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DOI

[10.23967/isc.2024.153](https://doi.org/10.23967/isc.2024.153)

Publication date

2024

Document Version

Final published version

Citation (APA)

Brinkgreve, R., Zekri, A., & Laera, A. (2024). *Towards an integrated and automated digital workflow in geotechnical engineering*. Paper presented at 7th International Conference on Geotechnical and Geophysical Site Characterization, Barcelona, Spain. <https://doi.org/10.23967/isc.2024.153>

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Towards an integrated and automated digital workflow in geotechnical engineering

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ABSTRACT

The use of soil data is essential in geotechnical design, but in a preliminary project phase such data are usually limited to that inferred from field tests, like CPT, SPT or DMT. In previous publications by the authors and co-workers, it was shown how such data can be automatically processed into soil profiles and parameter sets for geotechnical finite element analysis. Another publication demonstrated the automated processing and creation of geological models as an intermediate step to more advanced 3D geotechnical modelling in a BIM / Digital Twin environment, which facilitates the link with other disciplines and stakeholders in a project. The major challenge of connecting layers across multiple 1D boreholes to form 3D soil layers is overcome by using a Machine Learning clustering algorithm. As a next step, the previously introduced Automated Parameter Determination (APD) method (connecting correlations using Graph theory) is applied based on averaged CPT parameters from all contributing layer sections. The result is an automated system that creates a complete 2D or 3D finite element model, including constitutive model parameters, for geotechnical analysis purposes. An automated system may be very efficient when exploring different design alternatives in an early stage of a project. However, it is important to emphasize the role and responsibilities of the geotechnical engineer in the design process, which requires the system to be transparent, verifiable, and adaptable. This paper describes the state-of-the-art of this ongoing research project.

Keywords: integrated workflow; automation; clustering; APD.

1. Introduction

The first step in any geotechnical project involves the collection and investigation of available soil data from the project site, with the purpose to extract a soil profile and infer properties and parameters for the various soil layers. In an early stage of a new project, soil data is usually scarce. Cone Penetration Testing (CPT) is a relatively cheap way to obtain soil data for a preliminary design. Sometimes, databases exist with CPTs from former projects. Although each project requires new site investigation to be executed, existing data (when available for the project site) may still be useful for a desktop study or preliminary design. As an alternative to CPT data, Standard Penetration Test (SPT) or Dilatometer Test (DMT) data may be used.

The interpretation of CPT data is generally based on a Robertson chart (Robertson 1990, 2009, 2010, 2016), translating the cone resistance q_c and the friction ratio R_f (or variations thereof) into Soil Behaviour Type (SBT). Moreover, correlations exist to determine soil parameters from CPT parameters (e.g. Kulhawy and Mayne 1990; Cetin and Ozan 2009; Robertson and Cabal 2015), and methods exist to transform a single CPT into a layered soil profile (e.g. Wang et al. 2013). Much of this can be automated, but the creation of a stratified 3D subsoil model and corresponding parameters sets from multiple CPTs for 2D or 3D numerical analysis still requires

significant manual work from a geotechnical engineer. Recent and current research aims for further automation of this work, in which mostly probabilistic or Bayesian methods and Machine Learning are applied (e.g. Wu et al. 2021; Rauter and Tschuchnigg 2022).

This paper describes the state-of-the-art of an ongoing collaborative research project that started in 2019 on Automated Parameter Determination (APD) (van Berkom et al. 2022; Marzouk et al. 2022) and that is evolving towards an integrated and automated digital workflow in geotechnical engineering and design (Brinkgreve and Brasile 2022).

Section 2 describes our vision on the advantages and necessity of an automated digital workflow in geotechnical engineering. Section 3 describes the various components of such an automated system. In Section 4 an example is elaborated. Section 5 touches upon the responsibilities in view of an automated system and Section 6 ends with some conclusions.

2. Advantages and necessity of an automated digital workflow

Numerical modelling has changed geotechnical engineering and design. Where conventional methods focus on one particular design aspect, numerical models can deal with multiple aspects at the same time. 3D (or actually 4D) numerical models enable a realistic modelling of the various stages of a construction process

and the operation time of any infrastructural project. In this way, more complex situations can be analysed in detail and with great accuracy, provided that sufficient data are available, and the data are properly interpreted and translated into modelling details.

What also changed is that projects are designed by integrated multi-disciplinary teams rather than by individual specialists working independently. The development of Building Information Systems (BIM) and Digital Twins, containing a 'single source of truth' of all project data is well recognized and meanwhile being adopted by the construction industry. Although geotechnical engineering has never been in the forefront of adopting new technologies, research and development is moving forward in this direction. Besides the advantages of an integrated digital workflow, as mentioned by Brinkgreve and Brasile (2022), automation of data processing has more:

- It makes the workflow even more efficient.
- It reduces the possibility of making mistakes.
- It leads to more consistency in results.

On the one hand, the demand for geotechnical engineering will further increase in the coming decades, due to major challenges such as climate change and energy transition, growing world population and densification of urban areas, retrofit and extension of post WWII infrastructures, etc. On the other hand, it seems that the interest among students in civil and geotechnical engineering is decreasing. This means, more work needs to be done by less people. Automation may help or is even necessary to cope with all future challenges. Thereby, geotechnical professionals can concentrate on the essential part of their job and remain responsible for design decisions, while several parts of the workflow are automated.

The question is how far automation should go, which touches upon the responsibilities of the project engineers. The authors of this paper believe that automation is fine as long as it leaves the responsibility of a design with the engineers involved in the project. This requires the automated system to be transparent, adaptable, and verifiable. More about this in Section 5.

In the next section the components of the automated workflow will be discussed.

3. Components of the automated workflow

The workflow for creating a geotechnical numerical model for a project consists of the following steps:

1. Selection and basic interpretation of CPTs from the project site (Classification).
2. Combining CPT readings into soil layer sections per CPT (Stratification).
3. Combining soil layer sections to find similar corresponding layers across all CPTs (Clustering).
4. Averaging CPT parameters for all 3D layers.
5. Determining soil properties and parameter sets for the 3D layers from averaged CPT parameters.
6. Creating 3D soil layers from the stratification and clustering to form a 3D subsoil model.
7. Making cross sections from the 3D subsoil model and importing them in the numerical model.

A Python software tool was built in which the above workflow has been automated. The tool interacts with other software and can be integrated in a Digital Twin environment. In this way, geotechnical data is efficiently and securely shared with all stakeholders in a project.

Details of the various steps of the automated workflow are described below.

3.1. Classification

Several software packages exist in which the interpretation and classification of individual CPTs is automated, so this is not new. For every CPT reading in every CPT, the tool calculates the CPT parameters according to Robertson's method. Here, one can choose which version of Robertson's method shall be used: the one using normalised cone resistance (Q_m) and friction ratio (F_r) or the non-normalised version using the corrected cone resistance over the atmospheric pressure (q_t/p_a) and the corrected friction ratio in percent (R_f). Note that this requires the vertical stress to be calculated, which is based on the unit weight of soil, γ , which can be calculated from the well-known Robertson correlation:

$$\gamma = \gamma_w(0.27 \log(R_f) + 0.36 \log(q_t/p_a) + 1.236) \quad (1)$$

In which log is the log in base 10 and γ_w is the unit weight of water. For very soft or organic soils, the tool uses the correlation by Lengkeek (2022):

$$\gamma = \gamma_{sat,ref} - \beta \frac{\log(q_{t,ref}/q_t)}{\log(R_{f,ref}/R_f)} \quad [\text{kN/m}^3] \quad (2)$$

Where $\gamma_{sat,ref} = 19.5 \text{ kN/m}^3$, $q_{t,ref} = 9.0 \text{ MPa}$ and $R_{f,ref} = 20\%$, while q_t is in MPa and R_f is in %.

The identification of *SBT* is derived from the various regions in Robertson's chart, approximated by mathematical equations, while the very soft and organic soils (*SBT* = 2 and 3) are further divided in 2.1 (peat), 2.2 (organic clay), 2.3 (clay, organic matter) and 3 (mineral clay), using the equations of Lengkeek (2022).

The current version of the tool uses only CPTs, but future versions may also include other field tests.

3.2. Stratification

Stratification is less straightforward. Different methods exist, usually based on common *SBT* or a statistical approach or on minimization of the error in the averages per layer compared to the original CPT readings, while maintaining a minimum layer thickness. The tool uses an alternative approach (Brinkgreve et al. 2023), based on moving standard deviations of $\log(q_t/p_a)$ and $\log(R_f)$ with depth, and allows for a user-defined *minimum layer thickness* and *layer tolerance*. The latter is used to combine adjacent layer sections that turn out to be rather similar (within the tolerance). The larger the tolerance, the lesser number of layer sections remain.

In this way, all CPTs are stratified in layer sections, and average values of the core CPT parameters are calculated, while the other CPT parameters are derived from the averaged core parameters. Note that cone resistance and friction ratio need to be averaged based on their log-values.

3.3. Clustering

Finding corresponding layers across multiple CPTs is even more challenging. The tool uses a 3D Machine Learning clustering algorithm, to find clusters of similar layer sections. The three ‘coordinates’ of the data points that enter the clustering algorithm are $\log(q_t/p_a)$, $\log(R_f)$ and *depth*, and they are standardized using the *StandardScaler* routine in *Scikit Learn* (a Python library for Machine Learning). While in a previous version *DBSCAN* was used as clustering algorithm (Brinkgreve et al. 2023), the current version of the tool uses *KMeans*. In *KMeans*, the number of clusters is specified by the user, although it can also be determined automatically by means of the *Elbow Method*.

The use of *depth* as third coordinate is debatable and works only in the case of near-horizontal soil layers. Note that it is important to use depth with respect to reference level and not depth with respect to ground surface. For example, if the project location involves an embankment and CPTs are taken both on and besides the embankment, then similar layers are found at the same reference depth, but not at the same depth below the (elevated) surface.

Resulting clusters do not only consist of similar layer sections in different CPTs, but also similar layer sections in the same CPT may end up in the same cluster. This may be the case if a sand or clay lens is embedded in a soil layer, or simply if the *layer tolerance* was set to a small value such that adjacent near-similar layer sections still existed as separate data points before clustering.

Note that, although SBT is determined as a parameter for all CPT readings, layer sections and clusters, neither the stratification nor the clustering use SBT to determine layer sections or clusters. Both algorithms are purely based on the underlying CPT parameters.

The layer sections of all CPTs with their cluster numbers are stored as *Borehole* data. These data are used to create a 3D sub-soil model with 3D soil layers, which will be described further in section 3.5. But before that, soil parameters will be determined, and parameter sets are created.

3.4. Parameter determination

In a similar way as how core CPT parameters and derived parameters were averaged for layer sections in individual CPTs, these are now averaged for the 3D soil layers (clusters) based on contributions from all layer sections. The averaged CPT parameters per cluster are used to (automatically) determine soil parameters and model parameters by means of the graph method, as described earlier by Van Berkom et al. (2022) and Marzouk et al. (2022). In this method, ‘paths of correlations’ are used, starting from the CPT parameters via intermediate soil parameters to the final model parameters. The correlations (called ‘methods’) to be used and the parameters to be determined are available in accessible .csv files, which can be modified and extended by the user.

The current version of the software tool only uses the Hardening Soil model with small-strain stiffness (HSsmall; Benz 2007) as constitutive model for any type

of soil in numerical analysis, but other soil models will be supported in future extensions.

The parameter sets of all 3D soil layers can be sent to the PLAXIS finite element software (Bentley Systems Inc, 2023) by means of its command line interface. In the finite element software, the SoilTest facility can be used to see how the automatically obtained parameter sets perform in standard lab test simulations. In a later stage, when real lab test data is available, the parameter sets can be optimised by comparing the simulated lab test results with the real lab test data.

3.5. 3D sub-soil model

To create a 3D sub-soil model, the software package Leapfrog (Seequent, 2023) is used. Although Leapfrog is primarily developed to build geological models, it is quite suitable to create a 3D sub-soil model for civil engineering applications. Moreover, it is integrated in a cloud storage platform, and allows for exchange of data in a BIM or Digital Twins environment.

In Leapfrog, the pre-processed CPTs (Section 3.3) are opened as *Boreholes*, while the cluster numbers are used as *Lithology*. The respective layer sections of all CPTs are presented in the colour of their corresponding cluster.

A *Topography* (ground surface) is created from the top reference levels of all CPTs contained in the borehole data. Alternatively, a digital terrain model (if available) can be imported as ground surface.

The next step is to create a 3D *Geological model*. Leapfrog has several options to manually create geological formations from borehole data, but in the case of more-or-less horizontal soil layers, there is an option to generate the *Stratigraphy* (3D layer boundaries) semi-automatically. Since the horizontal extent of soil layers is usually much larger than the vertical extent, the *Trend* option can be used with a typical factor of 10 to the maximum and intermediate directions. The stratigraphy, the ground surface, and the lateral model boundaries are used to generate the 3D sub-soil model composed of consistent soil volumes.

From the 3D sub-soil model, cross sections can be taken, which can be imported in the 2D finite element software.

3.6. Numerical model

The previous sections describe the workflow that is embedded in a Python software tool in which CPT data is pre-processed into parameter sets and borehole data. In principle, this process can be executed fully automatically, using default values for the parameters to be selected (minimum layer thickness, layer tolerance, number of clusters). Although the process can be executed fully automatically, the results of every step can be reviewed and adapted. This ensures that the responsible geotechnical engineer can validate the outcome of the software tool based on their own knowledge and experience.

The parameter sets are directly sent to the finite element software, while the borehole data is further processed into a 3D sub-soil model, from which a 2D cross section (containing the various soil layers) is taken,

which is then imported as soil layer geometry in a 2D numerical model. Alternatively, the 3D layer boundaries (Section 3.4) can be imported in a 3D numerical model from which the 3D sub-soil model is recreated. The soil layer geometry and the corresponding parameter sets complete the numerical sub-soil model. From here, the numerical model can be extended with additional (structural) components and all necessary settings (boundary conditions, meshing, calculation phases) for the project to be modelled and analysed.

4. Example

In this section an example is elaborated, following the workflow as described in Section 3. Starting point is a series of CPTs taken from *DINoloket.nl*, a database of sub-soil data, including hundreds of thousands digital CPTs from publicly funded projects across The Netherlands. The project involves a location north-east of Rotterdam, near the A20 motorway. The 24 used CPTs are listed in Table 1.

Table 1. Used CPTs for a project location near Rotterdam (source: Dinoloket.nl)

CPT000000149485	CPT000000149714
CPT000000149488	CPT000000149732
CPT000000149495	CPT000000149736
CPT000000149506	CPT000000149742
CPT000000149552	CPT000000149750
CPT000000149576	CPT000000149764
CPT000000149586	CPT000000149767
CPT000000149621	CPT000000149771
CPT000000149661	CPT000000149824
CPT000000149696	CPT000000149829
CPT000000149701	CPT000000149840
CPT000000149707	CPT000000149864

All CPTs were classified as described in Section 3.1 and subsequently stratified (Section 3.2) and clustered (Section 3.3) using the parameters listed in Table 2:

Table 2. CPT interpretation and clustering parameters

Interpretation method	Robertson 2010
Min. layer thickness	1.0 m
Layer tolerance	0.1
Assumed gw level	1.0 m below surface
Number of clusters	7

Figure 1 shows the interpreted CPT000000149495. There are quite a few layer sections, and it seems that some subsequent layers are still very similar. However, further fusion of similar layers is done in the clustering.

The result of clustering of all layer sections from all CPTs is shown in Figure 2. Figure 2a shows all layer sections of all 24 CPTs, represented by the corresponding cluster symbol in the middle of the layer section. In this plot it can be seen

- that different layer sections of a single CPT may end up in the same cluster
- how layer sections in one CPT are ‘connected’ to layer sections in other CPTs.

Figure 2b is very similar as Robertson’s chart, except that the different SBT zones are not indicated. In that respect, Figure 2c can be regarded as a 3D version of Robertson’s chart, where the third dimension is *depth* (in reference coordinates).

From Figure 2b and 2c it can be concluded that the process to find corresponding layer sections across multiple CPTs cannot only be based on SBT or location in Robertson’s chart and that at least a third property is required (here *depth*).

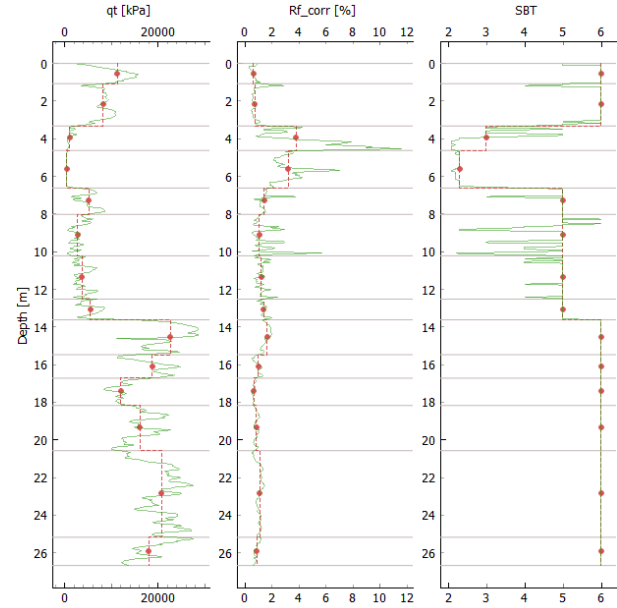


Figure 1. q_t , R_f and SBT with depth for CPT000000149495 with indication of layer sections.

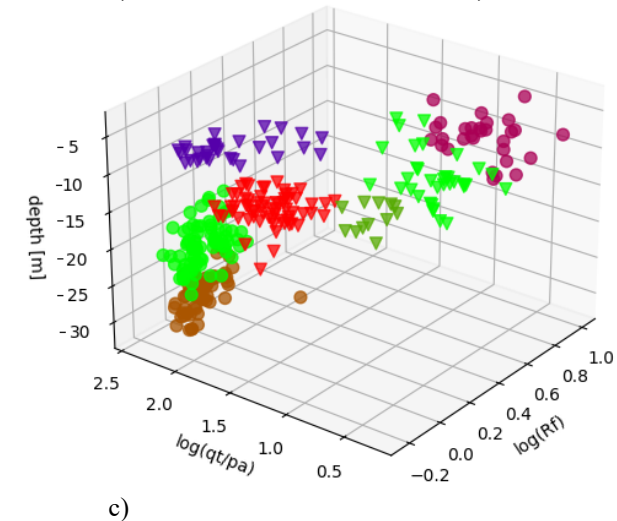
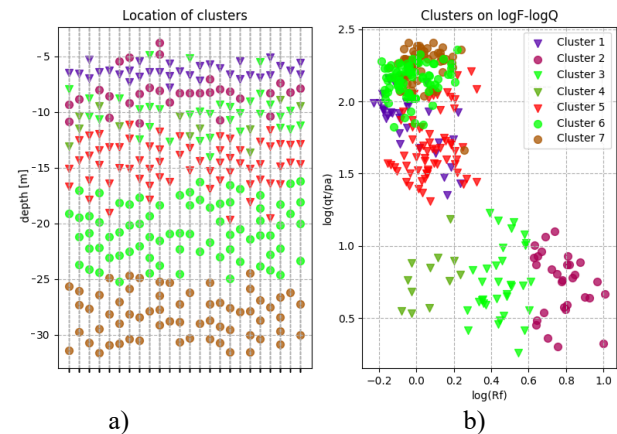


Figure 2. Results of clustering: a) Clustering of layer sections in all 24 CPTs; b) Clustering of layer sections in $\log(q_t/p_a)$ vs. $\log(R_f)$ diagram; c) Clustering of layer sections in a 3D diagram where the 7 clusters are clearly recognized.

The data of all layer sections with corresponding cluster numbers are stored as *boreholes* in .csv files for later use.

For each cluster, the software tool calculates CPT parameters based on contributions from all layer sections. These CPT parameters are used as input for the Automated Parameter Determination (APD). In principle, APD can be used at different levels: for each CPT reading, for individual layer sections and for 3D soil layers (clusters). Here, soil parameters and model parameters of the HSsmall model are automatically determined for all clusters based on the standard set of correlations (methods.csv file) available for the software tool. Table 3 gives an overview of the generated HSsmall parameter sets, which are to be used to simulate the soil behaviour in the 3D soil layers. The parameter sets are sent to PLAXIS 2D using the command line interface.

Table 3. HSsmall parameter sets for the 7 clusters

cluster	1	2	3	4	5	6	7
<i>SBT</i>	6	2	3	4	5	6	6
γ_{unsat}	18.2	13.1	16.3	15.5	16.9	17.8	17.8
γ_{sat}	20.2	13.1	16.3	15.5	19.7	20.1	20.1
E_{50}^{ref}	47880	2642	3231	4814	28180	41640	42640
E_{oed}^{ref}	48270	1585	1938	2888	27690	41420	41450
E_{ur}^{ref}	143600	13140	18460	28750	84540	124900	127900
G_0^{ref}	85300	58470	68300	54980	129400	156300	175700
p^{ref}	100	100	100	100	100	100	100
γ_{07}	0.120	0.278	0.221	0.172	0.153	0.131	0.129
<i>power</i>	0.51	1.00	1.00	0.80	0.56	0.52	0.52
c'	1.0	0.0	0.0	0.0	0.0	0.0	0.0
ϕ'	39.9	25.4	26.8	29.5	36.4	38.6	38.7
ψ	8.4	0.0	0.0	0.0	4.2	6.4	6.4
v_{ur}	0.20	0.20	0.20	0.20	0.20	0.20	0.20
R_f	0.90	0.90	0.90	0.90	0.94	0.91	0.91
K_0^{nc}	0.47	0.57	0.55	0.51	0.47	0.47	0.47

Units: γ_{unsat} and γ_{sat} in kN/m³; E_{50}^{ref} , E_{oed}^{ref} , E_{ur}^{ref} , G_0^{ref} , p^{ref} and c' in kN/m²; ϕ' and ψ in °; γ_{07} , *power*, v_{ur} , R_f and K_0^{nc} no unit.

In fact, cluster 6 and 7 are very similar and could be combined in one cluster.

The stored *borehole* files are imported in Leapfrog and a geological model is created, as shown in Figures 3 and 4, respectively. Note that at some locations the soft soil reaches the ground surface, which is reflected in the 3D sub-soil model.

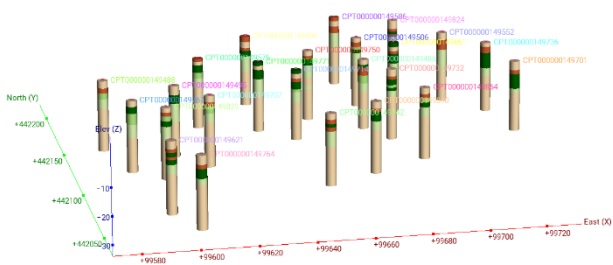


Figure 3. Visualisation of *boreholes*, generated from automatically processed CPT data.

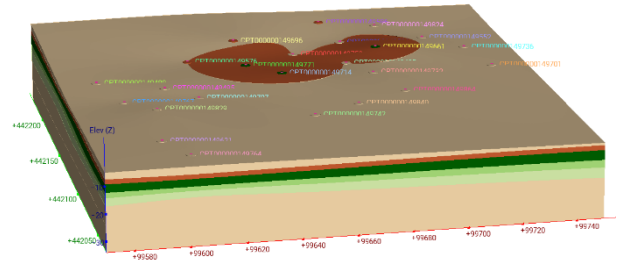


Figure 4. Geological model, created from the *boreholes*

A north-south cross section is made through the middle of the geological model at coordinate 99660 East. The geological model, together with the cross section, is stored, and the cross section is imported in the numerical model, as shown in Figure 5. The imported cross section will have its origin, by default, at the lower left-hand corner, while, in this case, the bottom level is at -34 m according to reference level. To maintain the levels in reference elevation coordinates, it is important to shift the cross section downward while being imported (in this case -34 m). The horizontal coordinate (x) represents the North direction. The left side of the model (x=0 m) corresponds to +442030 North, while the right side of the model (x=200 m) corresponds to +442230 North. All this information can be obtained from the geological model.

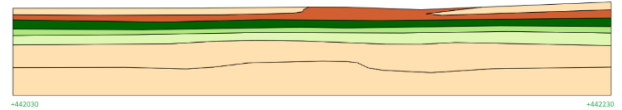


Figure 5. Imported cross section as input geometry for the numerical model

In the finite element software, the numerical model can be further processed. Here, only a generated finite element model of the sub-soil is shown (Figure 6), to demonstrate the consistency of the imported soil layer geometry (otherwise, the mesh won't generate).

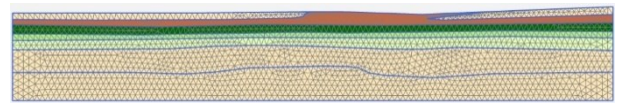


Figure 6. Finite element mesh of the numerical model

5. Automated workflow and responsibilities

In an automated workflow it is tempting to 'believe' the outcome of automatically generated results, provided the system is well validated for similar situations. This is even more so when more work needs to be done by less people. Nonetheless, an automated system is just a tool that helps the project engineers doing more work in less time, while the engineers remain responsible for the results and a design based on the results of an automated system. This responsibility can only be executed if the automated system is, to some extent, transparent, such that it is clear how the results are obtained, and such that they can be checked by the operating engineer. Moreover, the system should be adaptable and extendable, such that the engineer is able to interfere with

the system, modify some essential parameters, and add their own experience.

The automated workflow contained in the software tool, as described in Section 3, and demonstrated in Section 4, has several instances where the engineer can (and shall) execute their responsibility:

- **Classification:** Although the classification is straightforward, the results of classification are shown and can be verified by the user.
- **Stratification:** Besides visual inspection of the automatically generated layer sections per CPT, the user can modify the stratification parameters or manually change the layering based on their engineering judgement.
- **Clustering:** As for the stratification, the user can modify the clustering parameters or manually change the clustering of layer sections based on a visual representation.
- **Parameters:** The user can view the (averaged) CPT parameters and validate them as input to the APD method. In APD, the generated Graphs are visualised, and the user can follow the paths to see how output parameters are obtained from the correlations (methods) and their input parameters. Moreover, the user can add or modify parameters and methods in the respective .csv files used by the system. Note that the standard files with validated methods may become invalid when they are modified! Anyhow, resulting parameter sets may be changed any time based on other data that become available, or according to engineering judgement.
- **3D sub-soil model:** This part is not so much automated (yet). It requires knowledge and experience of geological modelling as well as engineering judgement to create an appropriate 3D sub-soil model. The 3D model can be visually compared to the generated boreholes or with the original CPTs.

All this ensures that the engineer can be held responsible for the geotechnical design, while significant parts of the workflow were automated.

6. Conclusions

In this paper an automated geotechnical workflow is presented, which is implemented in a software tool. All components of the tool are described, and the use and proper functioning of the tool are demonstrated in an example. The tool interacts with other software in a BIM / Digital Twin environment, which reduces the possibility of making mistakes, and it allows the various stakeholders in a project secured access to the various data sources and results (intermediate and final).

Despite the automated workflow, the geotechnical engineer operating the tool can interfere with the system and validate the outcome at various instances, such that they can properly execute their responsibility for the geotechnical design.

References

- Bentley Systems Inc. (2023). PLAXIS 2D (23.02). Available at: <https://www.bentley.com/software/%20plaxis-2d/>, accessed: 19/01/2024.
- Benz T. "Small-strain stiffness of soils and its numerical consequences". PhD thesis. Heft 55, Institut für Geotechnik, Universität Stuttgart. 2007.
- Brinkgreve, R. B. J., and S. Brasile. "Automatic Finite Element Modelling and Parameter Determination for Geotechnical Design". In Workshop Numerische Methoden in der Geotechnik, 2022, 53.
- Brinkgreve R. B. J., F. Tschuchnigg, A. Laera, and S. Brasile. "Automated CPT interpretation and modelling in a BIM/Digital Twin environment". Proceedings Numerical Modelling in Geotechnical Engineering, NUMGE. 2023, <https://doi.org/10.53243/NUMGE2023-111>
- Cetin, K. O., and C. Ozan. "CPT-based probabilistic soil characterization and classification." Journal of Geotechnical and Geoenvironmental Engineering, 135(1), pp. 84-107, 2009, [https://doi.org/10.1061/\(ASCE\)1090-0241\(2009\)135:1\(84\)](https://doi.org/10.1061/(ASCE)1090-0241(2009)135:1(84))
- Kulhawy F. H., and P. W. Mayne "Manual on Estimating Soil Properties for Foundation Design", EPRI EL-6800, Project 1493-6. Palo Alto: Electric Power Research Institute, 1990.
- Lengkeek, H. J. "Testing and Modelling of Sheet Pile Reinforced Dikes on Organic Soils – Insights from the Eemdijk Full-Scale Failure Test". PhD thesis. Delft University of Technology, 2022, <https://doi.org/10.4233/uuid:78df5e2b-740e-4268-a821-ed0ccaae93e5>.
- Marzouk I., F. Tschuchnigg, F. Paduli, H. J. Lengkeek, and R. B. J. Brinkgreve "Determination of fine-grained soil parameters using an automated system". In: Gottardi & Tonni (eds), Cone Penetration Testing 2022. Taylor & Francis, 2022, pp. 540-545, <https://doi.org/10.1201/9781003308829-77>
- Rauter S., and F. Tschuchnigg "Identification of soil strata from in-situ test data using machine learning". International Conference of the International Association for Computer Methods and Advances in Geomechanics, Cham: Springer International Publishing, 2022, pp. 37-44, https://doi.org/10.1007/978-3-031-12851-6_5
- Robertson, P. K. "Soil classification using the cone penetration test". Canadian Geotechnical Journal, 27(1), pp. 151-158, 1990, <https://doi.org/10.1139/t90-014>
- Robertson, P. K. "Interpretation of cone penetration tests – a unified approach". Canadian Geotechnical Journal 46(11), pp. 1337-1355, 2009.
- Robertson, P. K. "Soil Behaviour Type from the CPT: an update". In: 2nd International Symposium on Cone Penetration Testing, Huntington Beach: Cone Penetration Testing Organizing Committee, CA, USA, 2010, 2(56), pp. 8
- Robertson, P. K. "Cone penetration test (CPT)-based soil behaviour type (SBT) classification system - an update". Canadian Geotechnical Journal, 53(12), pp. 1910-1927, 2016, <https://doi.org/10.1139/cgj-2016-0044>
- Robertson, P. K., and K. L. Cabal. "Guide to cone penetration testing for geotechnical engineering." Signal Hill, CA: Gregg Drilling & Testing, 2015.
- Seequent, The Bentley Subsurface Company "Leapfrog Works, (2023-2.1)". Available at: <https://help.seequent.com/Works/2023.2/en-GB/Content/intro.htm>, accessed: 19/01/2024
- Van Berkom, I. E., R. B. J. Brinkgreve, H. J. Lengkeek, and A. K. De Jong. "An automated system to determine constitutive model parameters from in situ tests." In Proceedings of the 20th International Conference on Soil Mechanics and Geotechnical Engineering, Sydney, 2022, pp. 329-334
- Wang Y., K. Huang, and Z. Cao. "Probabilistic identification of underground soil stratification using cone penetration tests". Canadian Geotechnical Journal. 50(7), pp. 766-776, 2013, <https://doi.org/10.1139/cgj-2013-0004>

Wu S., J. M. Zhang, and R. Wang “Machine learning method for CPTu based 3D stratification of New Zealand geotechnical database sites”. *Advanced Engineering Informatics*, 50, 2021, <https://doi.org/10.1016/j.aei.2021.101397>