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ESTABLISHING A MACHINE-LEARNING-SUPPORTED TOOL FOR THE IDENTIFICATION OF NECESSARY BUILDING-STRENGTHENING MEASURES IN THE DESIGN PHASE OF URBAN TUNNEL PROJECTS

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SUMMARY: *Due to the construction of shallow tunnels in urban soft ground, surface settlements occur and can induce damage to buildings. To reduce these effects, preliminary strengthening measures (i.e. underpinning of foundations, construction of a foundation slab, jet grouting under foundations, …) need to be carried out. Identifying affected buildings in the catchment area of a planned tunnel tube can be of interest in an early stage of planning to have extra information for deciding between alternative routes. Therefore a machine learning tool based on two serial working random forest models was designed. The extension of the subway system in Vienna was chosen as a case study for the proposed method. In the course of this study by optimizing its' hyperparameters and the tool design, satisfying prediction accuracies can be achieved. The models became trained (calibrated) and tested (validated) on a dataset of up to 25 variables per building. The wide availability of open governance data enables a solid database for the model training process. The established random forest models show a prediction accuracy between approx. 72% and 81%. Variables with the most importance for these results are (1) parameters of the tunnel (cross-section, tunneling method), (2) distances of the building towards the planned tunnel (different vertical and horizontal distances), and (3) the construction year of the examined building. The dataset can be extended by data and information from future constructions. This will further improve the models' prediction accuracy when applying them to upcoming evaluation processes.*

KEYWORDS: *urban tunneling, strengthening of buildings, machine learning, decision models, sustainability, use of resources*

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1. INTRODUCTION

Urban public transport is crucial in big cities to ensure functioning mobility and contributes to the reduction of greenhouse gas emissions (Carroll et al., 2019). In cities all over the world, construction and extension of metro and subway systems are carried out (Hamburg, Paris, Vienna, New York, Tel Aviv, Beijing, Tokyo, Melburn, …). These works can be carried out on the outskirts of cities, where the development of future districts is planned. Within less populated areas, the erection of new lines may be executed above ground or underground with less need for preparatory works regarding existing infrastructure. But construction also takes place in an urban environment. Executing tunnel works under tensely populated districts holds special challenges. Precaution must be taken regarding the existing buildings and other structures (Schweiger et al., 2022).

The current case study is based on the subway extension in Vienna (Schweiger et al., 2022). The expansion of the underground network by extension of existing lines (U1 and U2) and the construction of a new line (U5) is based on the Viennese "urban development plan" (Rosenberger et al., 2014) and its special concept the "urban mobility plan" (Telepak, 2015). The base of the finally defined route of the expansion of line U2 was a variant study (Höfling, 2016). Due to its route under the inner districts of Vienna (see Figure 1), the construction of the new subway is implemented by a combination of shafts and tunnels.

Figure 1: Plan of the to-be-built lines U2 and U5 under the inner districts of Vienna (Huber, 2024).

The construction of two tunnel tubes in a depth of approximately 13 m to 35 m under the surface (Wiener Linien, 2021) in an urban environment holds the necessity of preliminary works (Schweiger et al., 2022). The scope of these works spreads widely and includes the adaption of gas, water or electricity services, reorganization of traffic, lowering the groundwater level, etc. The construction of the shafts and tunnels induces surface settlements (Chou & Bobet, 2002; Ercelebi et al., 2011; Greenwood, 2003). Buildings respond to the settlements and may be damaged (Farrell et al., 2014). To reduce the damage risk the foundations of houses will be strengthened by different measures. These measures are carried out in advance of the tunnel driving and shaft excavation works.

This paper provides a proposal for a method for optimizing subway routes based on a machine learning (ML) tool predicting strengthening measures for buildings. The proposed tool is based on the Random Forest (RF) algorithm (Breiman, 2001) , which uses a combination of different decision trees, each of which is formed from randomly selected subsets of the provided dataset. This algorithm has been proven to be an effective tool for classification and regression tasks, such as those described in this paper (Salman et al., 2024). The optimized prediction of strengthening measures holds the possible advantage of determining a more economical and more ecological route with fewer interventions in the existing building stock without major expenditure of time and money. It is important to reduce the number of strengthening measures needed by optimizing the route while maintaining upright the safety level for the possible affected structures.

The following paper will outline the current state of the art in identifying the need for preliminary strengthening in building works, explain the motivation behind proposing a data-driven tool based on the collected input data and describe the technical principles of the strengthening methods for the presented case study. It will then discuss the establishment of the ML tool, its setup and optimization, with the aim of achieving the best possible prediction accuracy. Discussion of the results of the proposed ML tool and the random forest-based tool setup method will provide insight into possible applications of the approach, model extension, and transfer to other locations and construction sites.

2. PROBLEM STATEMENT AND MOTIVATION

2.1 Literature Review

The paper consists of three main points:

- Measures to strengthen buildings against impacts from urban tunnelling
- Determining the need for strengthening methods
- Using a machine learning prediction tool based on random forest

Not only are strengthening methods applied to foundations to improve the resistance of the building against collapse due to external impacts such as the effects of tunnelling in inner-city environments, but also to enhance the resistance for adopted usage and extension of the building itself. Various sources (Cherney et al., 2020; Killer, 2007; Kucuk et al., 2009; Müller, 2008; Polishchuk et al., 2021), propose a small number of different strengthening methods, ranging from underpinning and foundation slabs to different types of injection (low and high pressure variants) using alternative grouting materials (e.g. cement based, hybrid and chemical materials) and different pile-based solutions.

Currently, identifying buildings at risk of potential damage typically involves two steps. The first step is to calculate surface settlement. The details of the settlement calculation vary depending on the project. These calculations can be performed in 2D or 3D, and the level of detail in the ground model can vary depending on the number of classes of homogeneous ground characteristic parameter, as well as the level of detail used to distribute the thickness of soil layers across the project area.

In the second step, buildings on the surface are classified. This classification can be based either on the maximum calculated rotation of the building due to surface settlement, compared to the proposed critical values (Kruschinski-Wüst et al., 2022; Röchter et al., 2016), or on detailed finite element (FE) calculations of the building's structural response, in order to predict potential damage (Franco et al., 2019; Moosazadeh et al., 2019; Obel, 2019). Depending on the degree of detail of the calculated surface settlement and the number of critical buildings identified, a lot of preliminary investments are needed.

- Ground investigation and characterization regarding soil parameters and local distribution
- FE settlement calculations induced by tunnelling, expanding over the complete project area
- building information regarding materials, foundations, statics and usage.
- FE building calculations and prediction of potential damage.

These works require a high level of expertise, preliminary work and calculations, resulting in time-consuming and costly investments that are not applicable at the early stages of planning and for different track routes due to the amount of additional costs involved.

Together with the preliminary prediction of potential damage and the determination of corresponding compensatory measures, monitoring structures during tunnelling is important. In order to verify the calculations and the buildings' reactions, the regular monitoring of surface settlements (Xie et al., 2018), building settlements (Gastine et al., 2007), and building slope and damage (Burland et al., 1995; Rankin, 1988), appears to be an appropriate tool (Kruschinski-Wüst et al., 2025; Weithe & Sterzik, 2011; Zhao et al., 2018).

Machine learning approaches have been applied to construction issues related to building damage during tunnelling, as well as to the prediction of surface settlement. For instance, neural networks have demonstrated promising results in predicting surface settlements and building damage (Cao et al., 2020; Wang et al., 2024). Other algorithms have also proven applicable for surface settlement prediction, such as support vector machines or random forests (Li et al., 2022; Tang & Na, 2021). Random forest classifications have not only shown satisfactory results in the prediction of building damage due to tunnelling, but also in the quantification of structural building damage (Chencho et al., 2021), and in the prediction of damage induced by earthquakes (Tesfamariam & Liu, 2010). These examples demonstrate the growing use of machine learning algorithms, including random forest, in civil engineering analysis.

2.2 State of the art procedure

To outline the motivation for establishing the proposed tool in this paper, the state-of-the-art determination of preliminary strengthening works is explained based on the procedure within the case study of the Vienna subway project.

In this case study, the process of defining the buildings with the need for a strengthening measure is the result of a planning process. Within this process, different stakeholders are involved (city council, public transport company (PTC), private property owners, …). For the final definition of the affected buildings, a detailed investigation of buildings must be carried out as well as in-field work on private property. These results are available at the end of the submission planning process.

The following restrictions can be extracted from the current state-of-the-art procedure:

- On-site construction work like foundation investigation or digging shafts.
- Time- and cost-intensive engineering work to define houses with strengthening needs.
- Disturbance of owners and tenants through investigation work (noise, dirt, usage restrictions …)
- Information about preliminary work cannot be considered during the variant studies and for the decision-making process of the final route.

As the construction industry is responsible for around 23% of the CO_2 emissions produced by the global economy (Huang et al., 2018), reducing unnecessary construction work is crucial for achieving the 1.5°C target of the Paris Agreement and combatting the effects of global change. The most effective way to achieve this is to increase the number of uninstalled building materials. Adoptions that consider reducing emissions can be more easily realized in the early stages of the planning process, especially in large projects. Therefore, it is important to consider as many parameters as possible when deciding on a tunnel route under urban environments. The presented case study shows that more than 110 building strengthening measures play an important role among preliminary works connected to urban tunnel construction. As the literature shows, the current determination of the impact of tunnelling requires highly specialized calculations that require in-depth knowledge of the project's ground and buildings. Therefore, these calculations are not carried out in the early planning phase.

As literature primarily focuses on predicting damage and surface settlement, this paper moves directly towards strengthening measures needed to prevent damage caused by surface settlement. By using easily accessible data to identify buildings in need of strengthening at an early stage of the planning process, this information can be taken into account with fewer resources. This approach has the potential to influence route decisions and possibly reduce the number of strengthening measures needed, as well as the carbon footprint of preliminary works of an urban tunnelling project.

The goal is to establish a ML tool (see I in Figure 2) based on known (data from the case study with a complete set of information) and easily available (mainly from a desk with as little need for in-field work as possible) and little invasive data to find an optimal, low-invasive route. Based on this tool and fed with future data from the area of interest (alternative route) (see II in Figure 2) it will be possible to estimate the number of buildings with the need for preliminary measures. This additional information about different routes can be considered in the decision-making process when comparing different variants (variant study). In this research, the focus was set on establishing the prediction tool (I) based on the case study of Vienna.

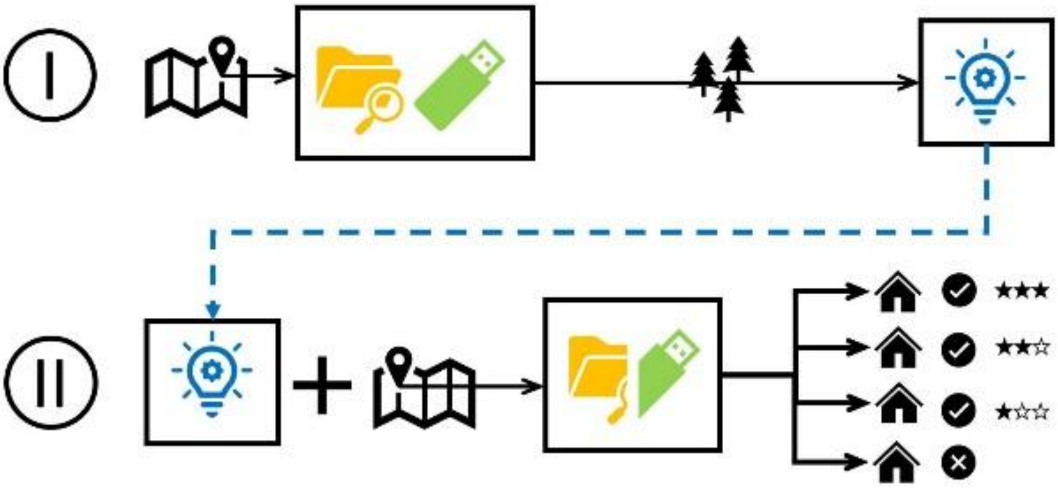

Figure 2: Sketch of the established tool and future prediction process.

3. MATERIALS AND DATA

3.1 Information on the existing building stock

Data of high quality and high expressiveness regarding possible strengthening measures is needed to set up the tool. In the current case study, the dataset is based on open government data (OGD), publicly available and accessible data from various official archives. In the case of Vienna, data was extracted from online sources (free of charge or paid data) as well as from paper records. The following Table 1 gives an overview of the data (1) forming the base of the machine learning process of the tool and afterward (2) serving as input data for the prediction of strengthening measures. The parameters are described and explained in the section following the Table 1.

Also, Google Street View and Google Maps can be used to generate or verify the parameters of the dataset. (Detailed information regarding the data availability and the data's sources in the case study in Vienna can be found in the appendix).

In detail, the address (1) including the ZIP Code (2) and the "Cornerhouse" (3) parameter can be found in city maps. These parameters are of interest as they can be linked to the history of a district and its past structural development. A first connection to possible regional characteristics of building types and structural features may be given.

Information regarding war damage to a building (4) is of high interest. It holds information on possible structural changes during reconstruction in the postwar era or possible "hidden" and creeping damages having their origin in wartime. A source may be specific historical maps (Bode, 1995; Enss & Knauer, 2023; Mason Betsy, 2016), data from war archives, analysis of post-war aerial photos or information from the construction files of the building concerned.

A major source for detailed information about the buildings, their recent histories, the construction, materials, the planned uses, and any structural changes are the construction files (4-5, 7-13, 23-26, 29). These must be submitted with the building application and are kept on file with the administrative authority. Extraction of parameters for the dataset can be more time-consuming compared to other sources especially if the amount of existing documents is high, the arrangement of the documents is mixed up regarding the chronological sequences and if the availability is only in hardcopy archives.

Information regarding the construction period (6) of the buildings can be extracted from historical maps. To detect the construction period of a building, maps of different years need to be compared to identify the matching building outlines. The construction year is highly linked to the history of building techniques, codes and regulations applicable at that time (Kolbitsch, 1989) and various other time-dependent parameters that may influence the building's condition today.

Table 1:Overview of the applied data for the established tool and its characteristics.

No.	Parameter	Scale	Data type in R	Unit	Values in case study
1	Address	Nominal	Character	-	Variable
2	ZIP Code	Ordinal	Integer	-	1050 - 1070
3	Cornerhouse	Ordinal	Logical	-	Yes/ No
4	War damage	Ordinal	Logical	-	Yes/ No
5	Construction year	Ratio	Integer	-	1711-2011
6	Construction period	Ratio	Character	-	1710-1772 – 1946- present
7	Number of main floors	Ratio	Integer	-	1-9
8	Number of attic floors	Ratio	Integer	-	0-4
9	Number of basement floors	Ratio	Integer	-	0-3
10	Use of ground floor	Ratio	Double	kN/m^2	1,5-7,5
11	Use of rest of building	Ratio	Double	kN/m^2	1,5-7,5
12	Load increase ground floor	Ordinal	Logical	-	Yes/ No
13	Load increase rest of building	Ordinal	Logical	-	Yes/ No
14	Min. distance (hor) tta	Ratio	Double	m	0-61,5
15	Max. distance (hor) tta	Ratio	Double	m	0-111,4
16	Diagonal distance (hor) tta	Ratio	Double	m	0-86,9
17	Depth (distance vert) bgl	Ratio	Double	m	13-32,9
18	Cross section	Ratio	Double	m^2	11,91-117,42
19	Tunneling method	Nominal	Character	-	NATM/ TBM
20	Building orientation	Nominal	Character	-	Variable
21	Tunnel system component	Nominal	Character	-	Variable
22	Track axis	Nominal	Character	-	Track 1/ Track 2
23	Static Model	Nominal	Character	-	Variable
24	Foundation	Nominal	Character	-	Variable
25	Basement ceiling construction	Nominal	Character	-	Variable
26	Foundation material	Nominal	Character	-	Variable
27	Ground characteristics	Nominal	Character	-	Variable
28	Groundwater	Ordinal	Logical	-	Yes/ No
29	Strengthening measure	Nominal	Character	-	Variable

Abbr.: bgl….......below ground level
hor……...horizontal
tta..........to the tunnel axis
vert…......vertical
green…...available from the desk
orange….available from archives

The use of the building on the various floors (10, 11, 12, 13) is shown on the construction plans, which show the purpose of the rooms or parts of the building. It is to be divided between the actual use and the use intended when the building was constructed. The actual use can be verified by looking at Google Street View, Google Maps or, in case of major doubt, an on-site validation. Signs on the façade, and next to entrances regarding shops, offices or other commercial uses often give indications for the actual use. The use gets transferred into a load class with the regarding payload in kN/m² based on the Eurocode regulations (ÖNORM B 1991-1- Eurocode 1-Einwirkungen Auf Tragwerke, 2006). For multiple different uses within the same unit of a building, the one with the highest loads is chosen and applied to the database. To define whether an increase took place during the lifetime of the building, the original and the actual payload were compared.

3.2 Tunnel-specific information

Information regarding the tunnel route and parameters connected to the tunnel construction (14-19, 21-22) can be found in planning documents, such as ground plans, length sections, cross sections and technical reports. This information is highly linked to the surface settlement that occurs during shallow tunneling in soft grounds (Ercelebi et al., 2011; Greenwood, 2003).

The distances of the buildings towards the tunnel (14-17) were collected as shown in Figure 3. The horizontal distances are always the direct perpendicular distances to the axes of the tunnel. The depth is defined as the vertical distance between the crossing point of the diagonals of the property at the surface level towards the top point of the tunnel ridges. Information about the boundaries of properties and the existing buildings is needed to determine the needed data.

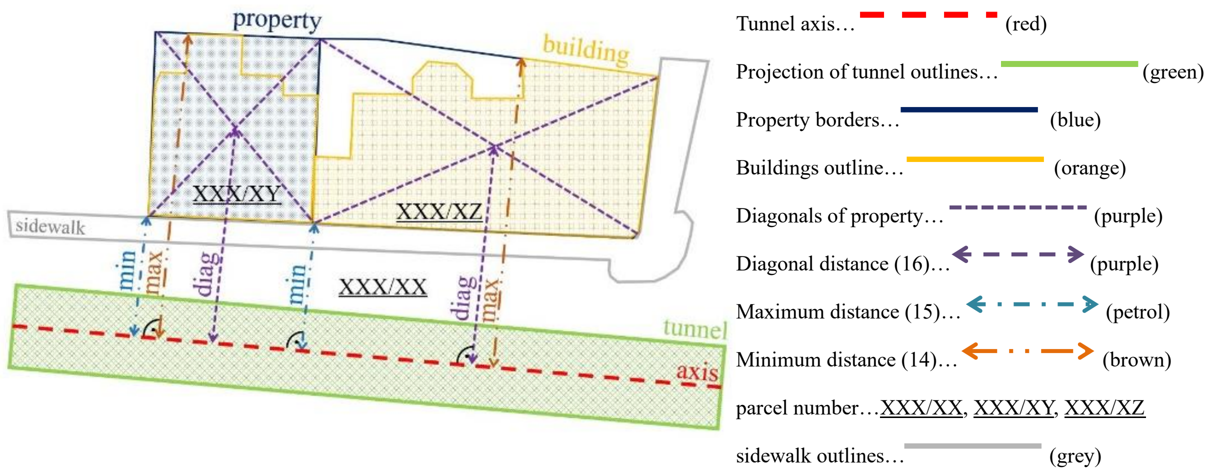

Figure 3: Example of horizontal distances of the buildings regarding the tunnel axis.

The building orientation (20) states how the main load-bearing systems of the buildings are located towards the tunnel axis. Examples of the applied definition of the different classes of the orientation can be found in Figure 4. The building orientation influences how the structure may move and react to surface settlement and which potential damage can occur.

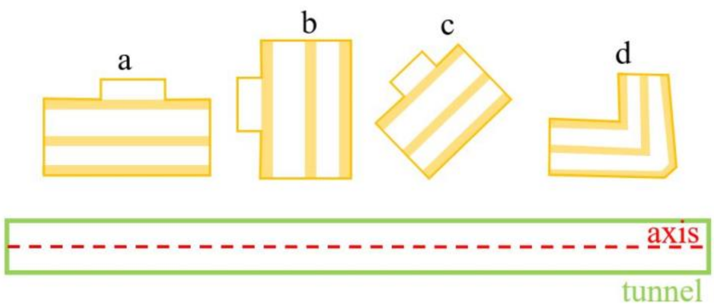

Figure 4: Examples of building orientation (a - parallel, b - orthogonal, c - 45°, d- 50:50).

The ground characteristics under the building (27) and information regarding the level of the groundwater (28) can be collected from available soil profiles/ existing shafts or probe drillings in physical proximity to the building of interest. These parameters influence the buildings' residence against surface settlement-induced damages.

3.3 Possibilities for building strengthening

Various strengthening measures (29) are listed in the database, they spread from measures preliminary to tunnel driving and shaft excavation, compensation measures during periods with surface settlement to a combination of different measures (Nebois et al., 2019). Following the different possible measures will be summed up (sketches of different systems can be seen in Figure 5):

- Underpinning of foundation (Makarchian, 1997): This method can be applied on single foundations or line foundations and gets executed section-wise. By underpinning, the existing foundation of a building gets deepened and/or widened The newly built structures may be connected by steel structures or reinforcement to the existing foundation.
- Post-installed foundation slab: This method can be applied when numerous line foundations need to be strengthened The steel-reinforced concrete slab is built in sections and is connected to the existing structures by intersections between the foundation and the new structures.
- Injections and low-pressure grouting (Witt, 2018): In this case the suspension gets injected by drilled lances into the ground under the foundation to improve its geotechnical characteristics. The grouting is executed at low injection pressures of up to 10 bars and uses cement, resins or other chemicals as a binder.
- Jet grouting (Makowski & Polańska, 2020; Voit et al., 2019): By this method, existing foundations can be strengthened but also force flows within the ground influenced (leading forces around to be built tunnels). The ground gets eroded by a highly energetic jet of cement suspension. The eroded soil and the suspension get mixed up and form a solid pile under the existing foundation.
- Compensation grouting (Essler et al., 2000; Pelzl et al., 2022): By injecting suspension horizontally into the ground under the building and increasing the volume locally, buildings and building parts can be lifted. The method is based on soil fractures around drilled and injected steel pipes. As injection material, a cement suspension is used. The foundation structure itself is untouched.

Different measures may be combined.

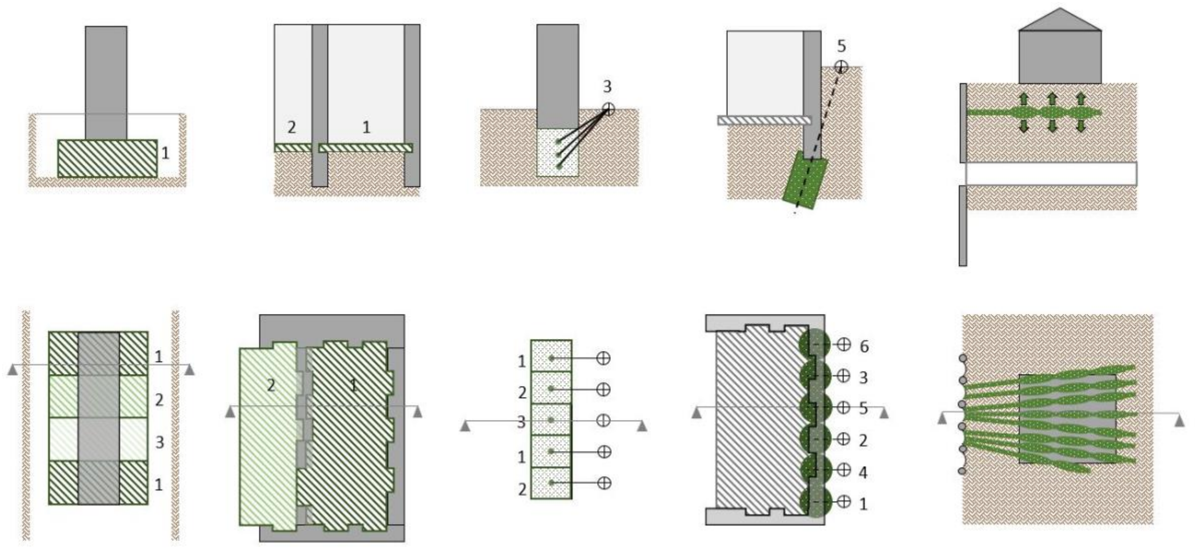

Figure 5: Strengthening measures (from left to right underpinning, foundation slab, injection, jet grouting, compensation grouting). Numbers in the sketches symbolize the production sequence of the strengthening method. The cross-section can be seen above the corresponding ground plan.

4. METHOD

The chosen method to identify buildings with the need for strengthening measures is based on the Random Forest (RF) algorithm (Breiman, 2001). The prediction tool is a combination of two serially arranged RF models with the ability to quantify building strengthening measures during the execution of variant studies of different tunnel routes.

The following steps were taken to set up the prediction tool based on the collected data described in chapter 3:

1. Data extraction, collection and preparation as input data for machine learning
2. Definition of the target parameter (linked to the research question)
3. Setting up the Machine learning (ML) Model
4. Combine best-performing models into one tool.

4.1 Data in the ML Model

The complete database (represented by the folder and USB-dive icons in Figure 6**Error! Reference source not found.**) contains all the available information. It must be considered that not all information can be used at the same time. Some data that is directly related to each other must be utilized within different models to avoid a bias or wrongly established correlation (for example, year of construction and building period). For this reason, the "complete database" with all available data will be split up into different input datasets for the different models. Data cleaning has to be performed before processing it in the ML model, (e.g. no spaces, no missing parameters, unique names for parameters, …).

4.2 Definition of the target parameter

The defined target parameter, predicted by the ML models, is the strengthening measure (No. 29 of the data shown in Table 1) that needs to be executed for a certain building. This parameter can be predicted in two ways, (1) by defining whether a measure is necessary or not or (2) by defining which measure/ or combination of measures is necessary.

The target parameter exists in the database that is used for the establishing of the RF models but is missing when applying the tool of this paper to a route in a future variant study.

4.3 Setting up the ML model

The process of setting up the machine learning model can be divided into the following steps:

1. Selection of ML algorithm (RF).
2. Coding the model structure
3. Establishing the RF structures by training (calibrating) and testing (validating) with the existing dataset.
4. Optimizing setups (hyperparameters of RF model, split between test and train) to get the best possible prediction performance.

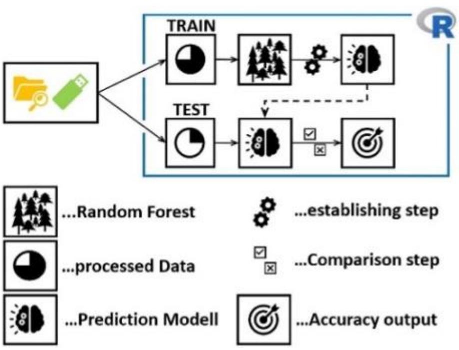

Figure 6: Sketch of the process of setting up a RF Model.

In Figure 6 the process is depicted as a sketch. It explains with icons the different steps and their orders as well as how the data is split, the RF algorithm and the coding program are connected. It also displays the accuracy of a model as one of the results for interpretation and comparison and the base for the final selection of a model as part of the prediction tool.

4.3.1 Random Forest

The Random Forest ML algorithm can analyze connections and dependencies of different input variables regarding a target parameter and further perform a prediction of the target parameter based on the given input data.

Various data of the complete set will be processed within the model to predict a chosen parameter. Due to the character of the target parameter and its possible values (nominal categorical variable), classification is an adequate method (Cutler et al., 2012) for the presented RF models.

RF is characterized by combining all created tree predictors (Breiman, 2001). It represents an advance of the bagging predictors (Breiman, 1996) where different random variables get chosen for generating trees. By repetition of this generating process, different independent trees get constructed (meta-learner (Livingston, 2005)) by using a bootstrap sample of the data set (only a subset of data is considered in each tree). All outputs of the tree predictors are given equal weight. The final prediction result is produced by counting the simple majority of all prediction results of all trees.

The hyperparameters (parameters of the learning process of a ML system that must be set before training a ML model (Yang & Shami, 2020)) of the random forest model in this application are the number of trees (ntree), the node size (nodesize), and the number of input features available at any time (mtry) (Scornet, 2017).

The advantages of Random Forest for the quality of the model and the predicted output are (Langsetmo et al., 2023):

- There is less risk of overfitting due to the combination of a higher number of non-correlating different tree predictors.
- Better quality of results by the combination of non-correlating tree predictors.
- Greater flexibility of the model by being able to work with regression and classification.
- Easier recognition of the importance of variables. (Livingston, 2005)
- Highly user-friendly by existence of a small number of hyperparameters.

To establish a RF model, the original dataset gets split up into two subsets, a train set an a test set. The train set is used for establishing the tree predictors (“calibration”) and the test set is used to determine the model’s prediction accuracy. The validation is executed by comparing the model’s prediction with the known result (“target-performance comparison”).

4.3.2 Coding in R

The coding of the model was executed in R (R Core Team, 2023). To set up the model and perform all the necessary operations the following packages were implemented:

- `randomForest` (Liaw & Wiener, 2002): includes the random forest algorithm based on (Breiman, 2001). By use of this package, the tree predictors were generated (based on the training dataset) and the model’s accuracy was calculated (based on the test dataset)
- `caret` (Kuhn, 2008): includes the tools for predictive models for classification and regression as well as for processing training and test data. The package was used to calculate the variable importance and visualize these results for a quick overview.
- `datasets` (R Core Team, 2023): helps to organize and format datasets for better use. The command of the package divides the dataset into test and train subsets and checks on its usability and non-processable mistakes regarding the entries. The division in subsets is done randomly. It holds the possibility to choose whether it shall be reproducible or not.

4.3.3 RF Model establishing

After the basic setup and coding process, optimizations were performed to improve the quality of the prediction. ´The aim was to have as little data for the testing process as possible but as much as needed, leaving as much data for the training process as possible.

The detection of the best split of the dataset into "train" and "test" (see Figure 6) subsets was performed. It is important to have enough data for each answer category of the target parameter in both subsets to achieve a good quality of the RF model. The following variations have been tested within the same model to find the best practice for the existing dataset:

- cross-validation (Berrar, 2018)
- division by the track axis
- randomly but reproducible division of the dataset by percentage (from 60 train/ 40 test to 80 train/ 20 test)

4.3.4 Optimizing model setups

The hyperparameters of the RF model were varied within the defined span (grid) to find the ones resulting in the RF model with the best prediction accuracy (Scornet, 2017). All possible combinations of hyperparameters within the defined grid are set to find the combination resulting in the highest prediction accuracies of the RF model (Probst et al., 2019). "Ntree" (400-700), "nodesize" (1-15) and "mtry" (1-10) were the hyperparameters the grid search was performed with. The results of this best-performance search were then taken for the RF model in the tool. The suggestions of (Breiman, 2001) and (Liaw & Wiener, 2002) were taken as a guideline.

4.4 Combination of models to a complete tool

The analysis tool consists of a combination of two RF models with different scopes of input data (see Figure 7). In "Step 1" (necessity of strengthening measure), all the existing buildings in the research area are run through the model. Those that show "No" as an output will not be further analyzed. In "Step 2" (type of strengthening measure), only those buildings are being further investigated that were characterized with "Yes". They are then characterized within the three possible categories (foundation strengthening (FS), compensation grouting (CG), and a combination of foundation strengthening and compensation grouting (CFC)).

This combination has been the result of the tool setup process. The high number of buildings to be categorized within the process (even more, when investigating multiple different routes during an early design phase or when adopting the route) results in a high amount of data needed. In the case study of Vienna in "Step 1" (necessity of strengthening) only data that could be collected from the workplace in an office by having access to the applications and sources mentioned in chapter 3 was used. No "field investigation" was needed.

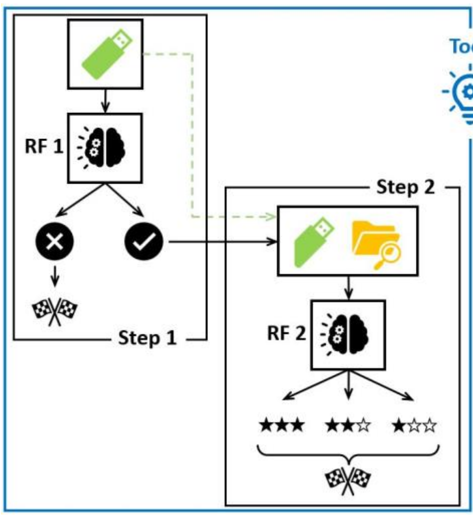

Figure 7: Sketch of the prediction tool based on RF models.

In “Step 2” (type of strengthening) the existing dataset from “Step 1” must be extended (or replaced e.g. the construction year) by detailed data which could only be collected in hardcopy archives in this case study or which has to be achieved from other sources.

The depicted information in Figure 7 is summed for the case study of this paper in the following (see also Table 1 for No.).

Step 1: Input data: *ZIP Code (2), corner house (3), constr. Period (6), nr. of main floors (7), nr. of attic floors (8), use ground floor (10), use rest of building (11), min. distance (14), max. distance (15), diagonal distance (16), depth (17), cross-section (18), tunneling method (19), building orientation (20), track axis (22), ground characteristics (27), groundwater (28)*

Target Parameter: need for strengthening measure

Possible Results: yes, no

Step 2: Input data: *ZIP Code (2), corner house (3), war damage (4), constr. Year (5), nr. of main floors (7), nr. of attic floors (8), nr. of basement floors (9), use ground floor (10), use rest of building (10), Load increase ground floor (12), Load increase rest of building (13), min. distance (14), max. distance (15), diagonal distance (16), depth (17), cross-section (18), tunneling method (19), building orientation (20), track axis (22), static model (23), foundation (24), basement ceiling construction (25), foundation material (26), ground characteristics (27), groundwater (28)*

Target parameter: type of strengthening measure

Possible Results: foundation strengthening (FS), compensation grouting (CG), a combination of foundation strengthening and compensation grouting (CFC)

The advantage of the tool is its possibility of steady growth. With an updated database the RF models of a future stage just need to be set up with the current code.

5. RESULTS

5.1 General

The results can be split into two parts. First the optimization of the RF models’ hyperparameters (see section 5.2) and second the results of the prediction of the final RF models (see section 5.3). The models showing their best performance were chosen to be implemented into the prediction tool.

To be able to compare the results, the number of parameters in the input dataset of the models (of the same step) has to be the same. Models with different amounts of input parameters result in different accuracies that can’t be compared because the training and testing were performed on different bases of information.

The advantage of splitting the tool into two serial working models is shown by comparing it to a one-step model. The input data as well as the optimization of parameters for this one-step RF model (OS RF model) were identical to the one for RF model 1. Only the target parameter was different (Table 2). The results of this model (finally not part of the tool) are also listed as a comparison.

5.2 Results of the optimization

The prediction accuracy was taken as a basis to compare and rank the different variants.

The split of the database in train/ test was performed with the following for all set-up models, 60/40, 65/35, 70/30, 75/25, 80/20, track axis 1/ track axis 2 (about 50:50), cross-validation (CV) 4, CV 5 (dividing the data set in 4 or 5 subsets – one for testing and the remaining for training purposes).

Due to the possible combination of these different boundary conditions, 16 variants were modeled each to find the final (best performing) RF models 1 (predicting the necessity of strengthening measure) and 2 (predicting the type of strengthening).

The best prediction results were achieved with a split of 70% of the data for training and 30% of the data for testing (all results in Table 2 to Table 7 were achieved with this split). Cross-validation with a total split of the dataset by

4 and by 5 showed similar results with slightly less prediction accuracy. The division of the dataset by the track axis resulted in an approximately 50% - 50% split which showed way weaker results. This is due to too little amount of data for the training process of the model.

All listed RF models were performed with a hyperparameter grid search because this optimization always resulted in better accuracies compared to models with predefined hyperparameters.

Table 2: Results of the hyperparameter optimization and overview of input data.

model	hyperparameters				No. of data (answers)				
	ntree	nodesize	mtry	No. of Parameters in database	yes	no	FS	CG	CFC
RF model 1	675	1	1	17	113	154			
RF model 2	575	2	7	25			60	32	21
OS RF model	500	4	1	25		154	60	32	21

Abbr.: FS foundation strengthening
CG compensation grouting
CFC combination of foundation strengthening and compensation grouting

5.3 Results of the prediction

The accuracy of the prediction ranged between 71.6% and 80.6% as listed in Table 3. The accuracy of the RF model in "Step 2" is higher. The accuracy can be calculated for the models in the testing phase. Due to the knowledge of the expected outcome of the prediction (part of the collected data) related to the RF model's prediction output (see also Figure 6) the accuracy can be calculated (see Equation 1). This value is a single number without scattering or distribution.

$$accuracy = \frac{\text{No. of correct predictions}}{\text{No. of total predictions}} \tag{1}$$

The sensitivity (see Equation 2) is a value that states the ability of the model of true positive prediction for a possible parameter (Yerushalmy, 1947).

$$sensitvity = \frac{\text{No. of true positives}}{\text{No. of true positives} + \text{number of fals negatives}} \tag{2}$$

Table 3: Results of the RF models.

Model	Prediction	Sensitivity of prediction				
	Accuracy	yes	no	FS	CG	CFC
RF Model 1	71.6%	73.7%	71%			
RF Model 2	80.6%			91.3%	100%	16.7%
OS RF Model	60.5%		65.7%	25%	37.5%	50%

Table 4, Table 5 and Table 6 show the confusion matrices of the three RF models listed. These tables show the models' predictions and highlight where they were correct and where they were incorrect. The columns in the tables represent the true labels, while the rows represent the predictions. The values on the diagonal represent cases where the predictions match the true labels. Values found elsewhere are misclassifications.

Table 4: Confusion matrix RF Model 1.

	Yes (Reference)	No (Reference)
Yes (Prediction)	14	5
No (Prediction)	18	44

Abbr.: Yes foundation strengthening needed
No no foundation strengthening needed

Table 5: Confusion matrix RF Model 2.

	FS (Reference)	CG (Reference)	CFC (Reference)
FS (Prediction)	21	0	2
CG (Prediction)	1	1	4
CFC (Prediction)	0	0	7

Abbr.: FS.......foundation strengthening
CG......compensation grouting
CFC.....combination of foundation strengthening and compensation grouting

Table 6: Confusion matrix OS RF.

	No (Reference)	FS (Reference)	CG (Reference)	CFC (Reference)
No (Prediction)	44	14	8	1
FS (Prediction)	2	1	0	1
CG (Prediction)	1	2	3	2
CFC (Prediction)	0	0	1	1

In Table 7 the parameters with the highest variable importance (estimated by random forest by looking at the change of the prediction error when data for the parameter is changed while all others are kept the same (Liaw & Wiener, 2002)) are shown. In the top five of the above-mentioned models only seven different parameters are represented (which are: max. distance, min distance, diagonal distance, depth, cross section, tunneling method, construction year). The importance is expressed in this table by the relative relation of the influence towards the most important variable of each model.

Table 7: Top 5 Variables of Importance for the Random Forest models.

Model	Variable importance				
RF Model 1	max. distance	diagonal distance	depth	min. distance	cross-section
	100%	93%	73%	68%	65%
RF Model 2	cross-section	tunneling method	depth	construction year	diagonal distance
	100%	91%	62%	58%	55%
OS RF Model	construction year	diagonal distance	depth	max. distance	cross-section
	100%	99%	91%	88%	74%

6. DISCUSSION

6.1 General

The output of the prediction tool provides additional information to compare different tunnel routes. It can be used as a valuable tool to improve a designated route regarding its possible resource use for strengthening measures. It can be seen as an optimizing parameter (but not a standalone) in the decision-making processes for a final tunnel route.

To create the implementation planning of strengthening measures, it is recommended to exercise detailed investigation and calculation. RF-based classification is an appropriate method for analyzing the present questions but is not established yet as a completely certain tool for determining possible local specifics.

In general, the proposed method of this research can be transferred to any location worldwide when dealing with shallow tunneling in an urban environment. It is important to train and test the RF models with highly characteristic data from the local project region. The accuracy of the tool's prediction and the expenditure for collecting depends on the availability and quality of the required data.

A big advantage of the presented tool and RF models is its chance for steady growth and improvement. The database can be extended by data gained in the future. Updating the models on an updated database holds a high chance of improving the prediction accuracy and being able to forecast necessary works with higher certainty.

6.2 Discussion of the results

The following conclusions can be drawn from the results regarding the predictions of the tool:

- A prediction accuracy of almost 72% in RF model 1 and about 81% in RF model 2 was achieved. This result can be identified as satisfying for an application of the model for the comparison of different variant routes in an early stage of planning. Correct and incorrect predictions will be the same in percentage terms for all different routes, allowing a comparison regarding the amount of necessary strengthening measures.
- The results of the confusion matrix for RF models 1 and 2 show the highest predictions on the diagonal, as expected. An exception can be seen in the prediction of compensation grouting measures. These results show the models' good prediction performance, but also highlight the problem of classifying compensation grouting based on the case studies' dataset. It indicates that the sample size, together with a high variation in the input dataset corresponding to this class, could be the reason for the prediction results. Further investigation into this issue would require access to more detailed information about the decision-making process for this measure. A wider dataset, as well as additional features, could also improve the accuracy of these predictions.
- The confusion matrix results for the OS RF model show that only 'no measure' was satisfactorily predicted. This class is the only one that shows lasting results in the diagonal. These results emphasize the decision to divide the tool into two separate RF models. It can also be seen that, for classes with little remaining testing data, the results can hardly be evaluated, especially for the combination of reinforcement and compensation grouting. Changing the split of the dataset for testing and training could perhaps improve the prediction of worse results, albeit at the cost of lowering the prediction accuracy for the class showing the best results.
- The sensitivity for prediction of the combination of foundation strengthening and compensation grouting is comparatively low. This can be attributed to the available amount of data for this type of strengthening. It can also be seen that the sensitivity for plain compensation grouting is a lot better with a similar amount of data. This demonstrates that the model can identify parameters triggering the need for compensation grouting well.
- Among the “Top 5” parameters with the highest variable importance (see Table 7) only seven different appear (out of 25). These variables can be summed up in three categories:
  - distance of buildings towards the to-be-built tunnel
  - characteristics of the tunnel
  - age of the building

The results of the variables with the highest importance show that the prediction tool output is comparable to the state-of-the-art identification of buildings with the need for strengthening measures. The calculation of surface settlement by tunneling is based on parameters regarding the tunnel (Cross-section, tunneling method) and the depth of the tunnel combined with parameters characterizing the ground (Ercelebi et al., 2011; Greenwood, 2003). The distance of buildings regarding the tunnel axis influences the possible rotation of a building due to the surface settlement (Camon i Andreu, 2015). The age of the building is linked to codes and regulations as well as historical circumstances such as material quality and availability and quality during erection (Kolbitsch, 1989).

6.3 Discussion of the model setup

The following conclusions can be drawn from the results regarding the setup process of the tool:

- The optimization of the models' hyperparameters leads to the highest accuracy of the results. Even the sensitivity of the prediction can be improved. This conclusion could be drawn from the comparison of the different models set up with and without hyperparameter optimization. For the compared models the hyperparameters were assumed as suggested in literature (Oshiro et al., 2012; Zekavatmand, 2025). It should also be noted that satisfactory model quality was achieved with minimal risk of overfitting or false establishment, due to the set hyperparameter values.

- Node size: “1” is the minimum node size for the RF package in R and defines the stop criterion for a decision tree. The size of the trees is reduced as this node size value increases, because the probability of reaching the stop criterion is higher. For the current models, this means that the trees have grown to a maximum or almost maximum size, allowing for deeper and more complex trees with more variance to be established.
- Tree size: The number of trees evaluated by hyperparameter optimization is sufficient to achieve the best possible results. Literature shows that the correlation between model error and the number of trees is exponential. From about 130 trees onwards, there is no need for extra trees as this has a very limited impact on the predictive outcome (Oshiro et al., 2012). At the same time, many trees do not cause problems with overfitting. Further optimization could be performed to improve calculation speed and performance when hardware power is limited (which wasn’t experienced in the presented study).
- Mtry: The hyperparameter analysis set different values for RF model 1 and RF model 2. In RF model 2, the mtry value of 7 showed the best results. The value is plausible as it is less than 25 (the number of variables). In RF model 1, the mtry value of 1 means that the split variable is chosen completely at random, which increases the risk of overly biased results. However, due to the algorithm used(Liaw & Wiener, 2002), a bias linear correction is built into R to eliminate this risk when using '1' as the mtry value.
- To be able to take the prediction tool as a basis for decision-making for the execution of strengthening work, more learning based on even more data must be performed. This data will be available with the upcoming construction phases of the subway infrastructure. This is especially important for strengthening methods with little available data such as combination of reinforcement and compensation grouting.
- The division of the tool into two steps is practical, as can be seen from the results. An improved performance is achieved with less input.
    - The overall prediction accuracy of the two models is between 10% and 20% higher than the prediction of the measures in one model (OS RF model).
    - Additionally, the analysis and comparison of the different confusion matrix also show, that sensitivity is higher for nearly all values, leading in better and more reliable results. Deviations from this observation as well as consequences are described in the points above.
    - Also, the data collection needed is improved. Parameters that can only be obtained from more detailed investigations (hardcopy archives in the case of Vienna) are input data in RF model 2 only. This leads to a more efficient use of resources, as no data is collected that may not be used du the classification “no measure needed” in RF model 1 and no further progression of these datasets in model 2.
- Buildings with special uses, e.g churches/ sacred buildings (as part of the case study). were excluded from the database. Their number is too low to allow solid RF model training for these structures. They should be investigated individually in any case.

6.4 Outlook

It could have been shown that the suggested method in this paper works with satisfying prediction accuracies. The usage of the tool can be a valuable application for the determination of a planned tunnel route in the case study region as stated in Figure 2. In a further step the performance of the tool in regions with different geological characteristics (e.g. in London clay or Frankfurt clay) should be evaluated.

Based on the gained knowledge further research fields open towards the following topics:

- In areas with little existing information regarding ground and soil characteristics under the building, supplementary research could be of interest. A combination of statistical analyses on an average basement floor-to-ceiling height (connected to the construction year) and foundation embedment depths connected to existing information regarding ground characteristics can be done. The result can be an estimation of the ground for selected buildings and serve as input data for future predictions.

- The extension of the model to determine a concrete measure (foundation plate, underpinning, jet grouting, …) together with an estimation of the needed masses. By this estimation, a monetary calculation for different routes could be able. Even an evaluation of different scenarios regarding their CO2 emission seems possible.
- The setup of a special prediction tool for necessary strengthening measures of special buildings as mentioned in chapter 6.3 affiliated with the research of this paper could be of interest. The focus may be on sacred buildings and is for sure of interest in regions with a high density of e.g. churches (for example Rome).

7. CONCLUSION

It can be concluded that by combining the available data and the random forest model a qualitative comparison of different routes with a specific certainty (up to 81%) is possible. To ensure maximum performance (maximum prediction accuracy by minimum input in resources), the division of the tool into two steps has been proven to be an adequate method.

The models' predictions correlate well with the identification based on calculating surface settlement and investigation of house characteristics but with the benefit of wider local applicability in an early stage of planning and less input of resources.

Due to regional characteristics, the RF models presented in this paper cannot be applied directly to a completely different project. For this application, the approach consisting of the necessary input data, the model setup performed, the data split and the hyperparameters used can be transferred, but training with specific regional data must be carried out to obtain a model resulting in satisfying and accurate prediction accuracies. The transfer of this approach is recommended in projects with similar project conditions to those found in the presented case study. These include combinations of conventional and TBM tunnelling, geological and hydrogeological situations, shallow tunnelling, inner city environments, comparable building structures, and similar state-of-the-art engineering approaches towards preliminary measures for the tunnelling process. In addition, it is important to be able to access the input data. Central Europe is most likely to be a field of interest for the application of the proposed tool.

In a second step, the approach can be applied to regions with conditions varying from those in the case study, in order to prove its applicability and identify any necessary changes. One example could be the excavation of an urban tunnel in hard rock followed by soft ground. The application of the tool to a region characterized by a high degree of constant parameters (e.g. tunnelling method, building structure, engineering approach, etc.) is recommended in order to achieve the clearest possible identification of differences.

Further research could be conducted on the ML algorithm used. Comparing the RF tool with convolutional neural networks (CNN) or k-nearest neighbor (k-NN) could help identify ways to improve prediction accuracy. The predictions presented also do not provide information on the measures or masses of the preliminary strengthening measures. Extending the tool, perhaps together with the use of different ML algorithms, could overcome the limitations of this paper's approach, resulting in a more precise determination of the strengthening measure. This would make it possible to take CO_2 emissions or cost effectiveness into account when comparing different planned routes.

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APPENDIX

In the table the sources of the parameters in the database are listed for the case study of the Vienna subway extension. The abbreviations used, are listed at the end of the table.

No.	Parameter	Source in the case study	Type of source	Reference
1	Address	Digital city map (MA 8, MA 37, MA 41, UA)	Digital OGD	(Stadt Wien, 2023a)
2	ZIP Code	Digital city map (MA 8, MA 37, MA 41, UA)	Digital OGD	(Stadt Wien, 2023a)
3	Cornerhouse	Digital city map (MA 8, MA 37, MA 41, UA)	Digital OGD	(Stadt Wien, 2023a)
4	War damage	Map of War Damages (MA 7, MA 37), SV [1]	Digital OGD	(Stadler Kevin, n.d.; Stadt Wien, 2023b)
5	Construction year	Construction files [2] (MA 37)	Hardcopy	-
6	Construction period	Digital historical maps [3] (MA 8, MA 41, UA)	Digital OGD	(Stadt Wien, 2023b)
7	Number of main floors	3D city maps/ 3D city models (MA 41), SV Construction files (MA 37)	Digital OGD Hardcopy	(Stadtvermessung Wien (MA 41), n.d.) -
8	Number of attic floors	3D city maps/ 3D city models (MA 41), SV Construction files [2] (MA 37)	Digital OGD Hardcopy	(Stadtvermessung Wien (MA 41), n.d.) -
9	Number of basement floors	Construction files [2] (MA 37)	Hardcopy	-
10	Use of ground floor [4]	SV, GM Construction files [2] (MA 37)	Digital Hardcopy	- -
11	Use of rest of building [4]	SV, GM Construction files [2] (MA 37)	Digital Hardcopy	- -
12	Load increase ground floor [5]	Construction files [2] (MA 37)	Hardcopy	-
13	Load increase rest of building [5]	Construction files [2] (MA 37)	Hardcopy	-
14	Min. distance (hor) tta	Construction information (PTC, MA 29, OMS)	Digital	(Hubert Christian Ehalt et al., 2016; Stadt Wien - Brücken und Grundbau (MA29), 2019; Stadtvermessung Wien (MA 41), n.d.; Wiener Gewässer Management Gesellschaft mbH & Wiener Gewässer (MA 45), 2022; Wiener Linien, 2023)
15	Max. distance (hor) tta	Construction information (PTC, MA 29, OMS)	Digital	(Hubert Christian Ehalt et al., 2016; Stadt Wien - Brücken und Grundbau (MA29), 2019; Stadtvermessung Wien (MA 41), n.d.; Wiener Gewässer Management Gesellschaft mbH & Wiener Gewässer (MA 45), 2022; Wiener Linien, 2023)

No.	Parameter	Source in the case study	Type of source	Reference
16	Diagonal distance (hor) tta	Construction information (PTC, MA 29, OMS)	Digital	(Hubert Christian Ehalt et al., 2016; Stadt Wien - Brücken und Grundbau (MA29), 2019; Stadtvermessung Wien (MA 41), n.d.; Wiener Gewässer Management Gesellschaft mbH & Wiener Gewässer (MA 45), 2022; Wiener Linien, 2023)
17	Depth (distance vert) bgl	Construction information (PTC, MA 29, OMS)	Digital	(Hubert Christian Ehalt et al., 2016; Leitner et al., 2017; Stadt Wien - Brücken und Grundbau (MA29), 2019; Stadtvermessung Wien (MA 41), n.d.; Wiener Gewässer Management Gesellschaft mbH & Wiener Gewässer (MA 45), 2022; Wiener Linien, 2021)
18	Cross section	Construction information (PTC, MA 29)	Digital	(Leitner et al., 2017; Wiener Linien, 2021, 2023)
19	Tunneling method	Construction information (PTC, MA 29)	Digital	(Leitner et al., 2017; Wiener Linien, 2021, 2023)
20	Building orientation	Construction information (PTC, MA 41)	Digital	(Stadt Wien, 2023a; Wiener Linien, 2023)
21	Tunnel system component	Construction information (PTC)	Digital	(Wiener Linien, 2023)
22	Track axis	Construction information (PTC)	Digital	(Wiener Linien, 2023)
23	Static Model	Construction files [2] (MA 37)	Hardcopy	-
24	Foundation	Construction files [2] (MA 37)	Hardcopy	-
25	Basement ceiling construction	Construction files [2] (MA 37)	Hardcopy	-
26	Foundation material	Construction files [2] (MA 37)	Hardcopy	-
27	Ground characteristics	public soil profile register [6] (MA 29)	Digital (GDC)	(Stadt Wien, 2023a)
28	Groundwater	public soil profile register [6] (MA 29)	Digital (GDC)	(Stadt Wien, 2023a)
29	Strengthening measure	Construction files [2] (MA 37)	Hardcopy	-

Abbr.:
MA 8 ---- city archives
MA 29 -- Department of soil mechanics and bridge engineering.
MA 37 -- construction office
MA 41 -- city surveyor's office
UA ------- Viennese urban archeologists
SV ------- Google Street View
GM ------ Google Maps
GDC ---- Governance data of charge
PTC ----- Public Transport Company
OMS ---- Federal Office of Metrology and Surveying of Austria

[1] The analysis was supported by Google Street View as a virtual on-site visit of house facades (existing signs on facades next to building entrances display the use of tax money for reconstruction).

[2] Date back about 150 years. Access to these documents is normally only available for building owners but can be granted for scientific purposes.

[3] Date back to 1710 as digitally available data.

[4] The use gets transferred into a load class with the regarding payload in kN/m² based on the Eurocode regulations (ÖNORM B 1991-1- Eurocode 1-Einwirkungen Auf Tragwerke, 2006). For multiple different uses within the same unit of a building, the one with the highest loads is chosen and applied to the database.

[5] To define whether an increase took place during the lifetime of the building the original and the actual payload were compared.

[6] The register ("Baugrundkataster") holds numerous soil profiles from shafts, probe drilling, soil probing or dynamic probing. For the density of the information in Vienna see also as an exemplary outtake.

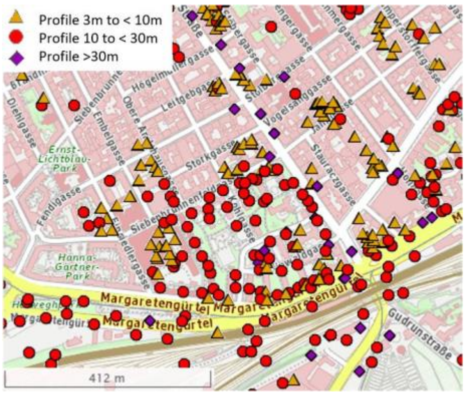

Figure 8: Example of register of soil profiles (Stadt Wien, 2023a).