Editorial:

Practice of artificial intelligence in geotechnical engineering

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Geotechnical engineering deals with materials (e.g. soil and rock) that, by their very nature, exhibit varied and uncertain behavior due to the imprecise physical processes associated with their formation (Mitchell and Soga, 2005). Modeling the behavior of such materials in geotechnical engineering applications is complex and sometimes beyond the ability of most traditional forms of physically-based engineering methods. In recent years, the application of artificial intelligence (AI) in a wide range of geotechnical engineering has grown rapidly (Nawari et al., 1999; Miranda, 2007; Javadi and Rezania, 2009; Shahin, 2013, 2016; Chen et al., 2018; Yin et al., 2018; Jin et al., 2019a, 2019b, 2019c; Zhang P et al., 2020a). AI can be very useful in solving problems where deterministic solutions are not available or are excessively expensive in terms of computational cost but for which there are significant observations and data available (Turk et al., 2001; Man and Furukawa, 2011; Rashidian and Hassanlourad, 2013; Makantasis et al., 2015; Pirnia et al., 2018; Wang and Sun, 2018; Wang et al., 2019; Yang et al., 2019; Gao et al., 2020). Due to the nature of materials, geotechnical engineering deals with more uncertainties than other fields of civil and mechanical engineering. There is also much monitoring and site investigation data in

geotechnical engineering which needs to be taken advantage of by using data analytic methods (Goh et al., 1995; Jan et al., 2002; Kung et al., 2007; Rechea et al., 2008; Hashash et al., 2010, 2011; Lü et al., 2012; Huang et al., 2014; Chen et al., 2018; van Boven et al., 2018; Chen et al., 2019a, 2019b; Jin et al., 2019a; Zhang, 2019; Zhang P et al., 2019, 2020a, 2020b). Therefore, AI can be a suitable and effective alternative route to solving geotechnical engineering problems and significant developments have been made in recent years as much attention has been given to the area. Unfortunately, there has been no dedicated special issue or workshop devoted to it.

This special issue contains original and hitherto unpublished works on the applications of AI in geotechnical engineering. Focal points of the issue include, but are not limited to, innovative applications of: (1) Metaheuristics and their applications in intelligent automation and global optimization including evolutionary algorithms, swarm intelligence, natural and biologically inspired metaheuristics; (2) Traditional machine learning (ML) methods, such as artificial neural networks (ANNs), genetic programming (GP), evolutionary polynomial regression (EPR), support vector machines (SVMs), and random forest (RF); (3) Deep learning and real world applications, such as deep neural networks (DNNs), convolutional neural network (CNN), and recurrent neural networks (RNNs); (4) Aspects of software engineering, e.g. intelligent programming environments, verification and validation of AI-based software, software and hardware architectures for the real-time use of AI techniques, safety, and reliability; (5) Big data analytics; (6) Industrial experience in the application of the above techniques, e.g. case studies or benchmarking exercises.

Thus, we invited prestigious scientists in the field to share their expertise and perspectives. The collected papers cover the various topics mentioned, such as application of long short term memory

(LSTM) neural network, gated recurrent unit (GRU), and RF to different kinds of geotechnical problems.

Zhang DM et al. (2020) developed a non-parametric ensemble AI approach to calculating the compression modulus (E_s) of soft clay in contrast to the traditional regression models proposed in previous studies. A gradient boosted regression tree (GBRT) algorithm was used to discern the non-linear pattern between input variables and the target response, while a genetic algorithm (GA) was adopted for tuning the GBRT model's hyper-parameters. The model was tested through 10-fold cross validation. A dataset of 221 samples from 65 engineering survey reports from Shanghai infrastructure projects was constructed to evaluate the accuracy of the new model's predictions. A comparison of the performance of empirical formulas and the proposed ML method for predicting foundation settlement indicated the rationality of the proposed ML model and its applicability to the compressive deformation of geotechnical systems, solved by retraining the model using local data. This research provides a useful reference for future multi-parameter prediction of soil behavior.

Lu et al. (2020) applied the LSTM deep-learning technique to calculate the shaft resistance of cast-in-site piles. The proposed method allowed accurate estimation of the shaft resistance of cast-in-site piles, not only under the ultimate load but also under the working load. Comparisons with empirical methods confirmed the effectiveness of the proposed method for the shaft-resistance estimation of cast-in-site piles on reclaimed ground in offshore areas.

Cheng et al. (2020) employed GP to obtain a simplified statistical model for formulating the relationship between field-monitored soil suction in drying cycles. They selected five influencing parameters, initial suction, relative humidity, drying time, the ratio of the distance from the tree to the tree canopy radius, and the depth from the ground surface. The data used for model development was collected from a field monitoring test in the campus of the University of Macau, China. The results indicated that the model gives a reasonable estimation for the spatiotemporal variations of soil suction near a tree with acceptable errors.

Godoy et al. (2020) applied ML methods, such as logistic regression, Naive Bayes, and hidden

Markov models, to classify quick and highly sensitive clays in two sites in Norway based on normalized cone penetration tests with pore water pressure measurement (CPTu). The results showed an important increase in the classification accuracy even with small training sets.

Sun et al. (2020) presented two examples to demonstrate the capability and accuracy of the probabilistic estimation method proposed in their previous study (Yang et al., 2019) to characterize soil spatial variability with displacement responses. The first example was a soil slope subject to a surcharge load, in which the spatially varied field of the elastic modulus is estimated with displacements. The results showed that estimations based on horizontal displacements were more accurate than those based on vertical displacements. The accuracy of the estimated field was substantially reduced by increasing the variance of elastic modulus. However, the estimation was generally acceptable as the error was not more than 10%, even for the high variance case ($COV_E = 1.5$). The accuracy of estimation was also affected by the type of covariance function and the correlation length. When the correlation length decreased, the accuracy of estimation was reduced. The second example was a validation of laboratory model tests where a horizontal load was applied on a layered ground. The estimated thicknesses of soil layers were close to those in the real situation, which demonstrates the capacity of the estimation method.

Liu et al. (2020) adopted the LSTM neural network, the RF algorithm, and the GRU algorithm to predict landslide displacement in the Three Gorges Dam reservoir. Three different landslides, each with step-wise displacement characteristics, were modelled with each of the ML algorithms. The prediction by each ML algorithm was validated with observations over a one-year period of three colluvial landslides in the Three Gorges Dam reservoir. The analysis results of the three landslides demonstrated that "deep learning" ML approaches were well suited to predicting landslide displacements. The LSTM and GRU algorithms gave the most encouraging results and can be recommended for prediction of the displacement of step-wise type colluvial landslides in the Three Gorges Dam reservoir. Such reliable predictive models should gradually become a component when implementing early warning systems and reducing landslide risk.

We believe this special issue has provided a special viewpoint for researchers and engineers to present and discuss the recent developments of AI in geotechnical engineering. The interdisciplinary between machine learning and geotechnics was well highlighted and expressed by the selected publications. We sincerely hope the new algorithms and advanced methodologies shared in this special issue will improve the understanding of AI technologies and strategies, promote the application of new technologies in the field of geotechnical engineering, and quickly realize the intelligent development of geotechnical engineering. We expect the selected articles will arouse the discussion of the majority of scientific researchers, and also hope to bring new inspiration to readers of this journal.

Contributors

Zhen-yu YIN provided the concept and edited the draft of manuscript. Yin-fu JIN conducted the literature review and wrote the first draft of the manuscript. Zhong-qiang LIU edited the draft of manuscript.

Conflict of interest

Zhen-yu YIN, Yin-fu JIN, and Zhong-qiang LIU declare that they have no conflict of interest.

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中文概要

题目：人工智能在岩土工程中的实践

概要：岩土材料的复杂和不确定性致使传统理论在模拟和预测岩土工程问题经常显得无能为力。近年

来，随着人工智能和大数据技术的快速发展，人工智能技术在岩土工程领域有了广泛应用，例如岩土参数的优化智能识别和预测、边坡变形的长期预测、基坑开挖过程变形的实时监测和预测以及盾构隧道的变形和盾构机刀盘参数的预测和更新等。为此，本专辑收集了在该研究领域具有代表性的研究成果，介绍了人工智能技术在岩土工程领域的进展和未来发展潜力，希望能帮助读者快速了解人工智能技术在岩土工程中的应用，以及推动岩土工程的智能化发展，为实现岩土工程智能化提供科学依据和技术支撑。

关键词：人工智能；岩土工程；大数据

Introducing Guest Editor-in-Chief and Guest Editors:

Guest Editor-in-Chief

Dr. Zhen-yu YIN has been an Editorial Board Member of *Journal of Zhejiang University-SCIENCE A (Applied Physics & Engineering)* since 2019.

Dr. Zhen-yu YIN has been an Associate Professor of Geotechnical Engineering at The Hong Kong Polytechnic University, China since 2018. Dr. YIN received his BEng in Civil Engineering from Zhejiang University in 1997, followed by a 5-year engineering consultancy at the Zhejiang Jiahua Architecture Design Institute. Then, he obtained his MSc and PhD in Geotechnical Engineering at Ecole Centrale de Nantes (France) in 2003 and 2006, respectively. Dr. YIN has been working as a postdoctoral researcher at Helsinki University of Technology (Finland), the University of Strathclyde (UK), Ecole Centrale de Nantes, and the University of Massachusetts (USA). In 2010, he joined Shanghai Jiao Tong University as a Special Researcher and received “Professor of Exceptional Rank of Shanghai Dong-Fang Scholar.” In 2013, he joined Ecole Centrale de Nantes as Associate Professor before moving to Hong Kong. Dr. YIN has published over 150 articles in peer reviewed international journals with an *H*-index of Web of Science of 33. Since 2012, he has been a member of the Granular Materials Committee of the American Society of Civil Engineers.

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