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Review article

# A comprehensive review on identification of the geomaterial constitutive model using the computational intelligence method

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ABSTRACT

It is crucial to determine geomaterial constitutive models to analyze the mechanical behavior of geomaterials and geotechnical engineering stability. Thus, identification of a geomaterial constitutive model is a very important aspect of back analysis. Because the real mechanical behavior of geomaterials are very complicated, it is difficult to identify a suitable geomaterial constitutive model based on traditional methods. Therefore, some computational intelligence methods have been used to solve this problem, and many related studies have been performed. In this study, previous research is reviewed according to the following four aspects: constitutive model approach via an artificial neural network, constitutive model description via an artificial neural network, constitutive model selection via an evolutionary computation, and constitutive model construction via an evolutionary computation. Moreover, the state-of-the-art research advancement of the four research aspects is summarized. The merits and demerits of these research aspects have been comprehensively analyzed and discussed. Finally, possible research directions to identify a geomaterial constitutive model based on computational intelligence are also provided.

## 1. Introduction

Studying the geomaterial constitutive model is a very important aspect of the theoretical study for geomechanics and geotechnical engineering. This model is the basis of geotechnical engineering research. Currently, there are many studies in this field, and numerous theoretical models have been developed for geomaterials [58,87,91]. However, the development trend is that models become increasingly complicated and model parameters become increasingly numerous. Thus, the practicability of constitutive models becomes poorer. However, for real engineering practices, it is more important that a constitutive model can describe the engineering behavior very well, whereas the precision of the material model is not crucial. Therefore, it is significant to study a geomaterial constitutive model based on real engineering behavior. This is an issue that back analysis can solve [71]. In reality, back analysis for a geomaterial constitutive model, called model identification, has existed since the 1970s [46]. However, although it is an important aspect of back analysis, model identification has not been rapidly developed, primarily because great controversy exists regarding the need for model identification. One viewpoint suggests that the merit of back analysis is using a simple constitutive model [31] and the reasons are as follows. First, the model parameters can determine the consistency of computing results with real measurements. Moreover, the mechanical behaviors described by the model probably do not reflect the real behaviors of the geomaterial. In other words, no model can comprehensively describe the real behaviors of geomaterials. Therefore, if a complicated model is constructed in the back analysis, which considers more aspects of the geomaterial, the original problem of computing the actual engineering will be faced again, thus violating the original intention of the back analysis [77]. Another viewpoint suggests that the back analysis of mechanical parameters should be called "parameter identification" [70]. The real back analysis must simultaneously inverse the mechanical parameters and constitutive model. Theoretically, identification of the geomaterial constitutive model is more important than identification of the mechanical parameters [85] and the reason is as follows. If the constitutive model does not reflect the actual behaviors of the geomaterial, the actual engineering behaviors cannot be described, regardless of the precision of the mechanical parameters. Thus, if the constitutive model is suitable, it is easy to back-calculate suitable mechanical parameters. However, another possible reason which may retard the development of model identification is that compared to parameter identification, model identification is an

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**Table 1**
Summaries of researches for geomaterial constitutive model identification via computational intelligence.

| Computational intelligence method | Identification method | Algorithm | Researches |
|---|---|---|---|
| Artificial neural network | Approach of the constitutive model | Radial basis function neural network | [78,54,63] |
| | | Back propagation network | [51,83,59,66] |
| | Description of the constitutive model | Feedback artificial neural network | [13,64,4,34] |
| | | Recurrent neural network | [93,69] |
| | | Nested adaptive neural networks | [30,74,36,19,37,35,80] |
| | | Back propagation network | [79,89,38,67,48] |
| | | Evolutionary neural network | [7,9,45] |
| | | Multi-layer perceptron | [3] |
| | | Cascade-correlation algorithm network | [69] |
| | | Time-delay artificial neural network | [5] |
| Evolutionary computation | Selection of the constitutive model | Simple genetic algorithm | [61,17,72,84,92,62,68,86,88,11] |
| | | Real coded genetic algorithm | [26] |
| | | Improved genetic algorithm | [27] |
| | | Parallel genetic algorithm | [52] |
| | | Genetic algorithm and gradient based optimization algorithm | [53,81] |
| | | Immune evolutionary programming | [20] |
| | | Ecological competition model | [23] |
| | | Differential evolution algorithm | [76] |
| | | Modified particle swarm optimization | [55] |
| | | Immune continuous ant colony algorithm | [21] |
| | | Black hole algorithm | [22] |
| | | One of evolutionary computation | [82] |
| | Construction of the constitutive model | Genetic programming | [15,90,8,6,11] |
| | | Evolutionary polynomial regression | [43,42,2,14,40,41,10] |

extremely complicated problem that cannot be solved well using a traditional method [24]. In 1987, Gioda and Sakurai proposed that model identification based on measurement displacement should be the main aspect of back analysis development [32]. Moreover, in 1997, Sakurai demonstrated that the identification of a constitutive model was critical [70]. Therefore, to solve the complicated problem of constitutive model identification, it is essential to broaden the research and determine appropriate methods. Previous studies [16,33,39] have shown that a multidisciplinary approach is the development tendency in all applied sciences and that the introduction of intelligent science can stimulate the development of geotechnical engineering research. Therefore, computational intelligence has been introduced into model identification research, and many related studies have been conducted. The main studies in computational intelligence are summarized in Table 1. In this study, previous studies are reviewed in Table 1 based on two computational intelligence methods, which are the artificial neural network and evolutionary computation, and four aspects, which include the constitutive model approach via an artificial neural network, constitutive model description via an artificial neural network, constitutive model selection via an evolutionary computation, and constitutive model construction via an evolutionary computation.

## 2. Brief introduction of computational intelligence methods

In modern intelligent science, the intelligence can be divided into three types, i.e., biological intelligence (BI), artificial intelligence (AI), and computational intelligence (CI), which are rated from high to low based on their intelligence levels [44,73]. BI, which is also called natural intelligence (NI), is generated by living entities, especially human beings and is the highest level of intelligence. AI originated from a machine learning study in the 1950s, whose typical research was the expert system. CI originated from scientific computation research of the 1990s and is the lowest level of intelligence. There are close relationships among the three types of intelligence. The ABC hierarchical model [44] of the three intelligence types is shown in Fig. 1.

As one new intelligence type, CI describes the intelligent behavior of numerical computation [12]. Compared with AI, CI has the following characteristics [12]: (a) CI relies on provided computation values and not on knowledge and (b) CI relies on the application of numerical computation methods. Therefore, CI addresses the information through numerical computation and the intelligent problem through study of numerical computation methods. Due to its mathematical characteristics, CI includes any random search computation methods [65]. From Table 1, the main CI methods used in model identification have been briefly introduced as follows.

### 2.1. Artificial neural network

An artificial neural network (ANN) [60,75] is one computational intelligence method that mimics the neural system of a human brain, which is a very complicated network system composed of neurons. The structure of the biological neuron is shown in Fig. 2 [60]. In an artificial neuron, the influence between two neurons is represented by a weight associated with their interconnection, and one neuron's influence is represented by an activation function. The artificial neuron is described in Fig. 3. A large number of artificial neurons are connected by different patterns; thus, different ANN models can be generated. From the viewpoint of the information process, ANN has the following properties: (a) ANN is a large, complicated, parallel-distributed information processing system; (b) it is very robust and has a strong ability to adapt, generalize, and cluster or organize data; and (c) it has a very strong self-learning ability.

The constitutive model of geomaterials is a map used to describe the complicated nonlinear relationship between stress and strain. However, ANN is a good method used to describe the complicated mapping relationship. Therefore, ANN is widely used in the identification of the geomaterial constitutive model, and many studies have identified geomaterial constitutive models based on ANN, which are shown in Table 1.

Because the multi-layer feed-forward neural network is the basis of many ANNs used in the identification of geomaterial constitutive models, this ANN is briefly introduced as follows. The multi-layer feed-forward neural network has one input layer, one or more hidden layers, and one output layer, which is shown in Fig. 4.

To train this ANN, the back propagation (BP) algorithm is generally applied. Thus, this ANN is also called the BP network. The BP algorithm is a typical, supervised learning algorithm. In this algorithm, the network learns according to the given input and output training samples. The learning effect is represented by changing the connection weights. The training process of the BP network is as follows.