Geoscience Frontiers 11 (2020) 1095–1106

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Geoscience Frontiers

journal homepage: www.elsevier.com/locate/gsf

Focus Paper

State-of-the-art review of soft computing applications in underground excavations

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ARTICLE INFO

Handling Editor: M. Santosh

Keywords:
Soft computing method (SCM)
Underground excavations
Wall deformation
Predictive capacity

ABSTRACT

Soft computing techniques are becoming even more popular and particularly amenable to model the complex behaviors of most geotechnical engineering systems since they have demonstrated superior predictive capacity, compared to the traditional methods. This paper presents an overview of some soft computing techniques as well as their applications in underground excavations. A case study is adopted to compare the predictive performances of soft computing techniques including eXtreme Gradient Boosting (XGBoost), Multivariate Adaptive Regression Splines (MARS), Artificial Neural Networks (ANN), and Support Vector Machine (SVM) in estimating the maximum lateral wall deflection induced by braced excavation. This study also discusses the merits and the limitations of some soft computing techniques, compared with the conventional approaches available.

1. Introduction

Due to population growth and urbanization, there is an increasing demand for the construction of underground projects such as the tunnels for mass rapid transportation services as well as the deep braced/anchored excavations for development of shopping malls, parking lots, and the skyscrapers. The responses of underground engineering systems in soils/rocks are complex, highly-nonlinear, uncertain, and not yet completely understood. In recent years, with rapid development of scientific computing software, evaluation of underground engineering responses or behaviors has entered a new stage. Engineers are now relying more on computational intelligence particularly soft computing analysis instead of carrying out huge complicated numerical analysis or computationally demanding calculations.

Soft computing methods (SCMs) allow computers to learn laws or so-called patterns from existing data, either from field instrumentation or case histories, without being explicitly programmed. These soft computing techniques include but not limit to Multivariate adaptive regression splines (MARS), artificial neural networks (ANNs), support vector machines (SVMs), Random Forest methods (RF), Decision Trees (DT), Gradient boosting machines (GBM), Logistic regression (LR), Gaussian process (GP), Hybrid methods such as the adaptive neuro-fuzzy inference system (ANFIS), and gene expression programming (GEP) and so forth. For the readers' interest, Table 1 compiles the use of soft computing use in underground excavations during the past 30 years. Table 1 also contains the note for abbreviation explanations of the SCMs.

Soft computing methods have been widely used in evaluating excavation performances such as the retaining wall deflection brought by deep braced excavation (Goh et al., 1995; Chua and Goh, 2005; Kung et al., 2007; Chern et al., 2009; Choi and Lee, 2010; Zhang et al., 2017a, b, 2018, 2019; Xiang et al., 2018) and the ground surface settlement induced by tunneling (Shi et al., 1998; Kim et al., 2001; Sen and Chuang, 2004; Neaupane and Adhikari, 2006; Suwansawat and Einstein, 2006; Santos and Celestino, 2008; Hou et al., 2009; Goh and Hefney, 2010; Tsekouras et al., 2010; Hajihassani et al., 2011; Pourtaghi and Lotfollahi-Yaghin, 2012; Ocak and Seker, 2013; Ahangari et al., 2015; Bouayad and Emeriault, 2017; Moeinossadat et al., 2017; Chen et al., 2019). Some researchers have focused on the effects of the geological

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Peer-review under responsibility of China University of Geosciences (Beijing).

https://doi.org/10.1016/j.gsf.2019.12.003
Received 25 September 2019; Received in revised form 19 November 2019; Accepted 5 December 2019
Available online 25 December 2019

parameters on stability assessment of underground constructions, such as Leu et al. (2001), Mawdesley (2004), Goh and Zhang (2012), and Goh et al. (2017a,b). Assessment of rock-burst and the risk prediction has been investigated by Su et al. (2010), and Zhou et al. (2012, 2016, 2018). Such as Zhou et al. (2016a) have compared ten types of learning algorithms including LDA, QDA, PLSDA, NB, KNN, MLPNN, CT, SVM, GBM and RF, and concluded that the best models for the prediction of rock-burst were GBM and RF. In addition, Zhou et al. (2018) have systematically discussed the use of statistical and intelligent classification methods of rockburst. Jang and Sun (1995), Dong et al. (2013), Jang and Topal (2013), and Mottahedi et al. (2017, 2018) have investigated the use of SCM in prediction of overbreak in tunneling and underground mining. Mottahedi et al. (2017) has applied 267 data sets of contributing factors and dependent response for overbreak prediction using the multiple linear and nonlinear regression analysis, ANN, FL, ANFIS, and SVM. It was concluded that the FL and ANFIS models have provided more appropriate predictions than other models.

The objective of this paper is to provide an overview of the features relevant to the process and operation of ANNs, MARS, RF, and SVM, and to present a review of their applications to date in underground excavation. Through the case study, this paper compares the performance of the SCMs mentioned above and discusses the merits and disadvantages of each method. It also discusses most of the current challenges as well as future directions in relation to the use of soft computing techniques in underground engineering.

2. Overview of SCMs

In this study, the predictive capacities of three groups of SCMs including machine learning (ANN and SVM), tree-based (CART, DT, RF and XGBoost) and regression (LR and MARS) models were briefly introduced while some of the methods are elaborated with detailed process.

2.1. ANN

ANN is one of the most rapidly growing research fields, attracting attentions from a wide variety of geotechnical communities. ANNs are information processing systems inspired by the way biological nervous system and the brain works. They are more generally configured for specific applications including the pattern recognition (stable or not), image processing and compression (concrete cracks), and conventional bearing capacity predictions. ANNs perform best if the relationship between the inputs and the target responses are highly non-linear and therefore, are especially suitable for solving problems where there are no inherent algorithms or specific set of rules, i.e., pre-assumed or pre-determined relationships.

An ANN basically comprises of three layers: input, hidden, and output layers, where each layer may have a number of nodes, known to be neurons perform the basic operations and the overall operation is the weighted sum of these basic operations. It has to be trained so that a known set of inputs produces the desired outputs. Training is usually done by feeding teaching/instructing patterns to the network and letting the network to adjust its weighting function according to some previously defined learning rules. The learning can either be supervised, semi-supervised or unsupervised.

There are actually many types of ANNs, such as Back-Propagation Neural Network (BPNN), Bayesian Neural Network (BNN), General Regression Neural Network (GRNN), Multilayer Perceptron Neural Network (MLPNN), and K-Nearest Neighbor (KNN), as well as the hybrid form of Adaptive Neuro-Fuzzy Inference System (ANFIS). Among them, backpropagation (BP) algorithm is used in most ANN as the method to train the network. Here, output of the neural network is evaluated against the desired output, and if the results are not as expected, the weights between layers are modified and the process is repeated until the optimization goal is satisfied. Factors affecting the performance of ANNs include the number of nodes/neurons in the hidden layer, the learning rate, and the training tolerance.

2.2. DT

In decision trees, the models are obtained via recursively partitioning the data space and fitting a simple prediction model within each partition. As a result, the partitioning can be represented graphically as a decision tree. Decision trees include the regression trees and classification trees. Regression trees are for dependent variables taking continuous or ordered discrete values, with prediction error typically measured by the squared difference between the observed and predicted values (Loh, 2011). Classification trees are for dependent variables that take categorical values (e.g. tunnel classes or rockburst severities). In the decision tree modelling, an empirical tree represents a segmentation of the data that is created by applying a series of simple rules. These models generate a set of rules which can be used for prediction through the repetitive process of splitting (Tso and Yau, 2007). The DT approach is built upon the implicit assumption that the relationship between features and target objects is either linear or nonlinear. In DT, features that carry maximum information are automatically selected for classification/regression and the remaining features are rejected, which increases the computational efficiency and averts the subjective uncertainty. The construction of a tree is also based on a binary recursive partitioning. The term "binary" implies that each group of observations, represented by a node in a DT, is split into two child nodes, a process through which the original node becomes a parent node. The term "recursive" refers to the fact that the binary partitioning process can be applied repetitively. It is an iterative process that splits the data into partitions. Initially, all the training samples are used to determine the structure of the tree. The algorithm then breaks the data using every possible binary split and selects the split that partitions the data into two parts such that it minimizes the sum of the squared deviations from the mean in the separate parts. The splitting process is then applied to each of the new branches. The process continues until each node reaches a user-specified minimum node size (Xu et al., 2005). Thus, each parent node can give rise to two child nodes and, in turn, each of these child nodes may themselves be split, forming additional children. The term "partitioning" refers to the fact that the dataset is split into sections or partitioned.

2.3. CART

CART is a recursive partitioning procedure that classifies the categorical (classification tree) or continuous (regression tree) data at each node (e.g., parent) using a set of if-then-else rules (Timofeev, 2004). CART begins with the root node at the top of the tree, which contains the whole data for the training pattern (Yap et al., 2011). A node in the CART model is either a terminal node (a node without children), or non-terminal node (a node with children). CART seeks the split using search algorithms to classify the data into binary or even multiple classes (Breiman et al., 1984) by checking all unique values across the range of data values of different predictors (Ayoubloo et al., 2011).

2.4. MARS

MARS was first proposed by Friedman (1991) as a flexible procedure to organize relationships between a set of input variables and the target dependent that are nearly additive or involve interactions with fewer variables. It is a nonparametric statistical method based on a "divide and conquer" strategy in which the training data sets are partitioned into separate piecewise linear segments (splines) of differing gradients (slope), which representing the integration of additive regression, the recursive regression, spline regression and recursive partitioning regression. With respect to other methods, the prediction accuracy of MARS is relatively high and it is also highly adaptive since it makes no assumptions about the underlying functional relationships between

Table 1
SCM applications in underground excavations.

References	SCM	Applications
Hou et al. (2009)	ANFIS	Settlements induced by shield tunneling
Bouayad and Emeriault (2017)	ANFIS, PCA	Settlements induced by shield tunneling
Cabalar et al. (2012)	ANFIS	Geotechnical engineering
Jang and Sun (1995)	ANFIS	Overbreak prediction
Mottahedi et al. (2018)	ANFIS-PSO	Overbreak prediction
Armaghani et al. (2015)	ANFIS	Predicting ground vibration
Ahangari et al. (2015)	ANFIS, GEP	Tunneling-induced settlement
Moeinossadat et al. (2018)	ANFIS, CAM	Ground settlements caused by EPB tunneling
Chern et al. (2009)	ANN	Wall deflection in top–down excavation
Goh et al. (1995)	ANN	Lateral wall movements in braced excavations
Goh and Zhang (2012)	ANN	Stability assessment of rock caverns
Hajihassani et al. (2011)	ANN	Settlements induced by NATM tunneling
Huang and Wang (2007)	ANN	Reliability analysis for deep excavation
Jan et al. (2002)	ANN	Deep excavation
Kim et al. (2001)	ANN	Ground surface settlements due to tunneling
Lai et al. (2016)	ANN	Soil deformation in tunneling
Lee and Sterling (1992)	ANN	Underground openings probable failure modes
Leu et al. (2001)	ANN	Tunnel support stability
Li et al. (2008)	ANN	Pit retaining structure displacement
Sen and Chuang (2004)	ANN	Ground settlement induced by deep excavation
Tsekouras (2004)	ANN	Tunneling problems
Tsekouras et al. (2010)	ANN	Settlements during tunneling excavation
Yoo and Kim (2007)	ANN	Tunneling performance
Yu et al. (2009)	ANN	Settlement induced by foundation pit excavation
Mottahedi et al. (2017)	ANFIS, SVM, FL	Overbreak prediction in drill & blast tunneling
Chen et al. (2009)	ANN, FL	Construction pre-control of a connection tunnel
Ocak and Seker (2013)	ANN, GP, SVM	Surface settlements caused by EPB
Alimoradi et al. (2008)	ANN, TSP-203	Geological hazardous zones of a tunnel face
Amiri et al. (2016)	ANN, KNN	Blast-induced ground vibration
Chen et al. (2019)	ANN, BP, RBF, GRNN	Settlement caused by EPB shield tunneling
Feng and Jimenez (2015)	BN	Predict tunnel squeezing
Chua and Goh (2005)	BNN	Wall deflections in deep excavations
Boubou et al. (2010)	BPNN	Settlements induced by shield tunneling
Darabi et al. (2012)	BPNN	Subsidence estimation
Santos and Celestino (2008)	BPNN	Tunnel settlement
Shi et al. (1998)	BPNN	Settlements during tunneling
Suwansawat and Einstein (2006)	BPNN	Settlements induced by EPB shield tunneling
Yun et al. (2011)	BPNN	Mechanical parameters of tunnel surrounding rock
Zhang et al. (2019a)	BPNN	Settlement prediction of foundation pit
Pourtaghi and Lotfollahi-yaghin (2012)	BPNN, Wavenet	Tunnel-induced ground settlement
Protopapadakis et al. (2016)	FFNN	Pile integrity tests
Goh and Hefney (2010)	ANN	Surface settlement caused by EPB tunneling
Zhou et al. (2016b)	GBM	Damage due to blasting vibrations of open pit
Su et al. (2010)	GP	Identify rockburst grades
Ahangari (2015)	GRNN	Lateral load bearing capacity of piles
Pal and Deswal (2008)	GRNN, SVM	Pile capacity
Atashpaz-Gargari and Lucas (2007)	ICA	Settlements induced by shield tunneling
Moghaddasi and Noorian-Bidgoli (2018)	ICA-ANN, ANN, MR	Surface settlement caused by tunneling
Ghasemi and Gholizadeh (2019b)	KNN, DT	Tunnel squeezing prediction
Ghasemi and Gholizadeh (2019a)	LDA, BLR	Tunnel squeezing prediction
Zhou et al. (2016a)	LDA, QDA, PLSDA, NB, KNN, MLPNN, CT, SVM, RF, GBM	Classification of rockburst
Lee et al. (2006)	LR	Ground subsidence hazard analysis
Li and Jimenez (2018)	LR	Rock burst hazard
Mawdesley (2004)	LR	Rock mass classification & excavation
Zhang and Goh (2016a, 2016b)	LR, MARS	Evaluating seismic liquefaction potential
Lee et al. (2006)	LR	Ground subsidence hazard analysis
Choi and Lee (2010)	DT based LR	Selecting retaining wall systems
Goh et al. (2017a)	MARS	Earth pressure balance tunnel
Goh et al. (2018)	MARS	EPB tunnel-related maximum surface settlement
Zhang and Goh (2014)	MARS	Serviceability limit state of twin caverns
Zhang et al. (2017c)	MARS	Lateral wall deflection in braced excavations
Zhang et al. (2019c)	MARS	Determination of wall deflection envelope
Adoko et al. (2013)	MARS, ANN	Predicting tunnel convergence
Zheng et al. (2019)	MARS	Earthquake induced uplift displacement of tunnels
Goh et al. (2017c)	MARS, LR	Underground entry-type excavations stability
Neaupane and Adhikari (2006)	MLP	Surface settlements induced by NATM tunneling
Moeinossadat et al. (2016)	MR, ANFIS, CAM	Settlement caused by EPB shield tunneling
Jang and Topal (2013)	MRA, ANN	Optimizing overbreak prediction
Feng and Jimenez (2015)	NBC, BNs	Tunnel squeezing prediction
Moeinossadat et al. (2017)	NGS, ANFIS, GEP	Surface settlement due to EPBM tunneling
Mahdevari and Torabi (2012)	RBF, MVR	Tunnel convergence
Liao et al. (2011)	RBFNN	Permeation grouting
Wang et al. (2014)	RBFNN	Geotechnical engineering
Zhou et al. (2018)	Review	Evaluation method of rockburst

(*continued on next page*)

Table 1 (*continued*)

References	SCM	Applications
Xie and Peng (2019)	RF	Excavation damaged zones
Zhou et al. (2017)	RF	Shield-driven tunnel induced settlements
Zhou et al. (2019)	RF	Risk prediction of deep foundation pit
Dong et al. (2013)	RF, SVM, ANN	Rockburst classification
Zhang et al. (2019b)	RF, PSO	EPB shield steering
Seker and Ocak (2019)	RF, ZeroR, GP, LR, MLP	Roadheader performance prediction
Armaghani et al. (2017)	SVM	TBM penetration rate
Mahdevari et al. (2014)	SVM	Predicting tunnel penetration rates
Mahdevari et al. (2013)	SVM	Tunnel convergence
Shi et al. (2019)	SVM	Rock deformation of shallow buried tunnel
Yao et al. (2010)	SVM	Tunnel surrounding rock displacement
Zhou et al. (2012)	SVM	Prediction model of rockburst
Wu et al. (2014)	SVM, ANN	Tunnel surrounding rock displacement
Zhang et al. (2017a)	SVM	Tunnel-induced ground settlement
Liu et al. (2019)	Improved SVM	Predicting rock mass parameters of tunnel data
Zhu et al. (1996)	TSAM	Displacement in tunneling
Wang et al. (2013)	RVM	Tunnel-induced ground settlement

Note:

ANFIS Adaptive Neuro-Fuzzy Inference System	KNN K-Nearest Neighbor
ANN Artificial Neural Networks	LDA Linear Discriminant Analysis
BLR Binary Logistic Regression	LR Logistic Regression
BN Bayesian network	MARS Multivariate Adaptive Regression Splines
BPNN Back-Propagation Neural Network	MLPNN Multilayer Perceptron Neural Network
CART Classification and Regression Trees	MVR Multi-Variable Regression
CT Classification Tree	NB Naive Bayes
DT DecisionTree	NGS Neuro-Genetic System
FCM Fuzzy C-Means Clustering	PCA Principal Component Analysis
FFNN Feed-Forward Neural Networks	PLSDA Partial Least-Squares Discriminant Analysis
FL Fuzzy Logic	PSO Particle Swarm Optimization
FORM First-Order Reliability Method	QDA Quadratic Discriminant Analysis
GBM Gradient-Boosting Machine	RBFNN Radial Basis Function Neural Network
GEP Gene Expression Programming	RF Random Forest
GP Gaussian Processes	RNN Recurrent Neural Network
GRNN General Regression Neural Network	TSAM Time Series Analysis Method
ICA Imperialist Competitive Algorithm	SVM Support Vector Machine

dependent and independent variables. In general, the splines are connected smoothly together, and these piecewise curves (polynomials), also known as Basis Functions (BFs), result in a flexible model that can handle both linear and nonlinear behaviors. The connection/interface points between the pieces are called knots. Marking the end of one region of data and the beginning of another, the candidate knots are placed at random positions within the range of each input variable.

In general, any model based on MARS follows three basic steps such as:

(i) Constructive phase, also named the forward phase;
(ii) Pruning phase, also named the backward phase;
(iii) Selection of optimum MARS.

As for the detailed introduction of MARS algorithm, the model development procedures as well as applications in underground excavations, please refer to Zhang and Goh (2013, 2016a, 2016b), Goh and Zhang (2014), Goh et al. (2017, 2018), and Zhang et al. (2017a, 2017b, 2019).

2.5. SVM

SVMs, firstly proposed by Vapnik (1995), was preliminarily introduced for classification and later for regression (Smola and Schölkopf, 1998). An SVM uses a device called kernel, such as the Gaussian and polynomial kernels, to map data into a high-dimensional feature space in which the nonlinear problem becomes linearly separable (Zhang et al., 2004). SVMs follow the same principles for classification and regression. It searches for the optimal hyperplanes which maximize the margin between classes of data and minimize unexpected errors.

In SVM, the main goal is to separate the two classes by a function which is done by placing a boundary between the two different classes and orient it in a way that the margin (i.e. the distance between the nearest data point of each class) is maximized. For example, in Fig. 1a, there are many possible linear classifiers that can separate the data but there is only one that can maximize the margin. This linear classifier is called the optimal separating hyperplane. Maximum margin has good generalization capability. The nearest data points are used to define the margin and are known as support vectors (see Fig. 1b).

2.6. RF

RF is an ensemble learning method proposed by Breiman (2001a), as a nonparametric and tree-based method (Zhou et al., 2017b). In this algorithm, using multiple DTs with the same distribution to set up a forest to train and predict the sample data (Kuhn and Johnson, 2013; Zhang et al., 2019b,d). As the primary intent of this review is to compare the prediction regression, so only the regression tree (RT) is introduced in this section. At each branching of RT, the mean of the samples on the leaf nodes and the Mean Square Error (MSE) formed between each sample were calculated. Pursuing the minimum of the leaf node MSE as branching condition, until no more features are available, or the overall MSE is optimal, the RT will stop growing.

To obtain an ensemble model with strong generalization ability, the base learner RT in the ensemble model should be made as uncorrelated as possible (Breiman, 1996, 2001). Bagging (bootstrap aggregating) is a parallel ensemble model proposed by Breiman (1996). The bagging flowchart is shown in Fig. 2 (Rodriguezgaliano et al., 2014). The RF procedures for regression are as follows:

Step 1: pick randomly n data points from the training pool. It should be stressed that the reason it is called random forest is due to the fact that the data points are randomly taken out from the pool and therefore the outcome tree is random.

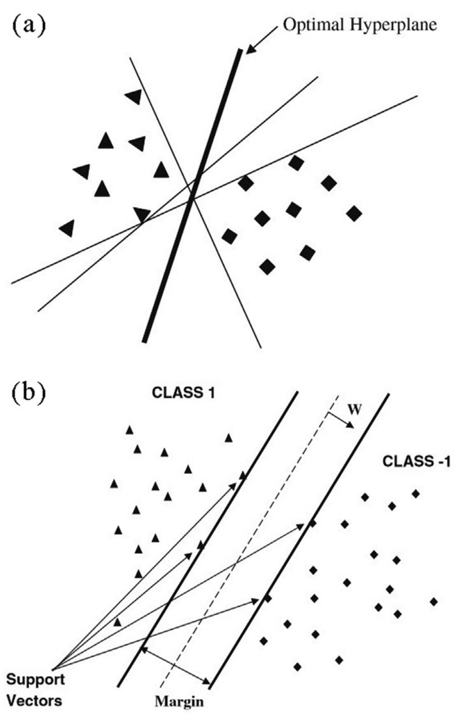

Fig. 1. Optimal separating hyperplane (a) and support vectors with maximum margin (b) (adapted from Sitharam et al., 2008).

Step 2: build RT 1 based on these n data points.
Step 3: repeat steps 1 & 2 to the pre-determined number K trees.
Step 4: generate the Forest by parallelly adding the K sub-trees together.
Step 5: the estimation process of each tree is independent, and take the average value as the final prediction. The random forests regression predictor is described by the following equation:

$$\widehat{f}_{rf}^{K}(x) = \frac{1}{K}\sum_{k=1}^{K} T(x) \tag{1}$$

2.7. XGBoost

XGBoost was proposed by Chen and Guestrin (2016), as an optimized distributed gradient boosting library designed to be highly efficient, flexible and portable. It implements machine learning algorithms under the Gradient Boosting framework. In boosting, the trees are built sequentially such that each subsequent tree aims to minimize the errors of the previous tree. Each tree learns from its predecessors and updates the residual errors. Hence, the tree that grows next in the sequence will learn from an updated version of the residuals. Quicker model exploration is possible as the parallel and distributed computing ensures faster learning. The prediction output function of the XGBoost model is as follows:

$$\widehat{y}_i = \sum_{k=1}^{K} f_k(\mathbf{x}_i), \quad f_k \in \mathbf{F} \tag{2}$$

where K is the total number of trees, k represents the kth tree, $\mathbf{x}_i$ is the features corresponding to sample i, $\widehat{y}_i$ corresponds to the predicted score from this tree, $\mathbf{F}$ is the space of RTs.

Bias-variance tradeoff is compromised to achieve a balance between model performance and operation speed, which defines the following regularized objective function as:

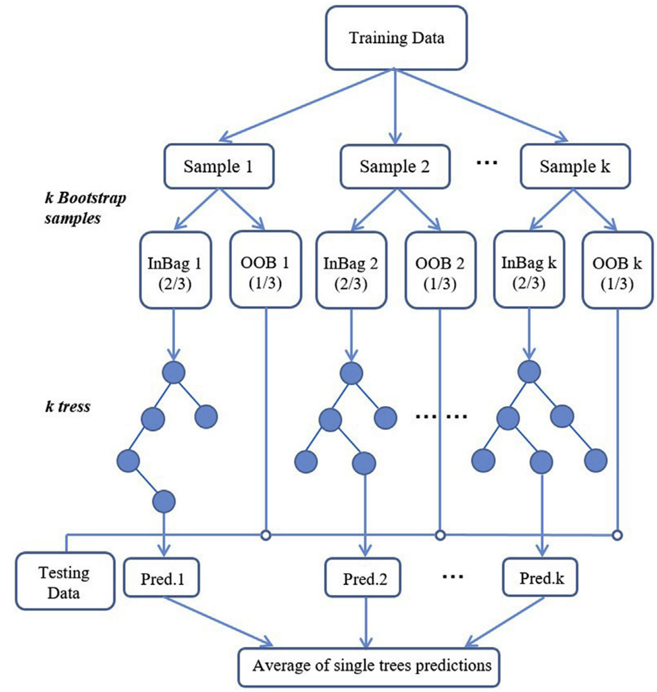

Fig. 2. Bagging flowchart.

$$Obj = \sum_{i=1}^{n} l(y_i, \widehat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{3}$$

where $\sum_{i=1}^{n} l(y_i, \widehat{y}_i)$ is the training loss function, quantifying how well the model fit on the training data. The second term $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$ as the additional regularization term penalizes the complexity of the model to avoid over-fitting, in which γ is the complexity cost by introducing additional leaf, T is the number of leaves, λ is the hyperparameter, $\sum_{j=1}^{T} w_j^2$ is used to measure how good a structure tree is, and the greater value it is of, the better. Therefore, under this objective function, the model of a simple predictive function is selected as the best model.

Start from the constant prediction, and add a new function each time. Therefore, the first term loss function is also related to all trees that have been built. It has already included the iteration results of all trees, so the entire objective function is related to the total number of trees. Formally, let $\widehat{y}_i^{(t)}$ be the prediction of the ith instance at the tth iteration, f_t is also included to minimize the following objective.

$$Obj^{(t)} = \sum_{i=1}^{n} l\left(y_i, \widehat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \tag{4}$$

To quickly optimize the objective in the general setting for the first term loss training function, we approximate it using the second order Taylor expansion.

$$Obj^{(t)} \simeq \sum_{i=1}^{n}\left[l\left(y_i, \widehat{y}_i^{(t-1)}\right) + g_i f_i(x_i) + \frac{1}{2}h_i f_t^2(x_i)\right] + \Omega(f_t) \tag{5}$$

where $g_i = \partial_{\widehat{y}}(t-1) l(y_i, \widehat{y}^{(t-1)})$ and $h_i = \partial^2_{\widehat{y}^{(t-1)}} l(y_i, \widehat{y}^{(t-1)})$ are first and second order gradient statistics of the loss function, respectively. The constant terms can be eliminated to get the following approximate objective in step t:

Table 2
Summary of the main features, merits and disadvantages for the four SCMs used in this study.

SCM	Main features	Merit	Disadvantage
XGBoost	An ensemble grouping model using subsequent trees learning from and minimizing the errors from the previous tree.	Each tree learns from its predecessors and updates the residual errors. Trees that grow next in the sequence will learn from an updated version of the residuals. Distributed computing ensures faster learning.	Susceptible to overfitting issues since it cannot deal with outliers when the model is trained by a small number of datasets.
MARS	Non-parametric regression that combines a series of linear splines for flexible model	Generates a flexible model that can handle both linearity and nonlinearity, with random knots and piecewise splines of differing gradients.	Susceptible to overfitting and limited to handling large data, less accurate for sparse data
ANN	A network model consisting of input, hidden, and output layers to emulate a biological neural system	Self-adaptive model as compared to traditional linear and simple nonlinear analyses, perform best if the relationship between the inputs and the target responses are highly nonlinear.	Local minima problem in which an optimization process often stops at a locally, rather than globally, optimized state.
SVM	Conducts optimal grouping of data and can be combined with a regression model for the optimal groups.	Supports optimal grouping of data by maximizing the margin between groups using kernel functions	Susceptible to overfitting issues depending on kernel functions used in optimal grouping

$$Obj^{(t)} \simeq \sum_{i=1}^{n}\left[g_i f_t(x_i) + \frac{1}{2}h_i f_t^2(x_i)\right] + \Omega(f_t) \tag{6}$$

By optimizing Eq. (6), the tth tree associated with the model parameters and predictions can be determined. The optimization procedures are repeated until the predefined stopping criterion is achieved, and meanwhile the ultimate predictions are obtained. More detailed explanations of the XGBoost algorithm are referred to Chen and Guestrin (2016). In this study, a Python-based XGBoost algorithm was adopted for modelling.

2.8. Main features, advantages, disadvantages of SCMs

Table 2 summarizes of the main features, merits and disadvantages of the main SCMs used in the performance comparison part of this study.

3. Case study and performance comparison

3.1. Database

The database includes results of 1120 plane strain finite element (FE) analyses of diaphragm walls in deep braced excavation. The influences of various parameters such as the excavation geometries, soil properties and wall stiffness on the wall deflections were investigated in Zhang and Goh (2015). For simplicity, brief introduction is as follows, including the cross-sectional soil and wall profile in Fig. 3 while the ranges of the design parameters are listed in Table 3.

The parameters depicted in Fig. 3 include: the excavation width B, excavation depth H_e, soft clay thickness T, soil unit weight γ. The parameters listed in Table 3 are: the system stiffness ln(S) [$S = EI/(\gamma_w h^4_{avg})$], where E is the Young's modulus of wall material, I is the moment of inertia of the wall section, the unit weight of water γ_w, and the average spacing of the struts h_{avg}; c_u/σ'_v is the relative soil shear strength ratio, where c_u is the undrained shear strength while σ'_v denotes the vertical effective stress; the relative soil stiffness ratio E_{50}/c_u, where E_{50} is the secant stiffness in standard drained triaxial test.

For brevity, the numerical simulation schemes as well as the parametric analysis are omitted. The database is enclosed in the Appendix A, for performance comparison with the adopted SCMs in this study.

Fig. 4 shows the distribution of wall deflection, it approximates to a lognormal distribution, and most of the wall deflection are between 50 and 200 mm, the mean and standard deviation are 137.53 mm and 69.36 mm, respectively. In this study, according to the distribution of wall deflection, the Spearman rank correlation coefficient was applied to determine the correlation coefficient of each two variables of the B, H_e, T, γ, ln(S), c_u/σ'_v, E_{50}/c_u and wall deflection, and then these coefficients are post-proceeded to a heatmap, as shown in Fig. 5. A heatmap is a graphical representation of data where the individual values contained in a matrix are represented as colors. In general, the parameter correlation coefficients are displayed in a heatmap because of its high efficiency and simplicity. It is clear that the wall deflection is highly influenced by ln(S), followed by E_{50}/c_u, γ, h, c_u/σ'_v, T and B. The correlation between each feature variable is not significant, which means that the data are not multivariate collinearity, and promising for modeling. Parameter correlation coefficients shown in this heatmap can be used as reference for examining the accuracy of the modeling.

For the ANN and SVM algorithms, datasets with different scales, distributions, and dimensions would significantly affect the optimization time. They can also affect the effectiveness of the optimizer, occasionally hindering the algorithm from reaching the optimum point. In addition, existence of outliers would affect the training if this aspect is not given proper consideration. To solve this problem, standardization or normalization of the data is important. By equalizing the range and distribution of input variables, these can help the optimizer to converge to the optimum point more efficiently, and they also avert the presence of outliers. Standardization converts the mean and standard deviation of the data to zero and one, respectively:

$$f_s(x_i) = \frac{x_i - \mu_i}{\sigma_i} \tag{7}$$

where f_s is the standardizer function, x_i is a value from series of input feature variable i into the model, μ_i is the mean of the input variable i, and σ_i is the standard deviation of the input variable i. However, for XGBoost and MARS, the standardization is unnecessary.

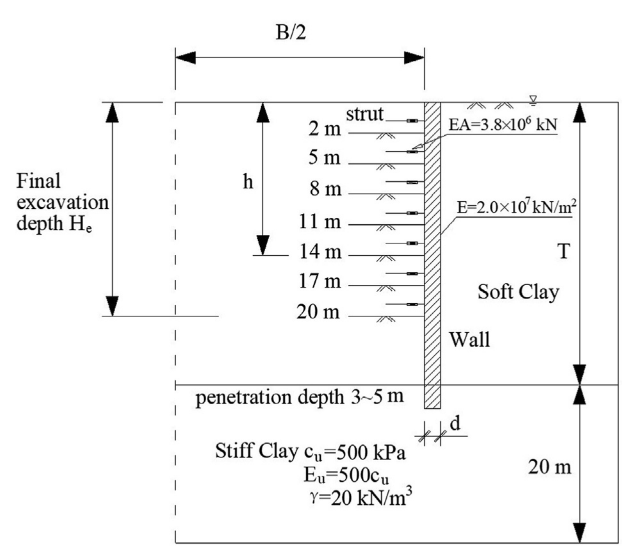

Fig. 3. Cross-sectional soil and wall profile.

Table 3
Parameter descriptions and the ranges.

Parameter	Ranges
Relative shear strength ratio c_u/σ'_v	0.21, 0.25, 0.29, 0.34
Relative soil stiffness ratio E_{50}/c_u	100, 200, 300
Soft clay thickness T (m)	25, 30, 35
Wall stiffness EI ($\times$ 10^6 kN m^2/m)	0.36, 1.21, 2.88, 5.63
Excavation width B (m)	20, 30, 40, 50, 60
Soil unit weight γ (kN/m)	15, 17, 19
Excavation depth H_e (m)	11, 14, 17, 20

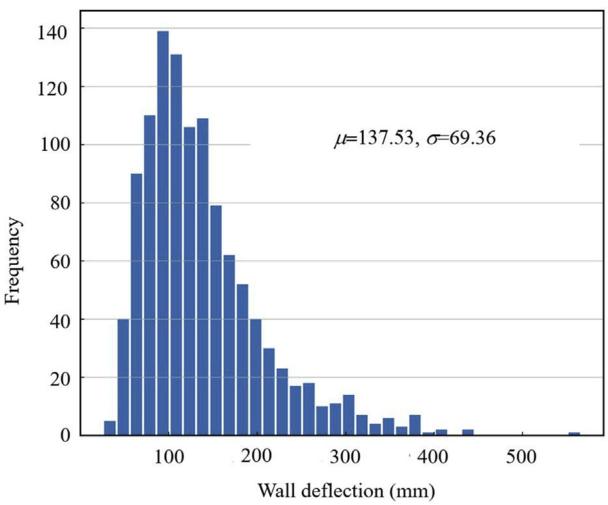

Fig. 4. Histogram of lateral wall deflections.

3.2. Performance indicators

Assessment of the performance of models are done based on the indicators. In the following equations, N is the total number of data; y_i and $\widehat{y}_i$ are the FEM value and the SCM estimations, respectively; $\overline{y}$ is the mean of the FEM results.

Root Mean Square Error (RMSE) (Kisi et al., 2013) value closer or equal to 0 indicates that the error in prediction is marginal.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(\widehat{y}_i - y_i\right)^2} \tag{8}$$

Coefficient of determination R^2 (Nagelkerke, 1991) values should be closer to 1 and also closer to each other shows that the model used most of the variability in soil parameters.

$$R^2 = \frac{\sum_{i=1}^{n}(\widehat{y}_i - \overline{y})^2 - \sum_{i=1}^{n}(\widehat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\widehat{y}_i - \overline{y})^2} \tag{9}$$

Bias Factor is a factor whose value more than unity represents the overestimated model, value of less than unity represents an underestimation model, and a value of unity indicates a prediction which is unbiased (Prasomphan and Mase, 2013).

$$\text{Bias Factor} = \frac{1}{N}\sum_{i=1}^{n}\frac{y_i}{\widehat{y}_i} \tag{10}$$

Mean Absolute Percentage Error (MAPE) (Armstrong and Collopy, 1992) value closer to 0 shows predictions of high accuracy.

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{\widehat{y}_i - y_i}{\widehat{y}_i}\right| \tag{11}$$

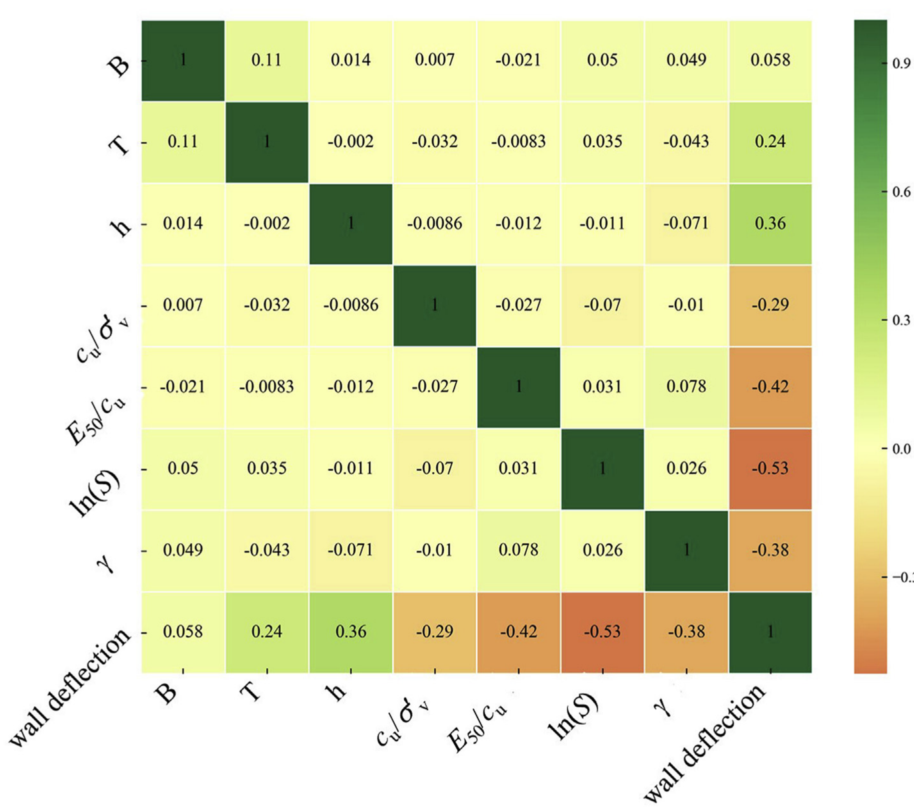

Fig. 5. Spearman rank correlation coefficient for parameters in this study.

3.3. Calculation and results

This section mainly demonstrates the comprehensive performance comparisons of the SCMs, including XGBoost, MARS, ANN and SVM. Out of the 1120 FE results, about 80% of the data points were randomly selected as the training dataset while the remains were used for testing. The PC used to develop the XGBoost, MARS, ANN and SVM model was with an i5 Intel (R) Core and 8500 CPU running at 3.00 GHz and 8 GB RAM with the Windows 10 operating system, under the Python development environment. The computational times for each of the four methods are all within 1 s and the efficiency difference is marginal.

It should be noted that the uncertainties of the key design parameters associated with the predictions via the four methods might be considered for robustness performance comparison, for which the probabilistic reliability analysis is more desired. In addition, to avoid bias in data selection, one of the most popular validation methods, 5-fold cross-validation (Kohavi, 1995; Wong, 2015), was employed in this study during the process of data pattern determination and the comprehensive model assessment.

Figs. 6 and 7 show the training and testing results of the prediction of wall deflection by XGBoost, MARS, ANN and SVM, respectively. It is clear that the four methods all achieved reasonable results since the data points representing different SCMs predictions fit well around the reference line. Table 4 lists the values of the performance indicators mentioned above. The RMSE, R^2, bias factor and MAPE between the FEM prediction vs SCM estimations provided by the XGBoost model were 7.90, 0.99, 1.00 and 0.04, respectively, for the testing data. The RMSE, R^2, bias factor and MAPE given by the MARS model were 11.10, 0.97, 1.02 and 0.07, respectively, for the testing patterns. The RMSE, R^2, bias factor and MAPE for the predicted values via the ANN model were 11.73, 0.97, 1.00 and 0.07, respectively. Lastly, the RMSE, R^2, bias factor and MAPE by the SVM model were 17.40, 0.94, 1.01 and 0.06 respectively. It is obvious that the overall performance has been improved by ensemble learning XGBoost method, compared with the more conventional MARS, ANN and SVM. As a strong tree-based tool, XGBoost is able to balance the relationship between the predictive accuracy and requirements of intelligibility.

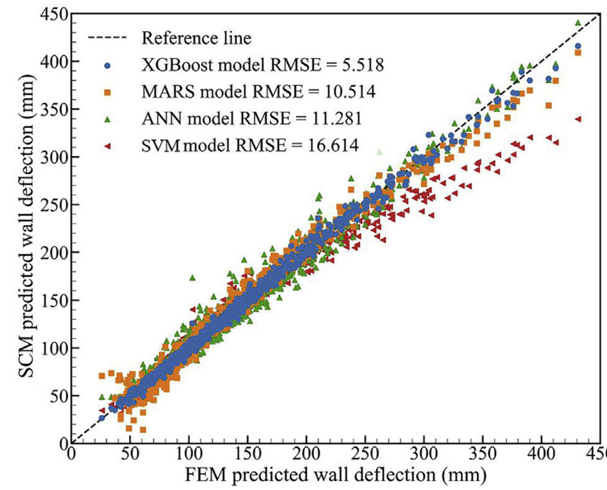

Fig. 6. Training results of FEM wall deflection.

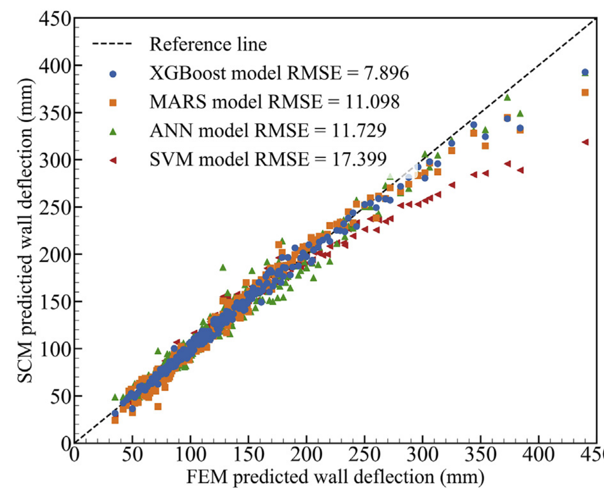

Fig. 7. Testing results of FEM wall deflection.

3.4. Feature importance analysis

The trained XGBoost model automatically evaluates the importance of the features, as shown in Fig. 8, in which the feature score can be obtained by the interface feature importance, i.e. the gain criterion. The gain represents the relative contribution of the corresponding feature to the model, calculated by assessing the contribution of each feature of each tree in the model. The higher the value of this indicator compared to other features, the more important it is for generating forecasts. For simplicity, percentage is used to sort the feature scores of the seven variables from high to low, as plotted in Fig. 8. It can be seen that ln(S) is the most important feature variable, followed by E_{50}/c_u, γ, h, c_u/σ'_v, T and B. This is consistent with the correlation coefficient reflected by the heatmap in Fig. 5. In addition, the XGBoost model is capable of giving reasonable results of feature scores within just 1 s. It is more applicable than FE analysis to some extent, or can be used for cross-checking with the FE numerical results.

4. Discussion and conclusions

It is inevitable for underground excavations to encounter problems that are very complex, highly nonlinear, multidimensional, and not well understood, especially for excavation constructions under complicated surrounding condition nowadays. In this regard, SCMs provide several advantages over traditional theoretical solutions, statistical analysis or numerical simulations. For most traditional mathematical models, the lack of physical understanding is usually supplemented by either simplifying the problem or implementing several more assumptions into the models. Numerical techniques also rely on assuming the soil/rock constitutive models (behaviors) in advance. Consequently, these approaches fail to simulate the complex behavior of most underground engineering systems. In contrast, SCMs are data-driven approaches in which the model development is based on training (learning) of input-output data pairs to determine the structure and parameters or hyper-parameters of the model. In this case, there is less need to either simplify the problem or incorporate assumptions. It should also be mentioned that the developed soft computing models are more apt to be updated to obtain better results by feeding the new training examples as the new observations become available.

The presented SCMs, including XGboost, MARS, SVM and ANN, are of powerful learning capabilities. Even under various influential factors, such as the size of the data sets, the number of features, they can still capture the complex relationship among variables and provide accurate estimations of the wall deformation induced by braced excavation. It should be mentioned that there is a limitation that the database employed in this study is generated by numerical simulation. There are very limited case histories can be used to develop the SCM models which demands a huge database of high quality instrumented recordings.

It should be stressed that actually it is the data and the features that determine the upper limit of accuracies by SCMs, while the various models and algorithms only try to approach this limit in different ways or perspectives. In this regard, high-quality data sets and the well extracted

Table 4
Performance indicators of the developed SCM models.

SCMs	Evaluation index							
	RMSE		R^2		Bias		MAPE	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
XGBoost	5.52	7.90	0.99	0.99	1.00	1.00	0.03	0.04
MARS	10.51	11.10	0.98	0.97	1.02	1.02	0.07	0.07
ANN	11.28	11.73	0.97	0.97	1.00	1.00	0.06	0.07
SVM	16.61	17.40	0.94	0.94	1.01	1.01	0.05	0.06

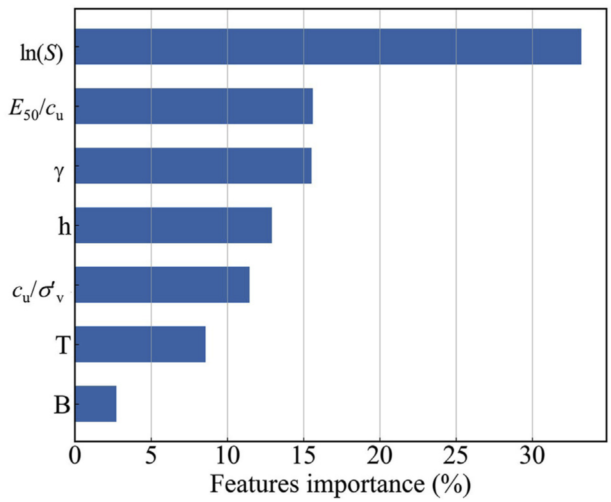

Fig. 8. Features importance analysis by XGBoost.

features which are closely related with the dependent responses are of vital importance for successful applications of SCMs.

Despite the success of SCMs, they are still facing conventional opposition due to some inherent shortcomings including the model interpretability, knowledge extraction, and model uncertainty. Therefore, special attention should be paid to incorporating prior knowledge about the underlying physical process based on engineering judgment or human expertise into the learning process. In addition, the implementation of the physics-based formulation into the data-driven characteristics will for sure greatly enhance the usefulness of SCMs and advance the field to the next level of sophistication and application.

Currently, the authors still hold the view that SCMs should be better adopted as a complementary measure to conventional computing techniques or field instrumentations rather than as an alternative, or even as the final solution. It may also be used as a quick check on solutions provided by more time-consuming and in-depth FE analyses.

Moreover, in recent years, Ensemble Learning technique including has been becoming a hot research topic. It is a meta-algorithm that combines several machine learning techniques into one surrogate model to reduce variance and deviation by bagging, boosting and stacking to improve the predictive accuracy. It adopts a good strategy on data sets of all dimensions and sizes, and have not widely been used in geotechnical engineering including underground excavations. Its application in underground geotechnical engineering is promising.

Declaration of conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors acknowledge the invitation for this review article from *Geoscience Frontiers*. They are also grateful to the authors of papers referred, as well as the suggestive comments from the two reviewers. This work was supported by High-end Foreign Expert Introduction program (No. G20190022002) and Chongqing Construction Science and Technology Plan Project (2019–0045). The financial support is gratefully acknowledged.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gsf.2019.12.003.

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