PARAMETRIC MODELLING OF THE GEOLOGICAL CROSS SECTION FOR SHIELD TUNNEL DESIGN AND CONSTRUCTION

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KEY WORDS: Underground construction; Shield tunnel; Parametric modelling; Geological modelling; Cross section

ABSTRACT:

Geological information is indispensable for the design and construction of underground structures, especially for large-diameter shield tunnels. The geological cross-section is expected to be accurately and efficiently modelled to provide sufficient geological information for decision-making. However, the existing methods are usually time-consuming, and the calculation results cannot be intuitively understood by engineers. To meet this demand, this study attempts to develop a parametric modelling approach for the geological cross-section of tunnelling construction. The proposed approach consisted of four steps. In the first step, the borehole records from the geological investigation are converted into the DataFrame format. Then, each point is assigned a soil type label and soil property parameter to form a data framework. In the third step, the cross-section is generated in mesh type and divided into two parts. Finally, the mesh models are rendered to visualize the stratum sequence and soil property distribution. The proposed approach potentially promotes a data-driven technology for underground engineering construction.

1. INTRODUCTION

In recent years, the demand for large-diameter and long-distance shield tunnelling technology has increased due to the rapid development of underground construction. However, the delivery of shield tunnelling construction often faces complicated geology and uneven strata, which brings challenges to structural design and excavation construction. In such a situation, geological modelling should be conducted to facilitate stratum identification and geological cross-section recognition, underground water conditions are also a serious factor to be considered during tunnel design and construction. For underwater shield tunnelling in karst ground, the presence of underground water flow sometimes makes backfill grouting difficult (Zhang, 2018). Therefore, geological modelling can reflect the uncertainty of actual tunnelling and illustrate hydrogeological conditions in correlating the structural performance of shield segments, both helping to enhance construction safety management.

However, existing geological modelling methods still have some limitations. First, the modelling procedures are of low efficiency because their adopted algorithms are usually time-consuming (Liu, 2019); hence, the spatial variability of soil properties cannot be represented in a time-dependent manner. Second, the integration level of geological data is not enough, and in many cases, the strata are identified by qualitative methods and used for visualization only. Although some methods apply quantitative identification, they are subject to the sparseness of sampled data from borehole records (Sava, 2011). Thus, the subsequent excavation works cannot be directly improved through data analysis. Third, the transverse cross-section region, such as the vertical plane of tunnelling or cutter head surface of the shield machine, has not received enough attention. Most geological modelling methods focus on the objects of longitudinal geology profiles. In fact, the transverse ground pressure calculation. The calculation results could be successively used in the tunnel structural analysis. Therefore, the proposed approach potentially promotes a data-driven technology for underground engineering construction.

Yu (2020) proposed an unsupervised architecture to extract geological-related features. Except for complex stratum recognition, underground water conditions are also a serious factor to be considered during tunnel design and construction. For underwater shield tunnelling in karst ground, the presence of underground water flow sometimes makes backfill grouting difficult (Zhang, 2018). Therefore, geological modelling can reflect the uncertainty of actual tunnelling and illustrate hydrogeological conditions in correlating the structural performance of shield segments, both helping to enhance construction safety management.
This paper proposes a parametric modelling approach for the geological cross-section of tunnelling construction. During shield tunnel design and construction, the transverse geology profile can be accurately and efficiently modelled, and the modelling results provide sufficient geological information for decision-making.

The next section introduces the framework and main algorithms of the proposed approach. Subsequently, the implementation of this approach is illustrated through a real-life case of the Wuhan Lianghu tunnelling project. Finally, in accordance with the practical applications, the results are concluded and discussed.

2. METHODS

2.1 Framework

Figure 1 presents the workflow of the proposed modelling approach, which contains four main steps.

I) Creating a geologic borehole DataFrame. As the geological information originates from the borehole data in the geological investigation report, the DataFrame format is proposed to uniformly collect the information of borehole name, borehole locations, stratum sequences, and levels. At the same time, some indexes must be labelled and assigned parameters, which will be convenient for later calculation.

II) Parametric modelling for the target cross-section. The cross-section includes the transverse plane of tunnelling and the cut head surface of the TBM. These surface models are automatically generated along the tunnelling route and transformed to mesh type by gridding.

III) Maximum likelihood estimation of stratum sequences, which is based on the mesh model of the cross-section, and the soil distributions are analysed and predicted following the space coordinates relations to the borehole locations.

IV) Maximum likelihood estimation of soil properties. According to the known drilling samples, the soil properties of unknown areas in the cross-section can be predicted through geostatistical methods.

After these four steps, the stratum sequence and the soil property distribution of the cross-section can be exhibited clearly. This modelling approach also provides a visualization strategy based on the color rendering of the modelling results. The subsequent sections will introduce the technical details of the individual steps.

Figure 1. Workflow of the proposed approach

2.2 Creating geologic borehole DataFrame

Generally, geological drilling information is logged in geological investigation reports (see Table 1), where $D_{a,:0}$ represents all of the row data of the $0^{th}$ column in $D_a$; $D_{a,:1}$ represents all of the row data of the $1^{st}$ column in $D_a$; and $D_{a,:x}$ represents all of the row data of the $x^{th}$ column in $D_a$.

<table>
<thead>
<tr>
<th>Drilling No. $(D_{a,:0})$</th>
<th>$X$ $(D_{a,:1})$</th>
<th>$Y$ $(D_{a,:2})$</th>
<th>$Z$ $(D_{a,:3})$</th>
<th>Soil Type $(D_{a,:4})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

Table 1. Borehole data format

As one borehole has various soil distributions from the top layer to the bottom, the $z$ parameters represent the top and bottom boundary for each stratum, and the borehole data can be collected in a DataFrame, $D_a$. To subdivide the interval and improve the data density, Algorithm 1 is proposed to give the function of automatic subdividing of borehole data to create Geological DataFrame, $D$, which has the same rows as $D_a$ but
contains more points being regularly distributed. Thus, the subsequent calculations and predictions can achieve higher accuracy. The transformation from $D_a$ to $D$ is illustrated in Figure 2. $D$ can be represented through point cloud modelling with $X, Y, Z$ parameters input and keeping the orders.

![Figure 2. Illustration of data processing](image)

Normally, the geological investigation report provides the property parameters corresponding to the soil type, which are logged as Gauss mean values from testing on the examples. In this case, programming scripts can be used to assign these specific values to DataFrame $D$ in an automatic manner. This procedure is illustrated in Figure 3.

![Figure 3. The soil property parameters assignment](image)

<table>
<thead>
<tr>
<th>Drilling No</th>
<th>X</th>
<th>Y</th>
<th>Z</th>
<th>SoilType</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>2</td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>3</td>
<td></td>
<td></td>
<td></td>
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<td>4</td>
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<td>5</td>
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<td></td>
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<td>9</td>
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<td>10</td>
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<tr>
<td>11</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Algorithm 1. Increasing data density of original geological information**

```
Input: The borehole data, $D_{bc}$; density of subdivision, $density$;
Output: The Geological DataFrame, $D$;
1. create a two-dimensional array in empty, $S$
2. calculate the number of boresholes, $N_a$
3. for i in range($N_a$):
4. count up the amount of points in each borehole, $N_i$
5. divide the borehole depth with $density$ into $N$ points
6. for j in range($N$):
7. create a depth interval between every two points in $N_i$ that have the same SoilType, $(a, b)$
8. for k in range($N$):
9. if f in (a, b):
10. assign SoilType to the $f$th point in $N$
11. put the fth point’s $X, Y, Z$ and SoilType in $S$
12. transform $S$ into DataFrame, $D$
13. return $D$
```

The target cross-section includes two parts: one is the cutter head surface, and the other is the surrounding strata. The location of the section is dependent on the mileage of the tunnelling route. The section’s size is adjusted to the diameter of tunnelling. During the excavation, these parameters are predesigned in the construction scheme and can be provided as input arguments for model generation. This study proposes Algorithm 2 to show the procedures of parametric modelling.

As the created cross-section model is a boundary representation (Brep) object, it still needs to be processed with grid division for transformation into a mesh model. An illustration of the cross-section modelling and grid division is presented in Figure 4. Then, unduplicated nodes are retrieved from the mesh model, and their coordinates (as $V$) are regarded as the estimating objects for maximum likelihood estimations. They are also required to be stored in DataFrame format.

\[
V = \begin{bmatrix}
  X & Y & Z \\
  0 & \cdots & \cdots \\
  V & \cdots & \cdots \\
  \vdots & \vdots & \vdots \\
  n & \cdots & \cdots 
\end{bmatrix}
\]

![Figure 4. Cross-section modelling](image)

**Algorithm 2. Parametric modelling for the target cross-section**

```
Input: The tunnelling route object in 3D curve model, $R$; mileage parameter of the route, $M$; diameter of tunnelling cross-section, $D_T$; The Geological DataFrame, $D$;
Output: The cross-section model of tunnelling, $CS$;
1. Based on $M$ to retrieve the corresponding point and tangent in curve $R$, as $P$ and $T$
2. Find and retrieve the nearest borehole’s attitude (the maximum $z$ value) in $D$, as $A$
3. Based on $P$ and $X, Y$ vectors of $T$ to create a plane, $P$
4. Based on $P$ to create a rectangle area as $R_m$ with $2D_T$ width and defining its top side at $A$, foot at -$D_T$ below $P$
5. Divide $R_m$ by subtracting a circle with diameter of $D_T$ that is centered on $P$
6. The circle and the rest part in $R_m$ are together defined as surface models, $CS$
7. return $CS$
```
With the retrieved unduplicated nodes, the nearest distances from them to the points of the borehole DataFrame should be calculated. Then, through the KNN (K-nearest neighbor) algorithm, the soil type for each node can be classified and labelled. In this way, the variable \( V' \) is transformed into \( V \) as follows.

\[
V' = V + 1 \quad \text{for}\ i \text{ in range(rows of } V'\text{)}
\]

Then, a sampling statistics method is adopted to calculate the stratum thickness, and the buried depth is determined with the \( z \) value. **Algorithm 3** is proposed to give the functions of classifying and outputting the stratum sequences.

### 2.3 Stratum sequence estimation

To estimate the stratum sequences for each cross-section, the thickness and the boundary of each stratum must be obtained. With the retrieved unduplicated nodes, the nearest distances

<table>
<thead>
<tr>
<th>SoilType</th>
<th>X</th>
<th>Y</th>
<th>Z</th>
<th>SoilType</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>1</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
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<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>0</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

**Algorithm 3.** Stratum sequence identification and thickness calculation

In addition, the prediction of the groundwater table is carried out in three steps.

I) retrieve the groundwater table parameter \( (h) \) of each drilling from the geological investigation report and combine the drilling locations \( X \) and \( Y \) to form a DataFrame \( W \) as follows.

<table>
<thead>
<tr>
<th>drilling No.</th>
<th>X</th>
<th>Y</th>
<th>h</th>
</tr>
</thead>
</table>
| 0            | ...| ...| ...
| \( W = 1 \)  | ...| ...| ...
| 2            | ...| ...| ...
| ...          | ...| ...| ...

II) using \( W \) as a data sample to train the ordinary kriging algorithm model with the help of programing language or program script execution. Then, the trained model is stored and transformed into a function for subsequent program invocation.

III) Define the target location or position with specific \( X, Y \), and input \( X, Y \) into the trained ordinary kriging model to ultimately predict the target’s groundwater table \( h \).

To enable a more intuitive understanding of the modelling results, the cross-section model can be rendered with vertex color processing. Different colors can be applied to various types of \( \text{SoilType} \). Additionally, the visualization of groundwater can be achieved by surface fitting in accordance with the predicted results.

### 2.4 Ground pressure determination

Combining the identified stratum sequences and the natural gravity parameters, the ground pressure acting on the shield linings can be determined in each cross-section. Normally, the pressure acts radially and can be divided into the vertical direction and horizontal direction. The horizontal ground pressure is dependent on the vertical earth pressure (Han et al., 2017). The vertical ground pressure could reflect the influence of the surrounding soil conditions on the shield lining design more directly. Thus, the ground pressure determination in this study mainly focuses on the vertical direction.

The vertical ground pressure acting on the crown of the lining can be determined as:

\[
H = \sum H_i + \sum H_j \quad (1)
\]

\[
p_e = \sum \gamma_i H_i + \sum \gamma_j H_j \quad (2)
\]

\[
p_e = \gamma_e H_e \quad (3)
\]

\[
p = p_0 + p_e \quad (4)
\]

where \( H \) represents overburden, \( m; \) \( H_i \) is the thickness of \( i^{th} \) stratum over the tunnel, \( m; \) \( H_j \) is the thickness of \( j^{th} \) stratum over the tunnel, \( m; \) \( \gamma_e \) is natural gravity of soil in the \( i^{th} \) stratum,
kN/m²; \( \gamma \) is natural gravity of soil in the \( j \)th stratum, kN/m²; \( P_s \) is earth pressure and \( P_w \) is water pressure, kPa; \( \gamma_w \) is natural gravity of groundwater, as 10 kN/m²; \( H_w \) represents groundwater table, m; and \( P \) is the total pressure of \( P_s \) and \( P_w \). These formulas are applicable to shallow sections. For deep sections, the pressure should be reduced following Terzaghi’s theory.

2.5 Maximum likelihood estimation of soil property distribution

To estimate the soil property distribution in a space field, Markov or Gaussian geostatistical models are commonly used (Wang, 2018). However, considering the practical demands for calculation speed and easy manipulations, this study proposes to use the universal kriging model for estimations. The information of geological borehole data, including \( X \), \( Y \), \( Z \) and property parameters in \( D_p \), is regarded as the input arguments for Universal Kriging model training. Unduplicated nodes from the cutter head surface are selected as the estimating objects (\( V \)). The trained universal kriging model is capable of estimating property parameters on the points of \( V \). To visualize the estimated results, the parameter values are represented by a greyscale map in high to low order.

3. CASE STUDY

3.1 Project Overview

Wuhan Lianghu tunnelling project is one of the largest underwater highway shield tunnel projects in the urban area. According to the geological survey by CCCC Second Highway Engineering Bureau Co., Ltd., the excavation progress is mainly sited in the strata of weathered mudstone, tuffs, argillaceous sandstone, and silty clay, of which the uniaxial compressive strength widely changes from 2.15 MPa. The overburden is in the range of 10-42 m, and the tunnelling route has a minimum radius of 600 m and a 4.5% longitudinal gradient.

This case study focuses on a 100 m tunnelling section of QK2+820–QK2+920 and investigates the neighborhood geologic conditions by using the proposed modelling approach. In this way, 1) the surrounding strata in the minimum radius curve section can be identified with the most likelihood, which helps to consider the most unfavorable conditions for determining the segment lining design; 2) the earth pressure variation in front of the cutter head surface during excavating can be predicted, which is helpful for controlling the cutter chamber pressure and keeping the shield advance speed stable.

The selected parametric modelling tool is the Rhino & Grasshopper platform with the Python module plug-in. The configuration of the computer includes an Intel(R) Core(TM) i7–10700 CPU 2.90 GHz, 32 GB RAM, and an NVIDIA GeForce RTX 2060 SUPER GPU.

3.2 Strata identification and ground pressure

By creating the DataFrame and representing it with point clouds, the geologic borehole data were expressed in an intuitive way with the tunnel model incorporated (Figure 5). The drilling positions were distributed along the tunnelling route, and the separation distances were kept at 10-50 m. Using Algorithm 1, the subdivided DataFrame \( D \) with SoilType labelled is displayed below, and Table 2 gives explanations for the SoilType.

<table>
<thead>
<tr>
<th>Drilling No.</th>
<th>X</th>
<th>Y</th>
<th>Z</th>
<th>SoilType</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>LH1X-ZK248</td>
<td>802400.812</td>
<td>382906.189</td>
<td>19.1</td>
</tr>
<tr>
<td>1</td>
<td>LH1X-ZK248</td>
<td>802400.812</td>
<td>382906.189</td>
<td>18.6</td>
</tr>
<tr>
<td>2</td>
<td>LH1X-ZK248</td>
<td>802400.812</td>
<td>382906.189</td>
<td>18.6</td>
</tr>
<tr>
<td>3</td>
<td>LH1X-ZK248</td>
<td>802400.812</td>
<td>382906.189</td>
<td>18.1</td>
</tr>
<tr>
<td>4</td>
<td>LH1X-ZK248</td>
<td>802400.812</td>
<td>382906.189</td>
<td>18.1</td>
</tr>
<tr>
<td>5</td>
<td>LH1X-ZK248</td>
<td>802400.812</td>
<td>382906.189</td>
<td>17.6</td>
</tr>
<tr>
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<td>LH1X-ZK248</td>
<td>802400.812</td>
<td>382906.189</td>
<td>17.1</td>
</tr>
<tr>
<td>7</td>
<td>LH1X-ZK248</td>
<td>802400.812</td>
<td>382906.189</td>
<td>17.1</td>
</tr>
<tr>
<td>:</td>
<td>:</td>
<td>:</td>
<td>:</td>
<td>:</td>
</tr>
<tr>
<td>7432</td>
<td>LH1X-ZK75</td>
<td>802676.783</td>
<td>382705.211</td>
<td>−37.8</td>
</tr>
</tbody>
</table>

Figure 5. The geologic borehole data representation with tunnel model

Then, a cross-section was created and analysed at 10 m intervals in the section of QK2+820–QK2+920 and fitted to the groundwater surface (shown in Figure 6). The time consumption of this procedure is approximately 25 s, while each cross section needs 2.2 s for prediction and modelling. The modelling results illustrated that the excavation progress underpasses pebble and weathered mudstone layers. Such strata identification results conformed to the traditional analysis method from geological investigators, and the proposed modelling approach was demonstrated to make the results more explicit and understandable.

Based on the modelling results, the tunnelling progress would encounter composite strata after the mileage of QK2+840. The bottom of the linings in this section has a large water content and permeability coefficient, which may cause serious water leakage in shield segments. According to these analyses, validation of the tunnel longitudinal structure in this section should be further carried out to ensure the structural safety of the tunnel.
Finally, each cross-section calculates its stratum thickness by using Algorithm 3, and the overburden with the groundwater table together was simultaneously determined by subtracting the tunnelling crown altitude in each cross-section (shown in Figure 7). This procedure is dependent on basic mathematics computing so that the time consumption is negligible. According to the results, the 10–20 m mileage would face a significant overburden growth from 19.79 m to 22.47 m. After 20 m, the pebble layer emerges and keeps the thickness increasing. The groundwater table also sees a continuous increase in the range of 17–20 m. Significantly, this tunnel section of 50 rings could have a changing ground pressure on the crown linings.

By referring to the natural gravity parameters in Table 2, the ground pressure over the tunnel can be determined (see Figure 7b). In this case, study, the overburden is smaller than double the diameter (i.e., 29 m), and this tunnel section should be regarded as a shallow tunnel. Thus, Terzaghi’s formula was not used. The interval between the two cross-sections was set at 5 m to clearly reflect the pressure variations. Along with tunnelling mileage, the pressure gradually increases from 566 kPa to 700 kPa, similar to the overburden growth. The ground pressure variation approximately conforms to the overburden growth rule. In addition, the ground pressure results are compared to geological surveys and design reports, and the discrepancy is below 10%. However, it is worth noting that other types of ground pressures, such as lateral arrangements or subgrade reactions, have not been considered in our method, and further

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**Table 2. Soil type and property parameters in the original geological investigation report**

<table>
<thead>
<tr>
<th>Soil Type</th>
<th>Explanations</th>
<th>Natural Gravity (kN/m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-1, 1-2</td>
<td>Earth fill</td>
<td>18.8</td>
</tr>
<tr>
<td>1-4</td>
<td>Mud</td>
<td>17.1</td>
</tr>
<tr>
<td>7-3</td>
<td>Clay</td>
<td>19.5</td>
</tr>
<tr>
<td>10-1</td>
<td>Silty clay</td>
<td>20</td>
</tr>
<tr>
<td>12e</td>
<td>Pebble</td>
<td>22</td>
</tr>
<tr>
<td>20a-1</td>
<td>Strongly weathered mudstone</td>
<td>25.7</td>
</tr>
<tr>
<td>20a-2</td>
<td>Moderately weathered mudstone</td>
<td>26.7</td>
</tr>
<tr>
<td>22</td>
<td>Structural fracture zone</td>
<td>25</td>
</tr>
</tbody>
</table>

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**Figure 6. Geological cross-section modelled by the proposed parametric method**

**Figure 7. Quantification of stratum sequences and ground pressure**

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This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
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improvements could be made on the basis of the proposed workflow to address these issues.

This parametric modelling method for 11 cross-section objects took approximately 25 seconds to visualize and calculate the ground pressure. Except for establishing DataFrame in the early stage, the entire modelling procedure was dependent on code manipulation and did not require any manual operations for parameter adjustment in each loop. Such a procedure makes the time consumption of our method shorter than existing methods (e.g., Graciano et al., 2018).

3.3 Soil property prediction

In this case, study, the natural gravity of soil was selected as the property parameter to be estimated since it can significantly influence the earth pressure acting on the cutter head surface horizontally during excavation. If the pressure on the head surface was too high, the excavation would bring an upheaval effect to the ground ahead; if the pressure was too low, the ground settlement would happen. Therefore, to help the TBM operators control the chamber pressure safely, it is necessary to provide them with real-time prediction of the natural gravity of soil ahead.

In the zone of QK2+820~QK2+920, the natural gravity variation in front of the 11 cutter head surfaces was analysed at 10 m intervals and was characterized by the peak and bottom values. At the same time, the cutter head surfaces were rendered with greyscale maps (seen in Figure 8). The Gauss mean values of related soils’ natural gravity in the geologic investigation report can be found in Table 2. Compared with the mean values range of 22-25.7 kN/m³ for the corresponding soils, the prediction results were in the range of 22.03-24.16 kN/m³, showing slight divergences. From 0 to 100 m mileage, the discrepancy between the maximum and minimum limitations remained stable. At 50-70 m, the natural gravity was at a high level, which can be attributed to the composite strata of moderately weathered mudstone and pebble that emerged. With the help of the universal kriging algorithm, the trend of the natural gravity distribution on the surface can be easily explored. The values on the surface bottom were larger than the crown values, which can be explained by the historic layering effect. On this basis, the TBM operators should focus on adjusting the tunnelling parameters since the natural gravity increment may bring unstable earth pressure in front of the TBM and lead to uneven settlement on the ground. The natural gravity prediction on each cutter head surface contains two steps: model training and model calculation. Although the two steps progress in automatic algorithm operation, the former requires 2 hours, and the latter requires 6 hours for 11 cross sections. However, the time of modelling and rendering is less consuming. In this case, property prediction can be arranged at the preparatory stage of the project.

![Figure 8. The cross-section modelling](image)

### Figure 8. The cross-section modelling

![Maximum limit](image)

![Minimum limit](image)

<table>
<thead>
<tr>
<th>Route mileage (m)</th>
<th>Natural gravity (kN/m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>22.03</td>
</tr>
<tr>
<td>20</td>
<td>22.56</td>
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<tr>
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<td>24.16</td>
</tr>
</tbody>
</table>

4. CONCLUSION

This study presents a parametric modelling approach for stratum sequence identification and soil property prediction based on drilling borehole data in the original geologic investigation report. The new insight of the approach is adopting a parametric modelling strategy to depict the stratum sequence and express the predicted soil property distribution. In addition, the drilling information logged in the geotechnical investigation report is sorted out and stored in DataFrame format to achieve data-driven modelling.

This study verifies a case study of the QXK+020~QXK+120 section in the Wuhan Lianghu tunnelling project. The case study confirms that 1) the geological cross-section model and the fitted groundwater surface can be efficiently generated within approximately 25 seconds; 2) at the same time, the overburden pressure on the crown of the correlating tunnel can be efficiently determined; and 3) the natural gravity distribution on the cutter head surface can be expressed through the greyscale map and helps the TBM operations. Although the prediction of it requires some hours, it can be arranged at other preparatory periods.

While the approach finally outputs the model in mesh type, rather than the Brep model, the nodes of mesh are capable of being exported as DataFrame for the subsequent work. Future work will focus on more practical demands of underground construction, such as load arrangements or constraint settings in the structure design.
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