ADAPTIVE GEOLOGICAL UNCERTAINTY MODELING IN EXCAVATION

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Abstract –

The accurate detection of soil boundary levels is vitally important for creating the correct solutions for the earthwork phases of construction. In Building Information Modeling (BIM), subsoil models are interpolated from information obtained from ground investigations. Our study focused on the adaptive use of geological uncertainty modeling to derive additional information during excavation. The results show that the continuous mapping of excavated ground is an effective estimation tool for modeling boundary levels. This adaptive tool can significantly decrease uncertainty in earthwork, presenting new possibilities for productivity and sustainability. The results of this study enable comparisons of alternative options in adaptive uncertainty modeling during excavation, allowing for the development of uncertainty-based subsoil models for construction.

Keywords –

Soil boundary level; uncertainties; excavation; geological mapping; building information modeling; model-based design; ground investigation

1 Introduction

As the development of construction technology is focusing on questions related to productivity, safety, and sustainability, many are facing the challenge of adopting progression with the prevailing conditions of practice. In response to this challenge, building information modeling (BIM) tools were introduced, and they have played a crucial role in coordinating the planning and construction phases, addressing unforeseen problems, and facilitating information sharing between disciplines. These interdependent interactions between various engineering disciplines are built on information that is initially available.

In many cases, the problems that arise during construction are a result of the limited or partial information available during the planning phase. Because unforeseen problems are solved onsite, they tend to be reactive rather than proactive. Although many construction phases are flexible in the face of emerging challenges, certain planning disciplines, such as geotechnical engineering, rely on preliminary information to develop solutions for the entire construction process. The reactive nature of problem-solving in such cases creates challenges in terms of not only timetabling and costs but also overall planning solutions.

Proactive modeling addresses this issue by providing a more accurate estimation of ground conditions, but it requires updated soil models. Until now, achieving this has involved additional soundings, soil sampling, or boreholes to create new modeling conditions, simultaneously incurring additional costs due to extra ground mapping.

A recent study by Satyanaga et al. [1], which reviewed the current state of BIM applications for geotechnical engineering, focused on the integration of geological and geotechnical information into modeling the planning and construction phases using case studies. Their findings correlate with our study's hypothesis that there is a lack of flexibility to create adaptive models for implementation when applying preliminary information with finite element method calculations. There is a need for further research to create less intricate and calculation-dependent modeling tools when applying geotechnical information. Vanicek et al. [2] concluded that BIM modeling is behind other engineering disciplines in terms of the effectuation of geological and geotechnical information. This has much to do with the site-specific properties of soil parameter determination. Constitutive models of ground conditions require soil sampling and sounding results to create a condition map of an entire area. Since soundings and soil samples represent point-specific information, there is an element of uncertainty in interpolating these points. Similar findings regarding soil parameter uncertainty in BIM modeling have found support in the studies of Beaufils et al. [3] and Wu et al. [4].

According to Wiegel et al. [5], the development of geotechnical modeling with geostatistical information and uncertainty modeling improves overall decision-making and sustainability in construction. They highlighted that tools for incorporating geotechnical information into BIM models are still under development. In addition, they pointed out that, although different methods of uncertainty modeling are available, the integration of these methods with BIM models is not ready. We found no study in which the uncertainty of subsoil models was updated with adaptive soil boundary detection during excavation.

Pakyuz-Charrier et al. [6] concluded that overlooking the amount of uncertainty distorts the accuracy of the modeled area. The handling of uncertainties in geological information can either enhance or distort a 3D subsoil model, as pointed out in studies between 2001 and 2018 [7], [8], [9], [10], [11]. All of these studies were founded on the understanding that information fed into the uncertainty model is gathered beforehand and interpolated to create the modeled area. As preliminary information, the sounding, sampling, and borehole information has only limited room for flexibility during construction.

The risks of utilizing subsoil models with partial or inaccurate information can, in many cases, actualize economic loss. Estimations of cut and fill volumes, for example, can significantly impact tendering bids, transportation estimates, contract schedules, and emission calculations. This was the case in the Autostrada1 motorway construction project, with Skanska Poland estimating that each centimeter of excess excavation at depth would incur costs of EUR 1 million [12]. In this way, uncertainty modeling, together with the automatic implementation of geotechnical and geological BIM models, can prevent major errors in calculations and analyses [13].

Developments in construction safety and productivity have had an increasing impact on the digitalization of infrastructure construction. Automation has allowed worksite information management to incorporate BIM modeling. For this, accurate subsoil models are crucial (Fig. 1), and with the state of the art of geotechnical modeling today, they require intermediary software and investment in data gathering and storage, according to Hiltunen et al. [14].

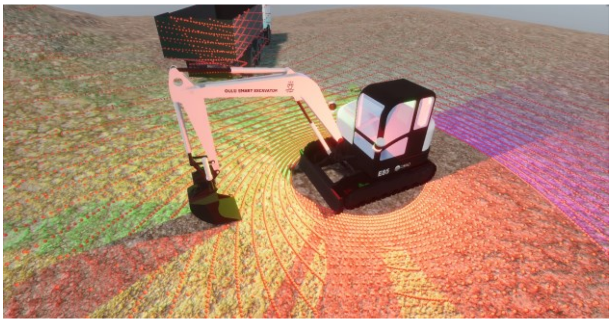

Fig. 1 BIM data and subsoil models create the basis for automated excavation in earthwork construction.

The aim of our study is to investigate the potential of adaptive geological information derived during excavation by studying the effects of incorporating new information into a geological uncertainty model and then creating a verified soil boundary and geological model for an entire excavated area.

Based on the main aim, the following questions are addressed by our study:

1. How does the uncertainty of a geological model develop when excavation is conducted
   a) systematically from one end of an uncertainty model to another
   b) from the most uncertain area of the model outwards?
2. What is the potential for adaptive boundary detection in geological modeling?
3. What are adaptations of uncertainty modeling with updated geological information in the future?

2 Materials and methods

2.1 Uncertainty modeling

The method used in our study for modeling uncertainties in the determination of geological boundaries was based on kriging interpolation and Bayesian statistics [15]. This approach was theoretically inspired by the 3D geological uncertainty modeling of Wellmann et al. [16], although it was adapted to typical geotechnical conditions in infrastructure projects. In such projects, relatively few geological boundaries are typically expected, and geological conditions are only of interest within a limited area below the ground surface. For computational efficiency, the uncertainty modeling code was developed in 2D, with the resulting surface representing a specific geological boundary of interest. The uncertainty model used in this study was implemented in Sweden by Tyréns AB as part of its GeoBIM concept, with the company providing a direct connection to a geotechnical database. Uncertainty modeling was performed using Python code running on a server and controlled by the user through a Microsoft Teams interface.

The user was asked to evaluate the most probable vertical location of the geological boundary at each measurement point (e.g., geotechnical drilling and soundings). The minimum and maximum possible locations of the same boundaries were evaluated by the user, and these input data were used to construct a skew-normal distribution for each measurement point. These distributions represented all possible boundary-level values in the measurement points and their corresponding likelihoods. The uncertainty modeling was then, in short, based on an iterative approach, in which random boundary-level values were drawn from the uncertainty distributions of Svensson et al. [17]. This was followed by kriging interpolation of the boundary surface. Since the input boundary levels varied for each iteration, the approach resulted in an estimation of how uncertainty in the determination of the boundary level propagated from individual measurement points to the surface model as a whole.

In addition to this propagated uncertainty, the variance of the kriging interpolation, which is linearly proportional to the distance to the measurement points, was also taken into consideration. Both types of uncertainties (i.e., spatial variance and propagated uncertainty) were weighted together for the final quantification of the total measurement uncertainty of the modelled surface. In addition, the model output is also the most probable bedrock level as well as the minimum and maximum bedrock levels.

2.2 Study area and data collection

In an earlier study, Svensson and Friberg [18] successfully validated the algorithm used in the uncertainty model implemented at Tyréns AB to study the top boundary of bedrock in three separate infrastructure projects in Sweden. From these infrastructure projects, five uncovered and surveyed areas were mapped and studied alongside the uncertainty model created using preliminary information derived from Swedish JB-sounding (Soil-Rock soundings) investigation points.

Svensson and Friberg [18] produced a one-step verification system in which the preciseness of the uncertainty model was verified according to the results of the uncovered bedrock boundaries. The uncertainty model was not updated during the excavation of the bedrock boundary.

Using a three-step process, our study verified the development of the uncertainty model when new information was introduced into the algorithm during excavation. First, the estimated soil boundary that had been updated during excavation was verified with additional sounding points not used in the initial model. This produced additional data points for the algorithm with the same estimated uncertainty as the initial points. Second, the updated model was verified with soil samples, which produced additional data points with minimal estimated uncertainty. Third, the true soil boundary was mapped from the excavated ground.

This three-step method enabled us to verify the development of uncertainty with adaptive information derived during excavation using the prevailing conditions of practice. This broad adaption of data points enabled the generalization of the adaptive uncertainty modeling, since it was not dependent on certain information-gathering methods while the ground conditions were mapped.

Our study area site description represents a typical Scandinavian friction subsoil consisting of an aggregate sandy gravel layer on top of a moraine base layer. The sandy gravel layer's depth varied from 1.00 m to 13.48 m below the ground. On average, the depth was 12.40–12.60 m (Fig. 1). This site was chosen because of the varying depth of the soil boundary, which created an uncertainty variation around the site area (Fig. 2).

The geological uncertainty model was created for a 50 m × 75 m area. The initial information for the uncertainty model was taken from nine measurement points. The soil boundary level was measured by static-dynamic penetration tests, producing an estimated soil boundary depth with a 20 cm difference in the evaluations of the minimum and maximum possible locations of the same boundaries. The actual boundary depth from these points was verified by soil sampling.

The test site was then divided into a 5 m × 5 m mesh grid, from which the verified soil boundary level of each grid square was introduced into the uncertainty model. The true soil boundary level was verified from surface model measurements of the excavation pit floor, additional soil sampling, and static-dynamic penetration test results not used in the initial uncertainty model.

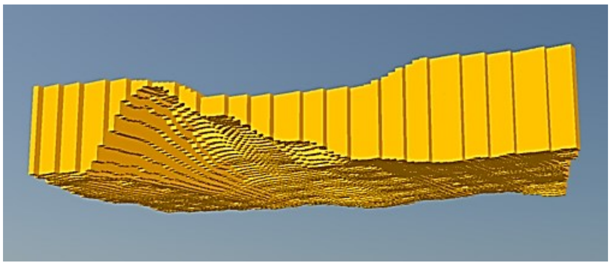

Fig. 1 Verified uncertainty model of the test site's sandy moraine layer.

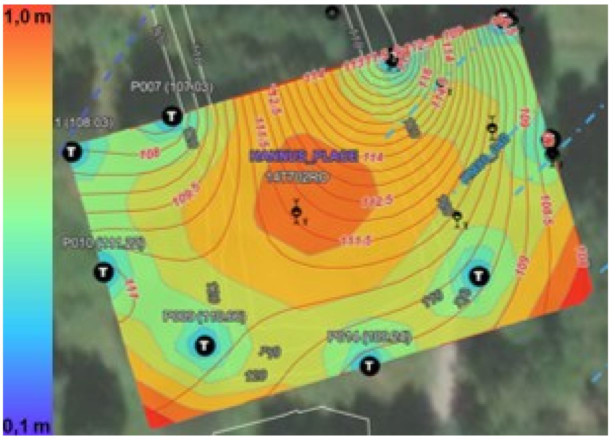

Fig. 2 Initial geological uncertainty condition map of the test site. Uncertainty increases according to the shade of red. The initial measurement points are visualized with black and white "T" symbols.

2.3 Data processing and analysis

The data collected from the surface model measurements of the excavation pit floor, additional soil sampling, and static-dynamic penetration test results were processed into the uncertainty model to create two separate scenarios. These scenarios were simulated to study the adaptive properties of the geological uncertainty model—that is, how the algorithm adjusted the estimate of soil boundary levels—when the calculation parameters were refined.

Because, in most cases, soil boundaries vary in height, the uncertainty model's development is dependent on the weighted distance in which the data points are defined in contrast to one another. The longer the distance, the greater the uncertainty (traditional standard procedure). In our study, we compared the development of the uncertainty model when the distance was largest between the data points (i.e., the uncertainty was adjusted at the beginning of the excavation) with a case in which excavation took place with a traditional one-end-to-another approach.

Using the aforementioned three-step verification system, additional sounding data points and soil sampling were introduced as alternative sources of adaptive information. The estimated soil boundary uncertainty between the minimum and maximum possible locations was kept steady at 20 cm throughout the entire area.

In the first scenario, the uncertainty modeled area was systematically excavated from the western boundary toward the east (Fig. 3). In the second scenario, the excavation was modeled from the most uncertain area outward (Fig. 4). The development of the uncertainty model was reviewed in 20% increments as an estimation of the volume of sandy gravel layers.

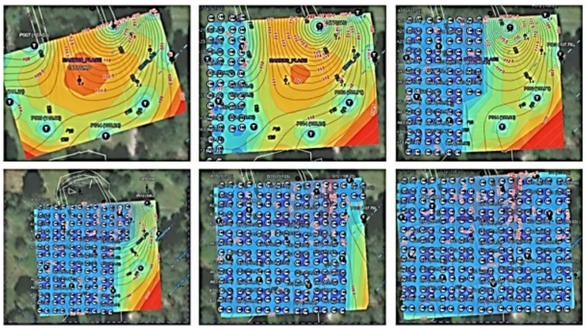

Fig. 3 Development of the uncertainty model in Scenario 1, with excavation boundary levels in 20% increments.

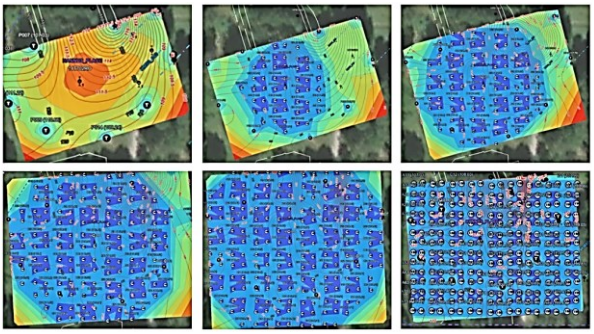

Fig. 4 Development of the uncertainty model in Scenario 2, with excavation boundary levels in 20% increments.

3 Results

3.1 Systematic excavation from west to east

The results show that the uncertainty of the model decreased methodically as the excavation proceeded toward the eastern end of the test site (Fig. 5). The most probable level of volume estimated for the sandy moraine layer decreased below the end result as the excavation advanced from 40% to 60%. This was due to the most uncertain area of the site being located at the approximate center of the excavation. As the excavation modeled the correct level for the uncertain area, with 60% of the excavation completed, the estimation corrected itself back to the original trend of the development.

Even with largely varying uncertainty around the test site, with 60% of the excavation completed, the difference in the volume-level uncertainty was 29.46% for the completed excavation (Table 1). The uncertainty in the volume level, with the initial measurement point data alone, had a difference of 82.58% compared to the completed excavation.

Table 1. Results of uncertainty during systematic excavation from west to east.

Model	Upper level (m^3)	Most probable level (m^3)	Lower level (m^3)	Difference in volume-level uncertainty (%)
0%	24,274	29,080	33,929	82.58%
20%	24,909	29,178	33,473	72.39%
40%	27,271	30,646	34,023	50.91%
60%	26,392	29,088	31,790	29.46%
80%	28,183	30,411	32641	10.53%
100 %	28,282	30,286	32,294	0%

Table 2. Results of uncertainty in the excavation from the most uncertain area outward.

Model	Upper level (m^3)	Most probable level (m^3)	Lower level (m^3)	Difference in volume-level uncertainty (%)
0%	24,274	29,080	33,929	82.58%
20%	26,523	29.749	33,473	53.60%
40%	27,252	29,901	32,992	35.44%
60%	27,854	30,185	32,518	15.03%
80%	28,275	30,317	32,363	1.88%
100%	28,282	30,286	32,294	0%

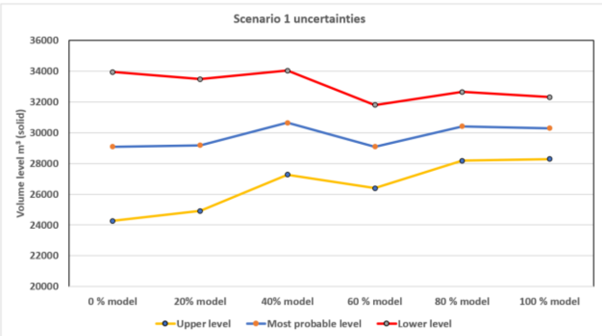

Fig. 5 Development of the uncertainty model as excavation systematically proceeded from west to east.

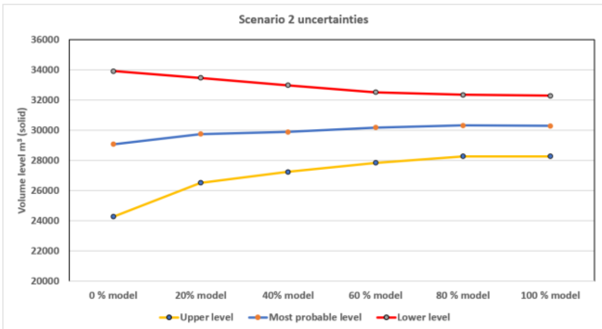

Fig. 6 Development of the uncertainty model as excavation proceeded from the most uncertain area outward.

3.2 Excavation from the most uncertain area outward

When initially mapping the most uncertain parts of the excavation area, and extending the excavation outward from there, the decrease in uncertainty was more effective and linear. The largest development in the uncertainty model, excavating with this approach, occurred in the first 20% of the excavation (Fig. 6). Here, uncertainty decreased by 35.09% (Table 2).

As the excavation progressed, the difference in volume-level uncertainty was 15.03% compared to the completed excavation, when 60% of the test site had been mapped. Compared to the systematic excavation from west to east, where the difference at the same percentage increment was 29.46%, the percentage difference between these two scenarios was 64.86%.

4 Discussion

4.1 Potential and limitations of adaptive boundary detection in geological modeling

The use of adaptive boundary detection reduces the level of uncertainty when interpolating between measurement points and mapping boundary levels. In the future, this could have a large effect on the planning phases of geotechnical solutions, excavation, and transport. As the expected volumes of excavated soil become more precise, the planning of cut and fill volumes and possible aggregate consumption and emissions calculations will become more efficient and effective. The detection of soil boundary depths will allow for more precise geotechnical calculations in earthwork solutions, such as stabilization, preloading, and settlement, and for a more proactive approach to be taken to unforeseen problem-solving. The need for additional ground investigations after the initial planning can be reduced to a necessary minimum in cases where the detection of boundary levels during excavation is sufficient. This can help in cost- and timetable-effective construction, as ground condition mapping is one of the most costly phases of planning. These benefits are vital for contractors and clients to ensure that projects proceed according to the expectations of the tendering proposal. An algorithm continuously updated with the best estimate (±2 std. dev., 95% uncertainty) [18] of boundary levels would be the best possible tool to achieve this goal.

Adaptive uncertainty models can potentially lead to precise, boundary-based autonomous excavation, with the excavation models dictating how the excavation adapts to changes in soil boundaries while in progress. This can create more dynamic uses for unmanned excavation through BIM–model interaction.

As the computational requirements of autonomous excavation do not seamlessly interact with the prevailing conditions of practice in excavation, a middle-ground solution utilizing modeling tools that can be incorporated in near real time into machine-control models can help with the interaction. Our proposed adaptive uncertainty model can create a tool that enables an autonomous excavator to excavate with precision, where earlier machine control models were more robust in their definitions. The uncertainty model could provide additional tools for contractors to create more precise and effective tendering offers while using traditional means of excavation.

As a tool, uncertainty modeling does not exclude the need for thorough ground investigations. Since the effectiveness of the model relies on the initial information fed into the calculations from measurement points, the ground investigation planning should be as detailed as possible. The initial uncertainty model provides vital information on the mapped area and, as our results show, allows for variable results depending on the execution of the excavation.

The evaluation of the minimum and maximum possible locations of boundaries plays an important role in total uncertainty. In our case, when the location difference was set at 20 cm, the degree of compaction in the soil played an important role. Due to the degree of compaction, static-dynamic penetration produced results per 20 cm increment. This is not the most precise sounding method available, and by choosing the most accurate method, depending on the soil type, the uncertainty can be minimized.

4.2 Adaptive geological uncertainty modeling in the future

BIM applications for geotechnical engineering are under widespread development, although one obstacle to their development concerns differences in the conditions of practice. To address this, uncertainty modeling allows individual uncertainties to be set for each investigation location, depending on the quality of the data to be obtained through various methods.

The same aspect of flexibility can be capitalized on in adaptive modeling since there are multiple methods for boundary detection. The integration of uncertainty modeling tools into BIM applications should be conducted with the same type of principles. To implement uncertainty modeling in everyday work, it is necessary to make the tool available without the need to install additional programs, learn new interfaces, and manage new data formats. An example of this is the uncertainty modeling tool used in our study.

This modeling method was incorporated into the Microsoft 365 Teams platform, which many users already know and can access. By making uncertainty modeling available on a platform that is already widely used in the industry, the threshold for starting to use the method was significantly reduced.

5 Conclusion

This study introduced an adaptive utilization method for geological uncertainty modeling. The results derived from the test site data indicate that adaptive updates of ground mapping information can significantly reduce the uncertainty of earthwork. Since the information utilized can be sourced from multiple information sources (i.e., the mapping of excavated ground), the method can be widely adapted to the prevailing conditions of practice. The main benefits of adaptive uncertainty modeling are the creation of precise and effective information during earthwork phases without additional work phases or significant costs.

At present, uncertainty modeling tools are not in widespread use. Further development of the algorithm depends on operational experience derived during field tests. Because the algorithm for calculating soil boundaries and the accompanying uncertainties depend on the individual uncertainty of each data point, the amount of information gathered from various test sites, which is effectively a ground condition database, can significantly advance the algorithm's development.

Such a database can help determine how various geological parameters and the distances between data points are weighted, depending on how much they should influence the calculation, thereby advancing the calculation of site-specific conditions by converging the predicted excavated soil boundaries with the individual uncertainties in each data point.

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