatives, with particular design parameters, simulation models are automatically generated and executed using the SatBimModeller. The simulation results are stored in a format suitable for meta model training. The data set obtained from the simulation model is trained by means of a hybrid training algorithm (described below) to create enhanced meta models. Finally, the resulting meta model is implemented in Dynamo (a visual programming tool for Revit) to enable interactive visualisation of the effects of design choices within the Revit design environment.

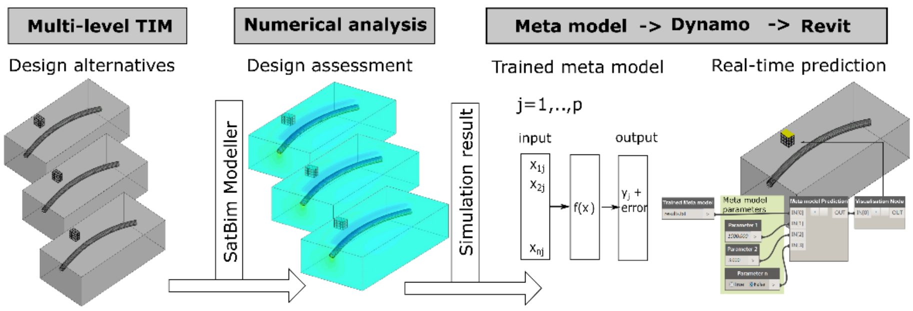


Fig. 2. Workflow of real-time predictions for design assessment within SATBIM.

2.2 Meta models for real-time prediction

Machine learning methods. For the purpose of real-time predictions of tunnelling-induced effects such as surface settlements, risk on building damage, etc., a meta model is employed to substitute for computationally demanding 3D numerical simulations. An algorithm is developed to select an optimal meta model by evaluating and comparing different methods for data training:

- Polynomial Regression (PR),
- Artificial Neural Networks (ANNs),
- Support Vector Regression (SVR) (with Radial Basis Function (RBF) kernel SVR-RBF and Polynomial kernel (SVR-Poly).

In the following, the fundamentals of the prediction models used in this paper are described.

Polynomial regression. This is a meta modelling approach for modelling the relationship between a scalar dependent variable y (output or target variable) and one or more independent variables $\mathbf{x}$ (in our case the input vector). For given a data set $\{\mathrm{y_i,, x_{i1}, \dots, x_{ip}}\}_{\mathrm{i=1}}^{\mathrm{n}}$of *n* patterns, a polynomial regression model assumes that the relationship between the dependent variable y and the *p* vector of input variables $\mathrm{x_i}$ is modelled as an *n*th degree polynomial in *x* [14].

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \cdots + \beta_m x_i^m + \varepsilon_i \, (i = 1, 2, \dots, n) \tag{1}$$

Where $\boldsymbol{\beta}$ are regression coefficients and an ε_i is an "error variable" that adds noise to the polynomial relationship between the dependent variable $\mathbf{y}$ and inputs $\mathbf{x}$. In our application, we are using second-order polynomials, so that the model now becomes:

$$y_i(\beta, x) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \beta_{ii} x_i^2 + \sum_{i=1}^{n} \sum_{j>i}^{n} \beta_{ij} x_i x_j = \boldsymbol{X}^T \boldsymbol{\beta} + \varepsilon_i \tag{2}$$

The vector of estimated polynomial regression coefficients is estimated using the Ordinary Least Squares (OLS) method, as the simplest and thus most common estimation method. The OLS method minimizes the sum of squared errors and residuals in statistics, and leads to a closed-form expression for the estimated value of the unknown parameter β:

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X}^T \boldsymbol{X})^{-1} \boldsymbol{X}^T \boldsymbol{y}. \tag{3}$$

This is the unique least-squares solution as long as $\boldsymbol{X}$ has linearly independent columns.

Artificial neural networks. This method of machine learning, as an attempt of mimicking the human brain and neural learning, is capable of learning the pattern associated with a large body of data [15, 2]. In this method, the relationship between the input parameters $\mathrm{x_i}$ (accepted through the input neurons) and output $\mathrm{y_k}$ (corresponding to output neurons) is established through a network of hidden neurons with corresponding connection weights **w**:

$$y_k(x, w) = f\left(\sum_{j=1}^{m}(w_{jk} + \theta_j) f \sum_{i=1}^{n}(w_{ij}x_i + \theta_i)\right) \quad (4)$$

In this equation, w_{ij} are connection weight between input and hidden neurons, w_{jk} are connection weights between hidden and output neurons, θ is bias and $f()$ an activation function used to transform the input values and transfer them to the next layer. The relation between the input and output is established by a training procedure, adjusting the connection weights $\boldsymbol{w}$ in order to minimise the error E between output $\boldsymbol{y}$ and target values $\boldsymbol{t}$ for number of patterns m. Using a gradient descent method, the connection weights are updated as follows:

$$w_{is} = w_{is-1} + \Delta w = w_{is-1} - \gamma \frac{\partial E}{\partial w} \quad where \quad E = \sum_{k=1}^{m}(y_k - t_k)^2 \quad (5)$$

Where γ is a learning rate. The training procedure is performed in a number of iteration steps *is* and the weights $\boldsymbol{w}$ are updated for all connections between input-hidden, hidden-hidden, and hidden-output neurons. The quality of the meta model training depends on both i) the network architecture (number of hidden layers and hidden neurons) and learning parameters (number of iteration steps and learning rate γ).

Support vector regression. This is a machine learning method where the so-called support vectors determine the approximation function [16]. In this method the multivariate regression function *f(x)* is established based on the input data set *x* to predict the output data $\mathrm{y} = \mathrm{f(x)}$ such as:

$$y = f(x) = \sum_{x_i \epsilon SV}(\alpha_i - \alpha_i^*)K(x, x_i) + b \quad (6)$$

where *K* is a kernel, *n* is the number of training data, *b* is an offset parameter of the model, α_i and $\alpha_i^* \neq 0$ are Lagrange multipliers of the primal-dual formulation of the problem, and *SV* is the support vector set. The transformed regression problem may be solved by quadratic programming and only the input data corresponding to the non-zeros α_i and α_i^* contribute to the final regression model.

The kernel *K* is a non-linear mapping from an input space onto a characteristic space through a dot product of the non-linear kernel function $\phi(x)$. In this application, two different types of kernel functions are tested:

- Polynomial function: $(\gamma\left(x, x\prime\right) + r)^d$ where *d* is the polynomial degree and *r* is an independent coefficient
- Radial basis function $\exp(-\gamma \left\|x - x\prime\right\|^2)$, with γ is a coefficient greater than 0.

Enhanced meta model. In all training methods, the simulation model input parameters x_i are taken as input variables for the meta model training while the tunnelling-induced effects, i.e. outputs of complex numerical summations (settlements, risk of damage, etc.) are target values for meta model training. Meta models are then trained to predict the output for given input values minimising the error between the target and output values. In order to achieve the best prediction capabilities of the meta model, the following steps are taken:

- data normalisation,
- data split, and
- optimisation of free parameters of machine learning methods.

In order to achieve better training performance, all input-output pairs are normalised, i.e. mapped to the interval [0.1; 0.9] using a data normalization algorithm. For a parameter V the normalized value V_{norm} is obtained as

$$V_{norm} = \frac{V - V_{min}}{V_{max} - V_{min}} (\bar{V}_{max} - \bar{V}_{min}) + \bar{V}_{min} \tag{7}$$

where V_{max} and V_{min} are the maximal and minimal value of the variable V, and $\bar{V}_{max}$ and $\bar{V}_{min}$ are the maximal and minimal values of the variable V after normalization, defined as 0.1 and 0.9.

For the training of the enhanced meta model, the data set is split into data for training, testing and validation of the meta model, according to prescribed portions, splitting the data of the whole set at random (see Fig. 2.). The learning process is performed with the training set, while the test set is used to test the prediction performance. Finally, the meta model quality is evaluated with the validation set. This data split is important i) to avoid model overfitting and ii) to double-check the prediction capabilities of the trained meta model.

Some of the mentioned machine learning methods are characterized by having parameters which influence the training performance (eg. neural networks: number of hidden layers, nodes and learning rate). In order to have enhanced meta models, those parameters are optimized with the Particle Swarm Optimization (PSO) method [17] as shown in Figure 3.

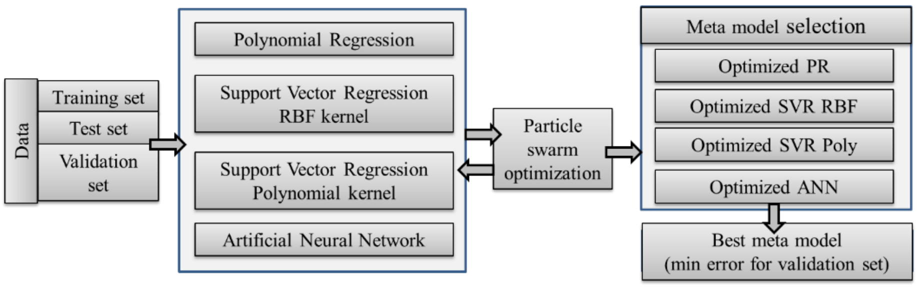


Fig. 3. Algorithm for generation of enhanced meta models. Optimisation of free parameters with the PSO method and selection of the best model with minimum error on the validation set.

In the PSO method, the system is initialized with a population of random solutions. PSO then searches for optima by updating subsequent generations. The potential solutions, called particles, “fly” through the problem space by following the current optimum particles. Each particle belongs to a swarm and has two properties: velocity (v_{ij}) and position (x_{ij}). The particle keeps track of its coordinates in the problem space, which are associated with the best solution (fitness), and achieves the particle-best value $pbest$ (x_{ij}^{pbest}). If a particle takes the complete population as its topological neighbours, the best value is a global best $gbest$ (x_{ij}^{gbest}). The new velocity and position of the particles are updated in each iteration using the following equations:

$$v_{i,j+1} = w_{ij} + \phi_1 r_1 \left(x_{ij}^{pbest} - x_{ij}\right) + \phi_2 r_2 \left(x_{ij}^{gbest} - x_{ij}\right)$$

$$x_{i,j+1} = x_{ij} + v_{i,j+1} \tag{8}$$

Where w are weights, r_1 and r_2 represent random numbers uniformly distributed over [0; 1] and ϕ_1 and ϕ_2 are so-called cognition and social learning factors.

The details about the optimisation algorithm are presented in Section 3.1.

2.3 Sensitivity analysis for model evaluation

Sensitivity analysis is a vital tool in the SATBIM framework for performing the following tasks:

- determination of the sensitivity/importance of the component LoD for a defined analysis scenario and w.r.t. design parameters,
- general study of sensitivity/importance of design parameters (geometrical, material and process) for predefined analysis scenarios, and
- generation of reliable meta models based on important parameters determined by the sensitivity analysis.

In this paper, we give an example of how sensitivity analysis can be used to evaluate the importance of input parameters for design assessment. For this purpose, the One at Time (OAT) design method is used. This method is based on the discretization of the inputs in levels, allowing a fast exploration of the model behaviour and identification of the influential inputs. In this variance-based method, the importance of the input parameter is quantified through i) the absolute mean μ^* of the elementary effect EE_i, representing the total sensitivity index and a measure of the overall effect of a factor on the output and ii) the standard deviation σ, which detects the interaction effects with the other parameters as well as the nonlinear relation between the corresponding input/output [18,19]. The elementary effect EE_j^i of the jth parameter X_j in the i^{th} repetition as well as σ and μ^* are calculated as:

$$EE_j^i = \frac{Y(X_1,\ldots X_j+\Delta,\ldots X_k) - Y(X_1,\ldots X_j,\ldots X_k)}{\Delta};$$

$$\sigma_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left\|EE_j^i - \mu_j\right\|} \qquad and \qquad \mu_j^* = \frac{1}{n}\sum_{i=1}^{n}\left\|EE_j^i\right\| \tag{9}$$

where $Y(X_j)$ is an output and Δ is a predetermined multiple of $1/(p-1)$, with p denoting the number of intervals of X_j.

If predictions in real-time are required and the simulation-based meta models are used as a tool, it is necessary to ensure the robustness and reliability of those meta models. One very important aspect of the robustness is that the meta models are defined with input parameters which are denoted as “important”, i.e. which have a significant effect on the output. This can be ensured by performing sensitivity analysis a priori to meta model generation. This will be an important matter of further research within SATBIM framework.

3 Workflow and implementation

In this section, the details of the implementation of robust meta models, visualisation of the simulation results and sensitivity analysis for evaluation of the numerical models are described.

3.1 Implementation of the enhanced meta models

The algorithm for the robust meta model training is implemented in Python following the main idea described in Fig. 3 and applying the methods of machine learning described in Section "Machine learning methods". For the implementation, the Python library SciKitLearn for supervised learning is used [20]. This toolkit contains implementation of regression models, ANNs and SVR. However, in order to achieve robust learning, the PSO method was implemented to optimize training parameters of different machine learning models. Moreover, the following additional methods were implemented:

- *ReadDatasetFile()*for reading the data set with its associated arguments file, and the training portion, test portion, validation portion;
- *ComputeError()* with arguments training method, training set, test set;
- *ForwardPass()* with arguments weights, data set, method parameters;
- *ViewPerformance()* with arguments training set, test set, validation set.

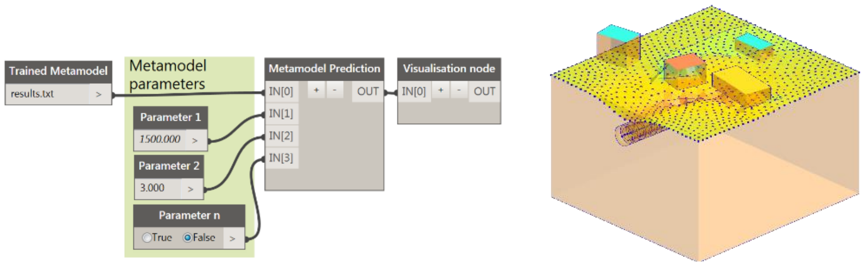
The main function for robust meta model training is given in Listing 1. As outlined in Listing 1, the free parameters of each machine learning methods are iteratively updated with the PSO method. To this end, the free parameters are initialised as particles characterised with position x_{ij} and velocity v_{ij}, moving through the solution space iteratively updating according to Eqn. (8) with the objective to minimise the prediction error of the validation set.

```
"Training, testing and validation of meta models."
def main():
   methods = [ linear_model.SGDRegressor(),
      svm.SVR(kernel='rbf', C=5, gamma=0.4),
      svm.SVR(kernel='poly', C=1e3, degree=3),
      MLPRegressor(solver='lbfgs', alpha=1e-4, random_state=1, max_iter=5000]
"Optimize model parameters."
   for clf in methods:
         param_svr_new = PsoOptimize(clf, model_param_, bx, by, bxt, byt, 20, 20 )
         clf.set_params(C = param_svr_new[0])
         clf.fit(bx, by)
         rrmse = ComputeError(clf, bxt, byt)
         tot.append(rrmse)
 "Choose best model, test and plot results."
   clf = meth[BestModel(tot)]
   rrmse_test = ComputeError(clf, bxt, byt ) # rRMSE of test set
   rrmse_train = ComputeError(clf, bx, by ) # rRMSE of tran set
   tr = clf.predict(bx) # training forward pass
   p = clf.predict(bxt) # test forward pass
   v = clf.predict(bxv) # validation forward pass
   ViewPerformance(by, tr, byt, p, byv, v) # plot image
```

Listing. 1. Algorithm for generation of enhanced meta models. Optimisation of free parameters with PSO and selection of the best model with minimum error on the validation set.

3.2 Real-time design assessment in Revit

Having established enhanced meta models, we can use them for the fast prediction of the effect of design actions in Revit. In order to do that, a Dynamo node was developed to calculate the forward pass of the meta model based on the model parameters set in Dynamo. The trained meta model is imported as a text file, while parameters are set using value boxes or sliders as shown in Fig. 4(a). The “meta model prediction” node calculates the forward pass, i.e. the analysis response for the selected design parameters. The results are then displayed in Revit with a “visualisation node”. This node is visualising simulation results, highlighting both the contour-fill coloured surface for the output quantities as well as the deformation for the case of surface settlements (which is made more visible using a deformation scale factor).



(a) (b)

Fig. 4. (a) Dynamo node for real-time design assessment based on meta models; (b) visualisation of numerical results in Revit using contour-fill coloured and deformed surface for surface settlements and contour-fill coloured surface for risk of tunnelling on buildings [18].

This simple and intuitive representation is crucial for improving the understanding of tunnelling-induced effects by design engineers who can’t afford computationally expensive numerical simulations or non-experts who may be involved in the decision process of the project development. Apart from surface settlements, the risk on existing infrastructure is also visualised as shown in Fig. 4(b), where the buildings are sorted in relative scale from green (safe) to red (in risk) based on the influence of the tunnel excavation [21].

3.3 Sensitivity analysis based on meta models

Calculation of the sensitivity measures is implemented in Python as shown in Listing 2. For the forward calculation of the effect of parameter variation onto the output, the meta models trained by means of finite element simulations are applied. This offers significant advantages, since the calculation of the elementary effect requires a large number of forward calculations to ensure the uniqueness of the solution. As explained in the previous section, meta models are excellent tools for interpolation and extrapolation of the trained data set, and therefore a reasonable solution for the forward calculations in this manner. In Listing 2, the following steps are performed:

- define the set of parameter ranges to be investigated (bxt);
- use the meta model to predict the model output (*sens_test*) based on given input (bxt) and trained meta model synaptic weights (*weights*) using the *ForwardPass()* method;
- calculate the μ_j^* (mean of the absolute value of EE_i) using the *ComputeVariance()* method;

- calculate the σ (standard deviation of EE_i) using the *ComputeDeviation()* method;

```
"Calculate sensitivity measures for data set “bxt” ."
def main():
"Read meta model ."
  w = ReadWeights(weights)
  sens = []
  devs = []
  bxt = [[0 for x in xrange( input_size)] for x in xrange(n_delta*time_steps)]
    for i in range (0, n_delta):
      for j in range (0, time_steps):
        bxt[i*time_steps+j][1] = 0.1+0.8/(n_delta-1)*i
        bxt[i*time_steps+j][3] = 0.1+0.8/(time_steps-1)*j

    sens_test = ForwardPass(w, bxt, arch_ann, 1, 'relu')
    variance = ComputeVariance(sens_test, n_delta, time_steps)
    dev = ComputeDeviation(sens_test, n_delta, time_steps)
```

Listing. 2. Algorithm for sensitivity analysts based on meta models.

4 Examples

4.1 Real-time prediction

In the example presented in this paper, we consider the problem of a tunnel passing in the vicinity of an existing building (see Fig. 5). The investigated design and modelling parameters are: i) building LoDs (1, 2 and 3); ii) the distance of building’s centreline from the tunnel in Y direction (0, 10, 20, 30, 40, 50, 60 m) and; iii) the tunnel overburden (5, 10, 15, 20, 25m). SatBimModeller is used for the generation and execution of a large number of simulations in order to obtain the data set for meta model training. In this numerical experiment containing 105 simulations for the construction of 25 tunnel rings with combination of three parameters (building LoD, overburden and distance), the selected monitoring quantities are the vertical displacements of the building top. This results in a data set of 2554 monitoring samples. This set is used for the generation of the meta model for prediction of building settlement w.r.t building LoD, overburden and distance. In the next step, this meta model is used for the forward calculations of sensitivity analyses.

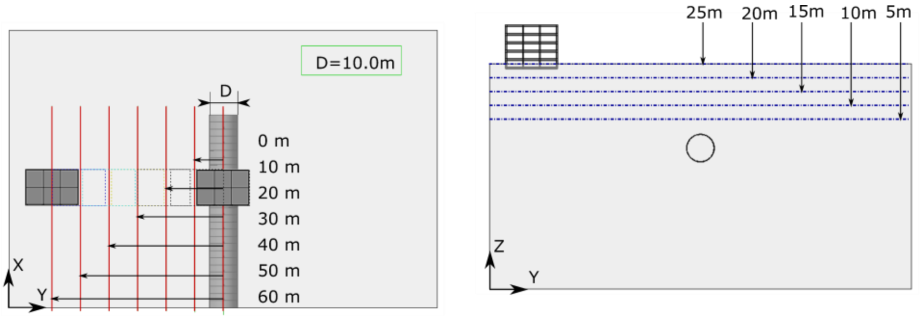


Fig. 5. Parameters for investigation of the building LoD sensitivity. Left: Design alternatives in terms of building distance from the tunnel alignment; Right: depth of tunnel w.r.t. foundation of the existing building.

Meta model training for the prediction of building settlement. The procedure and the algorithm described in Sections 2.2. and 3.1. are applied for the meta model training based on a data set of 2554 samples. Here, the data set is divided into portions of 80%, 15% and 5% samples for training, testing and validation, respectively.

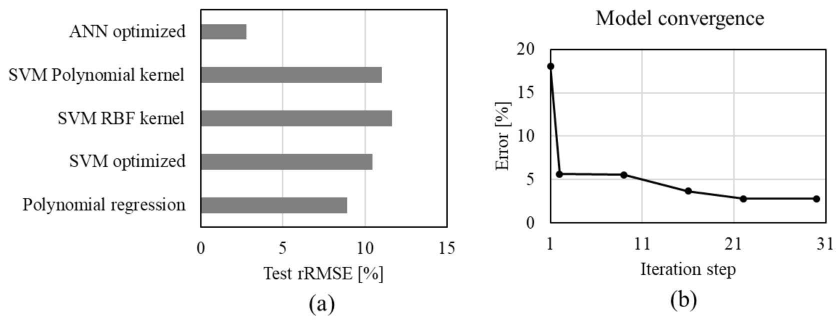


Fig. 6. (a) Training performance of the meta model using the various machine learning techniques; (b) convergence of the optimization process of the ANN architecture.

Figure 6(a) shows the relative Root Main Square Error (rRMSE) for different machine learning techniques applied for the data training. From the figure, it is clear that the optimized ANN shows the best performance for data set training. Figure 6(b) shows the convergence of the optimization of the ANN architecture leading to a minimized error for the test sample. PSO is used as optimization algorithm to determine the number of neurons in the hidden layers and the learning rate. From Fig. 6(b), it can be seen that the optimal solution is reached within approx. 22 iterations leading from non-optimized model with 18% rRMSE to the optimized model with less than 3% rRMSE of the test set.

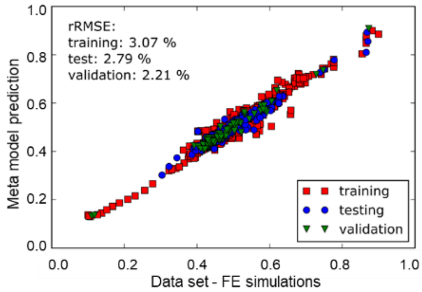


Fig. 7. Comparison between vertical displacements of the building obtained from the FE simulation and predictions of the trained meta model for the training, test and validation sets for the model with best performance

Figure 7 shows the comparison between the data set and meta model prediction for the training, testing and validation set for the best meta model. From this figure, it can be concluded that the optimized ANN meta model has excellent prediction capabilities, with the error on test and validation set being less than 3%.

On-demand design assessment in Revit. Figure 8 illustrates how simulation-based meta models can be used for real-time prediction and design assessment in Revit. In this example, to assess the impact of tunnel construction on an existing building, the influence of the distance of the tunnel from the existing building and the tunnel depth is evaluated directly in the design tool. The design parameters are set by user using value boxes and sliders in Dynamo as illustrated in Fig. 8. This design assessment approach can be applied in the early design phase when exploring different design alternatives to minimize the impact of tunnel construction on the existing building. Using the meta model, the results of the analysis are obtained and visualised instantaneously, while the full finite element simulations would have taken hours to calculate. Another advantage of using meta models for real-time design assessment is that meta models are able to interpolate and to certain extent extrapolate the prediction for the explored range of parameters. Thus, for a discrete number of test simulations characterised with a given range of input parameters, using the meta models, the response can be obtained for an infinite number of (continuous) parameter combinations within this range.

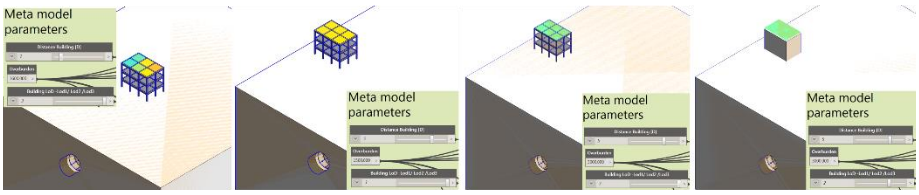


Fig. 8. On-demand design assessment in Revit based on simulation-trained meta models for different tunnel offset and tunnel depth from the existing building and LoD of building model.

4.2 Evaluation of the LoD importance

A variance-based global sensitivity analysis has been conducted in order to measure the sensitivities of the model output (settlements at the building top) to the input parameters (building LoD, overburden and distance). In this methodology, the importance of the input parameter is quantified through two sensitivity measures σ and μ^* as explained in Section 2.3.

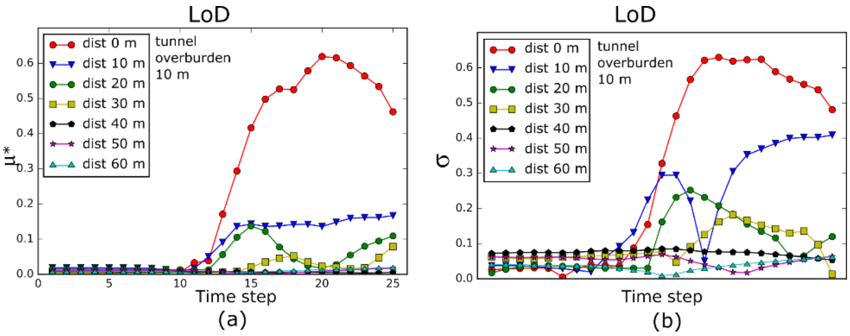


Fig. 9. Sensitivity of the building LoD for different building distance from the tunnel alignment for tunnel overburden of 10m: a) absolute mean of EE_i; b) standard deviation of EE_i.

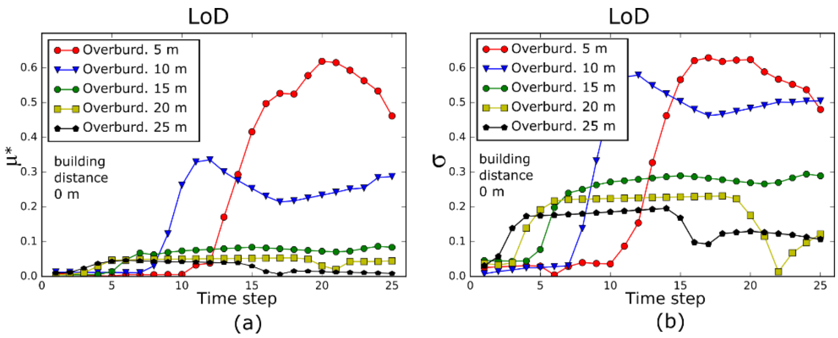


Fig. 10. Sensitivity of the building LoD for different tunnel overburden for building distance of 0 m: a) absolute mean of EE_i; b) standard deviation of EE_i.

In Figures 9 and 10, the sensitivity measures for the selected LoD of the building to vertical displacements are shown. From the plots, we can conclude that the global sensitivity μ^* as well as the interaction effect indicated by σ of the LoD drops with the increase of the distance of the building from the tunnel and the increase of the overburden of the tunnel. It is for instance obvious that when the distance of the building from the tunnel is approximately 4D, the selected building LoD becomes irrelevant, meaning that we can choose the lowest LoD and reduce computational costs.

Looking more closely at the results of the sensitivity measures σ and μ^* of the building LoD for different values of tunnel overburden (Fig. 10), we can see that both the global sensitivity and the interaction effect reduce with the increase of the overburden. However, these sensitivity measures are still significant even for the overburden of 25m - especially σ, which detects a nonlinear relation between the input and the output. This is due to two reasons: first, because the chosen limit of the overburden of 25m (2.5 D) from the tunnel crown is still in a zone of large influence, and second because of the building distance from the tunnel in Y direction of 0 m, where the interaction effect is the strongest (see Fig. 9).

5 Conclusions

In this paper, a concept for on-demand tunnelling design assessment in an engineering design environment is proposed. To this end, simulation-based meta models, trained a priori with complex 3D numerical simulation models, are employed for real-time prediction. The unified design-analysis- assessment platform SATBIM is used as a design tool, and as a basis for generation of a large number of simulations for creating a data set for meta model training. Moreover, a strategy and algorithm for generation of enhanced meta models based on different machine learning techniques is proposed. In the example given in this paper, we demonstrated on-demand design assessment of effects of tunnelling on existing building in Revit. Finally, meta models are applied for sensitivity analysis to explore the importance of model parameters.

In general, real-time predictions are required if a large number of alternatives has to be explored and if decisions have to be made in real-time (e.g. setting support pressures during the tunnel construction process). Meta models have been chosen in this approach to substitute complex 3D numerical simulation, since they have been recognised by the practitioners as an efficient method which compromises complexity and speed of calculation [22]. Meta models are able to account for the individual behaviour of each component and their complex interactions, giving a more physical response. Consequently, different design assessment measures can be evaluated at the same time (surface settlements, risk on buildings, stresses in tunnel structure). Certainly, to generate these meta models, a large number of simulation runs has to be performed a priori, and these calculations will require a significant amount of time. However, the advantage is that the generation of simulations is automatized and instantaneous by applying SatbimModeller and that the used simulation models can be parallelised [23]. Secondly, since meta models are able to interpolate and to a certain extent extrapolate the prediction from given parameter ranges, one can test an infinite number of parameter combinations within the chosen range from a discrete number of simulations used for meta model training. Another tradeoff is that trained meta models are characterised with a certain prediction error. Therefore, different machine learning methods and optimization were used here in order to ensure the best training performance. Consequently, in the example given in this paper, the prediction error is less than 3% and therefore acceptable for most engineering applications.

Finally, another important application of meta models, the sensitivity analysis and evaluation of the model output, is demonstrated by an example. Here, meta models are proved useful for fast prediction, since a large number of forward calculation have to be performed to obtain sensitivity measures. By applying meta model-based sensitivity analysis, we evaluated the importance of the building model LoD for numerical assessment. The results can be used in the future to select optimal LoD of building component. This then would lead to optimal information and numerical models in terms of model size and computational efforts.

The SATBIM toolkit will be made available as open source software together with tutorials, a complete manual, and a number of benchmark examples. The project's Github repository (not yet public) can be found at: https://github.com/satbim.

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