The fusion of physical mechanism and artificial intelligence – A case study of water-tightness estimation for geometrically imperfect cut-off walls

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Abstract. Underground cut-off walls are widely used in various applications to hinder groundwater flow and contaminant transportation. Although the cut-off walls are installed with due discretion, occasional construction errors were found to be inevitable, causing significant leakage or even failures. An on-site risk assessment tool is needed, to map the input construction error and water-tightness performance of the cut-off walls quickly and accurately. Although a highly efficient physical-based algorithm (three-dimensional discretized algorithm, TDA) is developed, its calculation speed may not suffice to serve as an instant on-site evaluation tool. In this regard, a direct relationship between the random seeds of positioning errors and seepage flow rate is expected to be explored, and based on this, a surrogate model using the AI approach is established. A novel physical-based Neural Network (NN) model is proposed to train NN from a more physical and interpretative perspective. The proposed physical-based NN is reasonably accurate but much more efficient than the benchmark physical-based method (TDA), and the prediction accuracy and result interpretability is also superior than the traditional NN.

Keywords: machine learning, cut-off wall, construction error.

1 Introduction

Cut-off walls are widely used to hinder groundwater seepage in deep excavation, tunnelling and dams, as well as leachate diffusion in landfills (Telling 1985; Shepherd et al. 2020). Depending on specific purposes, budgets and site conditions, various construction forms of cut-off wall have been developed and applied, such as jet-grouted wall, secant pile wall, slurry wall and diaphragm wall (Brown et al. 2002; Amos et al. 2008; Li et al. 2015; Modoni et al. 2016). Among the existing cut-off techniques, the jet-grouted cut-off wall (JGCOW) is getting increasing attention because of its economical and rapid-construction characteristic (see Fig.1). JGCOW is usually installed by the multiple injection of high-pressure grout into in-situ strata through rotating small-bore nozzles, and the solidified columns arranged in rows subsequently formulate an overlapped water-tight continuum (Pan et al. 2019a, Gazzarrini et al. 2020). Though JGCOW technique has achieved tremendous progress in recent decades, construction errors, such as the deflected orientations of column axis and deficient column diameters, cannot be avoided in the practical construction process (Bruce and Filz. 2012). Quantitatively evaluating the impact of JGCOW imper-
Infection on seepage discharge is of great importance for the project quality assessment and control.

Fig. 1. Illustration of JGCOW and its geometric imperfections

Finite element (FE) simulation, as a versatile numerical simulation method, is able to evaluate the seepage flow with complex boundary conditions (Xi et al. 2015; Wu et al. 2015). Despite the high prediction accuracy, it requires significant computation capacity and model complexity, especially when risk assessment with a very fine-meshed model is used (Qi and Zhou. 2017; Pan et al. 2020). Considering the random occurrences of small defects (~0.1 m in diameter) in the JGCOW, large amounts of repetitive FE calculations are needed, which magnifies the mentioned drawbacks of FE methods. To overcome the restriction of computational efficiency, Pan et al. (2017, 2019b, 2021) proposed an advanced evaluation approach, called three-dimensional discretized algorithm (TDA), to evaluate the seepage discharge for cut-off wall given the geometric imperfections. In these studies, the deviations of installation angles (azimuths and inclination angles) were considered as random variables, and the variation of column diameters was characterized by random process. The continuous untreated zones can be, hence, modelled by the above prescribed parameters and scanned by discretized eight-node cuboids. Since the untreated “nodes” were recorded and the continuous flow channels identified, the seepage discharge through the imperfection of cut-off walls can be readily estimated. It has been verified that the TDA results are accordant with the results from FE simulations, but at thousandfold lower computational cost. However, the TDA approach still requires some calculation capacity, and that may not be fast enough for an on-site risk evaluation. Therefore, a data-driven approach that can quickly map the result from the input values is highly required.

The Artificial Intelligence (AI), as the emerging field of geotechnical engineering, has the potential to learn autonomically from training datasets and be intelligent in making inferences according to the obtained information (Arel et al. 2010; Mitchell et al. 2013). Recently, AI technique has been successfully applied in underground construction sectors, including the model identification of soil constitutive relationship, parameter optimization for soil behavior description and risk management during construction or operation (Yin et al. 2018; Mikael et al. 2019; Zhang et al. 2020). Despite the many advantages AI applications, there are still some natural concerns on its validity and robustness among the geotechnical research and industrial community,
because of its inherent black-box nature (Sun and Scanlon. 2019). On the one hand, the black-box property endows AI models with strong data-driven skills and robust transferability; on the other hand, it results in the poor result interpretability beyond its excellent fitting capacity. Great efforts have been made for explaining AI models reasonably, but these subjective explanations may be “rootless” and infructuous (Rudin. 2019). The explanations are generally based on the specific datasets and hard to extend to universal situations. It has been an increasingly acceptable cognition that developing an interpretable model is much more practical than explaining black-box models (Reichstein et al. 2019). There are some attempts in the design of physical-based AI models, which have reported in the field of computer science and geoscience (Jiang et al. 2020; Li et al. 2021). Applying the redesigned physical-AI models into the posed JGCOW problem seems to be an available approach to meet the expected requirements for accuracy, efficiency, transferability and result interpretability. This paper proposes a novel neural network (NN) architecture, called physical-based NN, to evaluate the seepage discharge of imperfect JGCOW. The imperfect distances are firstly defined to transfer different inputs, such as azimuths, inclination angles and the random seeds for the description of column diameter variation, into physical quantities with uniform dimensions. The corresponding physical layer is then inserted between the input layer and hidden layer of traditional NN. Finally, the proposed approach is illustrated and validated using the single row JGCOW case with imperfection. The TDA method and tradition NN method are introduced to compare with the proposed method. Results show that the physical-based NN has a higher efficiency than TDA and a much better accuracy than traditional, and also with a transparent physical explanation.

2 METHODOLOGY

2.1 Three-dimensional digitalized algorithm (TDA)

Three-dimensional digitalized algorithm (TDA) is a state-of-the-art seepage evaluation method to efficiently evaluate the seepage rate of leakage amount through defective cut-off walls. The targeted volumes are represented by a fine-meshed grid of nodes (Pan et al. 2020). These nodes can be identified as the treated or untreated nodes. According to the classified nodes, the seepage paths are detected, and seepage rate is hence readily determined. The algorithm flow can be divided into four parts: generation of random numbers; identification of untreated nodes; penetration examination; and seepage flow rate calculation for penetrated or unpenetrated cases (Pan et al. 2019b).

The random imperfection of cut-off walls firstly characterized by the random orientations of column axis and variable diameters (Pan et al. 2017, 2021). Two independent parameters are utilized to describe the imperfect orientations, namely, azimuth ($\alpha$) and inclination angle ($\beta$), as shown in Fig. 1. The variation of column diameter is characterized as a random process prescribed by random seeds, wherein the spatial correlation is quantified by the scale of fluctuation (SOF). It is assumed that the injected columns are mainly influenced by the properties and structures of strata. Within a
small range, the strata will not change much along the horizontal direction, and hence the SOF in the horizontal direction is neglected. Consequently, the diameter variations of all columns are deemed as the same random process controlled by the vertical SOF. Based on the random numbers of defined imperfection variables, the geometry of untreated zone is determined. The ground domain is subsequently discretized into unified eight-node cuboids, and the coordinate of each node is calculated and recorded. The nodes outside the zone of treated columns are considered as the untreated nodes (illustrated by the solid points). Using the untreated nodes, the penetration detection can be performed. Considering the huge permeability difference between treated and untreated zone, the concentrated seepage channel should be identified as the continuous untreated zone. Thus, the inter-connection of untreated nodes along the possible seepage direction is of significance, and the question of penetration detection is translated into the scanning of untreated nodes.

Assuming that penetrating untreated zones existing, the flow rate is governed by the harmonic average of continuous untreated zone $A(t)$ as:

$$ Q = \frac{k_u H}{t} A(t) $$

where $k_u$ is the permeability coefficient of untreated soil, $H$ is the water head difference between two sides of cut-off walls; $t$ is the thickness of treated water-tightened barrier that takes no account of the random imperfection. The value of $A(t)$ can be calculated according to its definition as $\frac{1}{t} \int_0^t \frac{1}{A(u)} du$. However, the integral form brings computational complexity, while its numerical solution is easy to get for a discretized model. A discretized form of $A(t)$ can be derived as:

$$ A(t) = \frac{k_u H}{\frac{1}{n} \sum_{i=1}^{n} \frac{1}{A_{Si}}} $$

where $A_{Si}$ is the sectional area of untreated zone for discrete domain, $i$ is the number of seepage channels that have been divided. According to the Eq.(1) and Eq.(2), the seepage flow rate can be readily evaluated for different penetration situations. The accuracy and validity of TDA method have been verified compared with FE results, and hence, in this study, TDA method is considered as the benchmark method.

### 2.2 Traditional Neural Network (NN)

Neural Network (NN) method, because of its highly nonlinear fitting capacity, has received wide attention (Lee et al. 2003; Edincliler et al. 2012). Like the structure of human brain, the interconnected neurons form different layers and convey information between layers. The single neuron performs a similar function as multiple linear regression (Anthony and Bartlett. 2009).

A common neural network consists of three layers, including the input layer, output layer and hidden layers (Wang. 2003). The input layer is utilized to construct communication between the input data and NN. The output layer provides the pre-
dicted results given by the trained NN. The hidden layers are sandwiched between the input layer and output layer. The hidden layers are, in general, composed of multiple layers of neurons, in charge of the comprehension and mining of data.

The training of NN has an enormous impact on the performance of NN. The synaptic weights between neurons are assumed to be identical for the initial NN, and gradually adjusted during the data training process. The goal of NN training is to seek out a reasonable set of synaptic weights that ensures the minimum error between the prediction and target. Several training algorithms have been developed for data with different characteristics, such as Backpropagation, Quasi-Newton, and Levenberg-Marquardt algorithm (Ilonen et al. 2003). The Levenberg–Marquardt algorithm is a robust and widely used training algorithm and, hence, adopted in this study.

In addition, the success of NN application relies on its network topology, mainly on the structure and number of neurons in hidden layers (Wilamowski et al., 2009). It is designed based on the complexity of confronting problem and the size of training datasets. A two-layer hidden layers, with 20 neurons (40 neurons for comparison) in the first hidden layer, are employed against the proposed problem (see Fig. 2). Besides, two imperfection angles (including azimuths and inclination angles) and the random seeds for the description of column diameter variation are selected to be the input variables in input layer. The seepage flow rate is the expected result of output layer.

![Fig.2. Illustration of traditional neural network (NN) method](image1)

**2.3 Physical-based Neural Network (NN)**

NNs possess highly nonlinear fitting capacity and strong robustness, which have been verified by numerous applications in the field of computer science, medical science, physics, etc (Gharehchopogh and Khalifelu. 2011; Dhillon and Verma. 2020). However, NNs are also criticized to be non-transparent and their predictions hard to be traceable by humans. In the previous research, the role of single neuron in the whole NN is still unable to be described concretely, as well as the message conveyed between neurons (Rudin. 2019). Improving NN physical mechanism awareness, especially constructing physical-based NN, is one possible path to improve the result interpretability for NN and even for the whole AI field.

Observing the dimension of input variables for traditional NNs, there are not only angle related variables but also dimensionless variable (i.e., random seeds). These unprocessed inputs do not follow the basic physical knowledge as dimensional homogeneity law. A physical layer is hence introduced between the input layer and hidden layer. The physical-based variable called imperfection distance is derived, and all the
input variables in the input layer are translated into unified dimensional variable through physical-based layer. The imperfection distance $d_{im}$ is defined as the width of untreated zone between the centers of two adjacent columns and illustrated in the Fig.3.

The flowchart of physical-based NN is listed as below:

1. divide all the columns as several identical layers (the red line in the Fig.1) according to the value of SOF (scale of fluctuation) along z direction.
2. calculate imperfection distance for two specified columns at a prescribed height (along the connecting line of pile centers at given layers). According to Fig.3, if two piles intersect with each other at the height $h$, the corresponding imperfection distance will be set as zero.
3. sum up the imperfection distances at a prescribed height for the column group (in here assuming that the soil and cement stabilized column are spatial homogeneous material, and the water head remains unchanged along y direction).
4. the NNs with the appropriate architecture are set up, in which the input layer is composed of the angle imperfection variables and random seeds for different columns, and the physical-based layer is also introduced between the input layer and hidden layer, which translates the input variables into the defined unified dimensional variables (see Fig.4).

divide $N_c$ pairs of imperfection variables and their associate seepage flow rate into training set, validation set and test set, following which the corresponding datasets are fed into the program for training.

3 ILLUSTRATIVE EXAMPLE

In this section, the TDA method is utilized to generate the benchmark datasets for the training of traditional NNs and physical-based NNs. Adopted case simulates a row of 10 columns with the same length of 10 m. The diameters vary along the axes of columns, and the column axes tilt at any direction. The azimuths ($\alpha$) are assumed to be uniformly distributed within $[0, \pi]$, which indicates that the axis of column can rotate toward any direction. The inclination angles ($\beta$) are assumed to follow a normal distribution with zero mean and a standard deviation of $0.1-0.3$ degree, as indicated from the measured site data by Croce and Modoni (2007). A negative value of $\beta$ means the opposite direction for the prescribed inclination. And the above two variables regarding angles are assumed to be independent. For the description of diameter variation, the number of random seeds must be plentiful and, in this study, chosen as 64. Therefore, a total 84 input variables can be divided into 3 types, including 64 random seeds, 10 azimuths $\alpha$ and 10 inclination angles $\beta$. In this study, 5000 random realizations are firstly performed using TDA method, and the calculated seepage flow rate values are collected.
Fig 4. Illustration of physical-based neural network (NN) method

3.1 The performance of traditional NN

The generated datasets are fed into the configured NN. A two-layer hidden layers NN is employed to construct surrogate model between the random seeds of positioning errors and seepage flow rate. The number of first hidden layer neurons is set as 20. As shown in Fig.5a, the NN prediction agrees well with given data for the training dataset, however, the results for the validation set and test set are very bad with a relatively small R value. After increasing the number of first hidden layer neurons to 40, the similar situation occurs (see Fig. 5b). Though there is some improvement for R value of training dataset, the imitative effect for the validation set and test set cannot turn better. It is account for too many input variables, which cause the overfitting of data. Though too much details are supplied in the model creation, the model will actually be created perfectly, but just for specific training data.

3.2 The performance of physical-based NN

The traditional NN did not achieve the desired effect in the surrogate model construction. A physical layer is hence introduced into the traditional NN structure. The 84 input variables at the input layer are translated into the defined imperfection distance through the physical layer. The hidden layer keeps the same setting with the traditional NN. As shown in Fig.6a, the training dataset, validation dataset and test dataset all obtain satisfactory results when the number of first hidden layer neurons is set as 20. As its number increase at 40, the fitting effect does not get much improvement, and the R value maintains at 0.94 (see Fig.6b).
Compare with TDA method, the physical-based NN shows remarkably computational efficiency. For a desktop computer with 8 GB RAM and four Intel Core i5 CPU clocked at 3.2 GHz, the computation of one realization for TDA method takes about 10s. In contrast, the calculation time of physical-based NN of same realization is only 0.03s, which account for only 3/1000 computational resource for the TDA counterpart.
4 SUMMARY AND CONCLUSIONS

This paper points a new direction making AI method more interpretable and traceable by the well-designed physical-based neural network (NN). The physical-based NN is applied in the engineering practice of water-tightness estimation for geometrically imperfect cut-off walls. Results show that, compared with traditional NNs, the prediction accuracy and result interpretability of physical-based NNs achieve tremendous progress. The problem of data over-fitting confronted by traditional NNs is trickly solved by the definition of imperfection distance. More importantly, the fusion of physical mechanism and AI technique endows pure AI system with physical way of thinking and reasoning. Starting from this point, this novel NN architecture provides a promising strategy to educate AI system with more in-depth and comprehensive geotechnical knowledge. Further research will focus on designing a smarter physical-educated AI system and further extending the developed framework in the broader geotechnical field.

There is a lack of field data of the defects of cut-off walls and leakage through defective cut-off walls because the leakage flow rate is usually hidden underground. Future work can be done by associating flow rate of drainage wells with existing jet-grouted cut-off walls with recorded inclination.

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