Digital optimisation workflow in early project phases and what it can bring when looking at the MacLeamy curve

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ABSTRACT

It is known from the MacLeamy curve that early effort in project developments pays off. Any change in early project phases takes less effort and is more effective in impacting cost and success of the project than a change that incurs later. This contribution points out possible savings by employing numerical optimisation for achieving the optimal design with respect to both code-conforming performance and construction costs for common geotechnical systems such as ground improvements. One of the bottlenecks for the widespread use of numerical optimisation for design is perhaps the lack of a workflow management program. In the present paper, a structure of a functional workflow management program based on Python, its standard library, third-party packages, and external APIs will be detailed. In addition to that, some fundamentals of how optimisation works will be presented. One meaningful use case of the automated optimisation applied to the design of ground improvements for LNG tank foundation is presented. Extensions to digital ground model provided by the BIM process and seamless information transfer to the construction site purposed for the implementation of the observational method in geotechnical design will be drawn.

Keywords: geotechnical design, numerical optimisation, digital workflow management, productivity

1 INTRODUCTION

Although a lot of innovations and great improvement effort, the AEC industry is still faced with low figures in either productivity or sustainability indicators. The McKinsey Institute reported an averaged 1 percent labour-productivity growth in construction over the past two decades, compared with 2.8 percent growth of the total world economy and 3.6 percent growth in manufacturing sector (Barbosa et al. 2017). Being one of the largest industrial sectors this poor development in productivity has caused great economic loss and adversely impacted resource efficiency and sustainability.

The above-mentioned McKinsey report drew out 7 measures to increase productivity in construction, among them rethinking design and engineering processes and leveraging digital technology, new construction materials and advanced automation. What was not mentioned as a measure to increase productivity in construction is the use of computerized optimisation methods. Although numerical optimisation as a sub-field of applied mathematics is the backbone in many scientific research and engineering fields, its use in geotechnical design practice has been very limited to date, at least to the author's knowledge while working in the topic for several years.

Aside technical enhancements and the adoption of advanced technologies, new ways of collaboration and information integration have been introduced to reduce fragmentation and backwardness in design/ build/ manage processes (MacLeamy, 2004). The MacLeamy time-effort curves (Figure 1) are often used in AEC to draw the effort or effect of changes with respect to time in the realisation of a construction project.

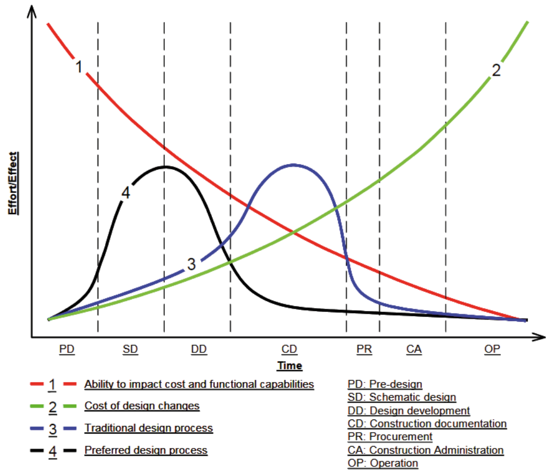


Figure 1. The MacLeamy time-effort curves (MacLeamy, 2004)

In Figure 1, curve (2) is self-explained: a design change at later project phases cost incurs more cost than a change that happens earlier. The opposite is true for curve (1): the ability to impact cost. A traditional design and construction process will likely result in curve (3) where high cost and effort are required by late changes. A preferred curve is curve (4): impactful changes are made early at low cost. The MacLeamy theoretical curves imply that expenditure at early project phases will pay off quickly by saving unnecessary changes that usually occur lately. The AEC started to adopt digital building information modelling (BIM) which is considered as one of the measures to bring the project execution from curve (3) to the one that is closer to curve (4).

It is noted that ground data and their uncertainty exist as they are provided by standard soil investigations and geotechnical laboratory tests. Design optimisation offers no solution to reduce uncertainty either in spatial ground variability or in the values of geotechnical parameters. Ground uncertainties should rather be handled by the selected design code, for example, with using partial safety factors in design. Some design codes, such as Eurocode 7 (EN 1997) even advocate the use the observational method in design in the face of high uncertainty.

It must be stated that the amount of ground data can increase during project development phases if further soil investigations and laboratory tests are further requested. The uncertainty associated with ground data can reduce as a result. This condition is not ideal for the design approach that is followed here. The deployment of design optimisation is therefore most meaningful if a rather complete soil investigation campaigns have been carried out. Early project phases therefore mean from this time.

This paper advocates for more expenditure and effort in the design stage to achieve the optimized solution for a geotechnical design problem. In support of a seamless integration of optimisation in design, the following requirements are to be made available:

- a detailed 3D ground model,
- a sophisticated calculation program that well captures geo-mechanical behaviour and soil-structure interactions of the design problem, and
- a workflow management program with numerical optimisation method.

In early geotechnical design, usually a very simplified 2D geological model is considered from information of the bore logs. Similarly, soil and rock parameters are only roughly estimated, allowing the geotechnical designer to deliver the design solution very soon so that a project cost can be quickly estimated by the tender engineer. The flip side this process is 1) any mismatch or misinterpretation of the ground model and soil/ rock parameters will then change the design significantly and 2) the design is often far conservative or not optimal.

Given the same amount of soil investigation data, however, additional information can be gained for design. In particular, more often than not, a 3D ground model can be built if some extra time budget is allowed. If the BIM process is adopted from the beginning, the 3D ground model is preferably extracted from the BIM model. Here, machine learning methods for soil type classification based on in-situ CPTs can be used (Rauter and Tschuchnigg 2021). An extension to automated soil parameter determination and building entire 3D underground models, which serves finite element and BIM model building, will greatly benefit the geotechnical design engineers (Brinkgreve and Brasile 2022). In the case detailed oedometer and triaxial laboratory tests are available, an automatic constitutive model calibration scheme can also be carried out for getting parameters of advanced constitutive models, such as for the hypoplastic soil model (Machaček et al. 2022).

The second requirement is relatively easily achieved today as many proprietary geotechnical software providers implement state-of-the-art sophisticated soil models based on plasticity or critical state soil mechanics theories, and structure and soil-structure interactions under monotonic/ cyclic loadings in drained/ undrained conditions. Many geotechnical construction/ consultancy companies and research institutes have also developed their own advanced computation code for specific geotechnical design tasks, which can also be suitable for design optimisation. It remains for the geotechnical designer to create an adequate calculation model using soil parameters from soil investigations, laboratory tests, or proper correlations.

The third requirement is often not ready. The reasons can be 1) optimisation is not needed in a traditional design approach and 2) design software providers usually do not see the potential to optimize or do not have insight in how much benefit optimisation can bring while geotechnical design engineers working with a consultancy or construction company are often not involved in extensive coding nor have reserved time and budget to do so.

In the following, I will show that such a workflow management program can be developed using Python, its standard packages, and any external APIs provided by a proprietary/ in-house software. A use case for the optimisation of ground improvement is then provided to showcase the power of numerical optimisation for geotechnical design.

2 WORKFLOW MANAGEMENT

2.1 Implementation

It is a conception that implementation of such workflow programs is the job of PhD students and researchers who have plenty of time to mock-up such a complex workflow management program to test old and new algorithms on a benchmark problem. This is not true anymore with today’s array of development tools, machine learning and optimisation algorithms one can reach at the fingertips from public domain. But as for geotechnical design, one should understand how soil, rock, and structural elements behave to carry out geotechnical design, to leverage the power of an algorithm, one should understand why and how it works. There are plenty of books and short courses available in the object for self-learning if one has not attended such a class at university. After having some basics, one can practise implementing from scratch one of the optimisation algorithms of preference or one can also pull the source code from a good implementation stored in Github repository for practice. While coding such a program in Python, the core libraries in Python and third-party packages, such as numpy, scipy, pandas, matplotlib, already provide sufficient tools for numerical calculations and visualisation.

For a rigid implementation of an automation workflow, it is very beneficial to organize the program in an object-oriented programming paradigm. Figure 2 displays such a workflow for geotechnical optimisation which task is mainly to plug a solver of choice in a selected optimisation algorithm. It is noted that many software design patterns can be used to build the workflow’s components and connections that are easy to expand and maintain.

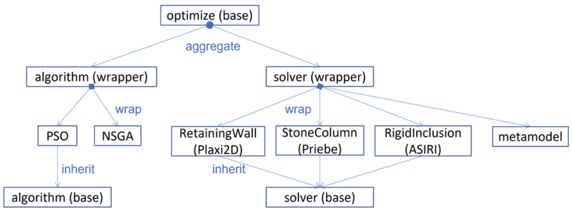


Figure 2. Object-oriented organisation for design optimisation workflow

It is noted that interfaces to an external calculation such as Plaxis2D/ Plaxis3D solver can be quickly built by using the API provided by the software.

If the calculation model is computationally intensive, such as a large finite element or finite difference model, building a surrogate model, also called meta-model, can be very beneficial. The idea behind meta-model is to approximate the original computationally heavy model by a lightweight reduced order model. Such a reduced model can be trained from a set of sampled data points generated by the original model by using, for example, a multi-layer artificial neural network as used for back back-calculating soil parameters in tunnelling (Nguyen and Nestorovic 2013) or by using a Gaussian process (GP) as presented in (Nguyen and Haddad 2022) for the design of foundations and retaining walls. The process of meta-model building requiring model training and model validation steps is illustrated in Figure 3. It is noted that the once the meta-model is built, it can be deployed for various purposes, such as sensitivity analysis, back analysis, and design optimisation.

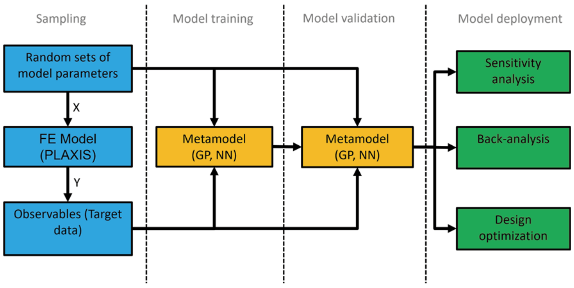


Figure 3. Meta-model building process

2.2 Multi-objective optimisation for geotechnical design

Multi-objective optimisation (MOO) has been used in structural designs in manufacturing engineering, for example, as an engine for generative design. MOO can be readily used for optimizing geotechnical design as well.

A geotechnical design problem is most often multi-objective rather than single-objective in which the design objectives compete each other. For example, in the design of pile-group foundation or ground improvement, it is of interest to minimize the total concrete volume and reinforcement amounts (monetary cost) and to maximize the serviceability performance, such as the minimisation of settlements.

Multi-objective optimisation methods most often belong to the family of meta-heuristic optimisation methods. An effective population based meta-heuristic optimisation methods used for multi-objective optimisation is the non-dominated sorting genetic algorithm 2 (NSGA-II) (Deb et al. 2022). One fundamental mechanism for the algorithm to work is the ability to randomize candidate solutions, which helps the algorithm to explore the design possibilities. The coded gene evolution mechanisms such as mutation, cross-over, and selection make sure that diversity and survival of the best solutions are maintained in the optimisation process. One big advantage of the multi-optimisation approach is that it results not only one design solution, but also a range of optimal solutions that can be selected based on certain preference such as cost or settlement requirement.

Early introduction of MOO to foundation design includes the work of Kinzler et al. 2007 in which the authors proposed to use the optimisation method to the design of pile groups. Recently, Shen et al. 2022 proposed a generative design framework supported by meta-modelling for the design of wind turbine foundations. The NSGA-II is perhaps most often used for multi-objective optimisation in engineering. The newly introduced Generative Design module in (Autodesk Revit 2021) is told to use NSGA-II optimisation in its implementation for multi-objective optimisation.

As soon as the computational model has been created for the geotechnical problem at hand, the computational model can be parametrized with the selected design parameters. The choice of design parameters can be intuitively decided by the design engineer or by performing a thorough sensitivity analysis. In design of geotechnical structures, there are often a few parameters to be considered. For example, the most important design parameters for ground improvement by reinforcements are the size or diameter of the reinforcement's cross-section, the depth of reinforcements, and the grid spacing between reinforced elements. The process to arrive at a set of design parameters that works often requires repetitive trials that are manually carried out in the design process. Because of the complex load transfer mechanism between surrounding soil and reinforcements, iterative tuning is required to get to a satisfactory result, which does not necessarily mean the best solution that can be drawn for the problem at hand.

We, however, propose to use a numerical algorithm in the search for the optimal design solutions. Assume that three design variables x_1, x_2, and x_3 are selected for the design optimisation problem at hand. The optimisation problem is formulated as:

$$\text{find: } x_1, x_2, x_3 \tag{1a}$$
$$\text{such that: } f_1() \text{ and } f_2() \text{ are minimized,} \tag{1b}$$
$$\text{while being subject to: } g_1(), \tag{1c}$$

where $f_1()$, $f_2()$ are objective functions, $g_1()$ a constraint function. Both objectives and constraints are functions of the selected design variables. It is noted that there can be more than two objectives and additional constraint rules in a design optimisation problem. An objective function is a function that defines the intended goal for the optimisation algorithm to minimize or maximize, for example settlement and construction cost. The constraint rules, on the other hand, will guide the optimisation algorithm to skip candidate solutions that violate certain project defined rules or code based and construction related constraints, for example the column grid spacing should not be less than a certain ratio to the column diameter.

3 A USE CASE

Ground improvements by installing reinforcement elements into the ground provide economic solutions over foundation piles in applications, such as foundations for structures of moderate loads such as warehouse, water or LNG tanks, etc. By adding reinforced elements into loose or soft soils, stiffness and bearing capacity of the composite soil-structure system are increased, allowing to reduce settlement, susceptibility to shear failure, and even liquefaction potential.

The design of ground improvements often consists of iterative trials of various reinforcement configurations. Especially when purposed to work as floating foundations, the choice of reinforcement diameter, depth, and spacing become hard to decide without iterative trials as one design parameter influences the others. Most often, under a strict deadline for design delivery, a geotechnical designer will have a preference for a configuration of design parameters that works with respect to the ultimate and serviceability limits. Although achieving a design that works is good, the fact that the cost of the design solution can further be optimized is not further pursued makes overdesign a source of inefficiency.

The little effort spent in this early design likely leads to a suboptimal design, which may need substantial design change later. For a contractor, this means higher bidding price and therefore lower chance of getting the project granted. For the owner, it can be unbeneficial, especially if a kind of lump sum contract was signed based on the initial design. Looking back at the MacLeamy curve in Figure 1 at this point, one can see that those cumbersome issues are best solved by spending effort at the early design phase. Running a thorough optimisation campaign using numerical optimisation in the early design phase can help to minimize the additional costs caused by late substantial design changes.

The question many engineers, consultants, and owners ask is: can a geotechnical design solution that works also be an optimal solution? State-of-the-art mathematical optimisation provides the answer to it. Nguyen and Haddad 2022 showed that numerical optimisation can help achieve a set of optimal solutions for the design of ground improvements and retaining walls. A standard procedure for design optimisation of ground improvements, e.g., for tank foundations, is presented in Figure 4. Compared with a conventional design approach, one needs to set up the design problem as an optimisation problem with design variables, objectives, and constraint rules and let the automated iterative optimisation process run on a computer.

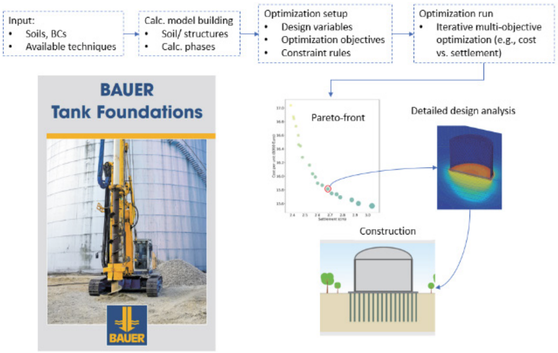
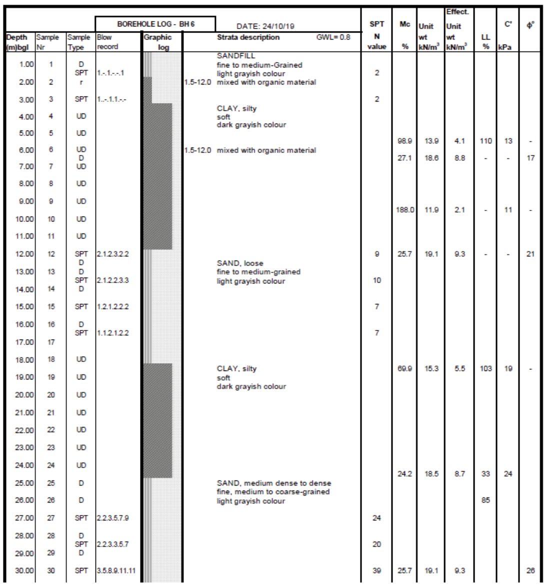


Figure 4. Optimisation workflow for tank foundation by rigid inclusions

In the example here, a rigid inclusions design for an oil tank is optimized using a multi-objective optimisation algorithm NSGA-II. Working surface load of the tank is 155 kPa. The soil profile represents various layers of very soft clays and loose sands that are alternately present until the depth of 25 m (Figure 5).



BOREHOLE LOG - BH 6 DATE: 24/10/19

Depth (m)bgl	Sample Nr	Sample Type	Blow record	Graphic log		Strata description GWL= 0.8	SPT N value	Mc %	Unit wt kN/m³	Effect. Unit wt kN/m³	LL %	C' kPa	φ°
						SANDFILL							
1.00	1	D				fine to medium-Grained							
		SPT	1.-.1.-.-.1			light grayish colour	2						
2.00	2	r			1.5-12.0	mixed with organic material							
3.00	3	SPT	1..-.1.1.-.-				2						
						CLAY, silty							
4.00	4	UD				soft							
						dark grayish colour							
5.00	5	UD											
								98.9	13.9	4.1	110	13	-
6.00	6	UD			1.5-12.0	mixed with organic material							
		D						27.1	18.6	8.8	-	-	17
7.00	7	UD											
8.00	8	UD											
9.00	9	UD											
								188.0	11.9	2.1	-	11	-
10.00	10	UD											
11.00	11	UD											
12.00	12	SPT	2.1.2.3.2.2				9	25.7	19.1	9.3	-	-	21
		D				SAND, loose							
13.00	13	D				fine to medium-grained							
		SPT	2.1.2.2.3.3			light grayish colour	10						
14.00	14	D											
15.00	15	SPT	1.2.1.2.2.2				7						
16.00	16	D											
		SPT	1.1.2.1.2.2				7						
17.00	17												
18.00	18	UD											
						CLAY, silty		69.9	15.3	5.5	103	19	-
19.00	19	UD				soft							
						dark grayish colour							
20.00	20	UD											
21.00	21	UD											
22.00	22	UD											
23.00	23	UD											
24.00	24	UD											
								24.2	18.5	8.7	33	24	
25.00	25	D				SAND, medium dense to dense							
						fine, medium to coarse-grained							
26.00	26	D				light grayish colour					85		
27.00	27	SPT	2.2.3.5.7.9				24						
28.00	28	D											
		SPT	2.2.3.3.5.7				20						
29.00	29	D											
30.00	30	SPT	3.5.8.9.11.11				39	25.7	19.1	9.3			26

Figure 5. Soil profile needing rigid inclusion foundation for oil tanks

The optimisation problem is set out with using the full displacement columns of diameter 44 cm as rigid inclusions. To keep a practical replacement ratio, allowable grid spacing is limited in the range [1.8 m, 3.6 m]. Considering weak soils in the first 25 m, the allowable column length is set in the range [25 m, 45 m]. The two objectives for optimisation are

- Minimisation of the surface settlement in serviceability. The settlement is calculated following the ASIRI method (IREX 2017).
- Minimisation of cost. The cost function is simply proportional to the concrete volume with a base unit price.

Results of optimisation run clearly show convergence towards the so-called Pareto-optimal solutions. The optimal design solutions achieved after 20 iterations are displayed in Figure 6. It can be seen in the variable space that column lengths are just enough for the column to be embedded in the competent sand, where tip resistance is given. Grid spacings of the column raster range from 1.7 m to 2.8 m, providing a range of settlements with correspondingly construction costs.

A remarkable outcome of the optimisation run is that it results in a pool of optimal design solutions. Then a preferred design solution can be chosen for submission depending on the settlement requirements and/ or the client's budget. The impact of allowing for more settlement on saving in construction costs can also clearly be presented for the client and engineers for discussion and decision making.

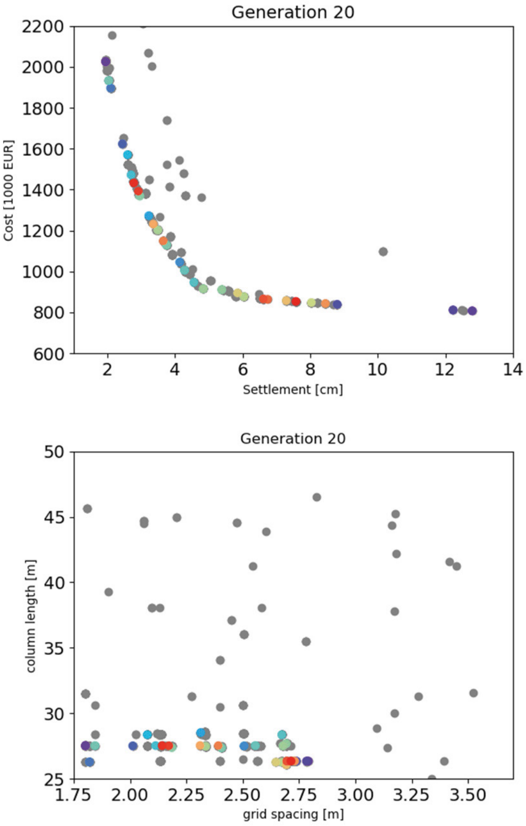


Figure 6. Optimisation results. The points in color are design solution converged at the 20th generation of NSGA-II run. The points in grey are points at previous generations.

Transfer optimized design to a sophisticated finite element (FE) model for detailed geomechanical analysis can be readily automated by using a Python scripting that interfaces with the FE program's API. The FE model shown in Figure 7 displays results of settlement analysis for one of the optimal design solutions shown in Figure 6.

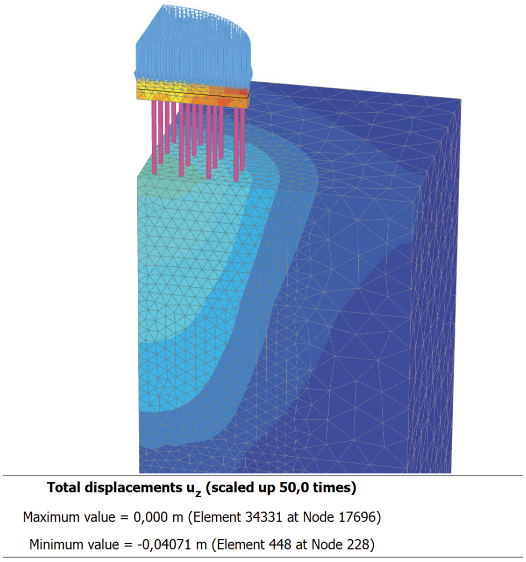


Figure 7. Transfer of the optimized design parameters to a 3D finite element model for detailed analysis

In the same way, any design in the pool of the optimal designs can be conveniently linked to a BIM software such as Revit for effective presentation and discussion with the client and consultant. Figure 8 displays in Revit, for example, one among 20 optimal designs seen in Figure 6. The information in the BIM model serves as a basis for construction work and semi-automated quality control during and after construction.

This connection between design and 3D visualisation is best carried out by a compact automated workflow such as using the visual scripting language Dynamo (Dynamo BIM). An open BIM format or a proprietary BIM software such as Revit offers a convenient method to realize this task. Interoperability is key to stakeholders, which enables data transfer among various software tools, helping to eliminate data silos that often occur in realisation of a construction project.

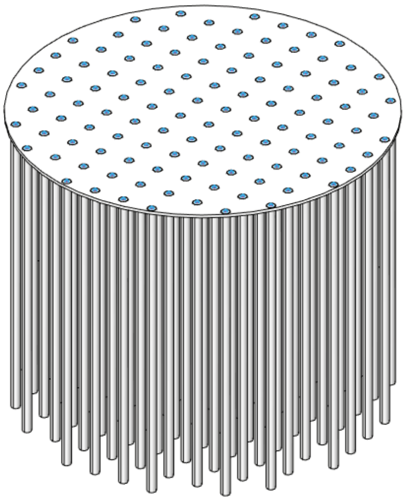


Figure 8. Transfer of the optimized design for visualisation and inspection in a BIM model

The integration of IoT sensors installed at the construction site is a further step forward. Easy and reliable access to monitored data at the construction site will facilitate the implementation of the observational method (OM) in geotechnical design (Peck 1969, Powderham and O'Brien 2020). OM in geotechnical design can be implemented using data such as wall deformations and surface settlements received from continuous monitoring with IoT sensors. OM will help the geotechnical designer, for example, to quickly modify the design of the supporting struts or ground anchors given the actual ground and groundwater conditions encountered at site. In the case of challenging excavation, OM assists in predicting stability of the excavation pit by providing the designer with the most updated geotechnical parameters obtained from performing back analyses. OM ultimately corrects the initial design based on information from the soil investigation, which can be conservative or incorrect, toward a design based on actual soil conditions and parameters found on the ongoing construction site.

4 CONCLUSION

Heavy exploration in the design parameter space at the early design stage is made possible using a multi-objective optimisation as presented in this paper. This early upfront effort, which is readily orchestrated with the help of a workflow automation program, can help to achieve fine-tuned optimal design solutions right in the first design round. Value engineering can well work in tandem with optimisation workflow to come with the most suitable geotechnical system among many comparable techniques, for example pile foundation vs ground improvement and secant piled wall vs diaphragm wall and set up the most meaningful scenarios to be optimized.

The optimal design solutions can then be transferred to a sophisticated 3D visualisation and simulation model for further detailed analysis and discussions. This step is preferred carried out automatically for speed and accuracy.

The integration of IoT sensors' data provides a good platform for the implementation of the observational method in geotechnical design, which helps to reduce uncertainty in geotechnical parameters and therefore increases confidence in design.

All the measures ultimately help to bend the MacLeamy curve of each project to the one closer to the preferred curve (4) in Figure 1.

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