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Estimating Model Parameters of Conditioned Soils by Using Artificial Network

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***Abstract*—The parameter identification of nonlinear constitutive model of soil mass is based on an inverse analysis procedure, which consists of minimizing the objective function representing the difference between the experimental data and the calculated data of the mechanical model. The ill-poseness of inverse problem is discussed. The classical gradient-based optimization algorithm for parameter identification is also investigated. Neural network models are developed for estimating model parameters of conditioned soils in EBP shield. The weights of neural network are trained by using the Levenberg-Marquardt approximation which has a fast convergent ability. The parameter identification results illustrate that the proposed neural network has not only higher computing efficiency but also better identification accuracy. The results from the model are compared with simulated observations. The models are found to have good predictive ability and are expected to be very useful for estimating model parameters of conditioned soils in EBP shield.**

***Index Terms*—parameter estimation, neural network, inverse problem, shield machine**

I.INTRODUCTION

The problem of parameter identification in distributed parameter system ha been studied extensively during the last three decades. The term “distributed parameter system” implies that the response of the system is governed by a partial differential equation and parameters imbedded in the equation are spatially dependent. The inverse problem of parameter identification concerns the optimal determination of the parameters by observing the dependent variable collected in the spatial and time domains [1]. With inverse models used to determine parameter values that optimize the fit of the model results to the field observations for a given model configuration, parameter values and other aspects of the model are adjusted until the dependent variables match field observations [2]. Tan presented a fast and robust technique for the experimental identification of soil. This technique, based on the Newton–Raphson method, estimates the unknown parameters of the soil mechanics equations by minimizing the error between measured failure forces and estimated failure forces. The measured failure forces can be obtained by measuring the forces acting on the bucket during the excavation operation, while the estimated failure forces were obtained by an analytical soil model [3]. Mertens developed a coupled simulation global optimization technology and evaluated its suitability for multi-objective inverse modeling. In particular, the trade-off between goodness of fit against leachate volume and soil moisture content in unirrigated and irrigated lysimeters was evaluated [4].

The Duncan model for describing deformation behaviors of soils uses isotropic hyperbolic stress-strain relationship. The elastic parameters from this relationship vary according to the stress state. The Young’s modulus increases with confining pressure and decreases with increasing shear stress. In a finite element simulation of a geotechnical problem, calibrations of the models used to reproduce soil behavior often pose significant challenges. Real soil is a highly nonlinear material, with both strength and stiffness depending on stress and strain levels. Numerous constitutive models have been developed that can capture many of the important features of soil behavior. An effective and more objective way to calibrate a soil model employs inverse analysis techniques to minimize the difference between experimental data (laboratory or field tests) and numerically computed results. The Mohr-Coulomb criterion has been extensively used to model the static and dynamic behaviour of retaining walls in both analytical and numerical studies, the main advantage being its simplicity. In the field of computational geomechanics, more sophisticated soil models have been proposed with take account of the inter-mediate principal stress, giving rise to an increase in the equivalent friction angle when analyzing plane strain problems. Artificial neural network is a powerful tool of information processing. Due to its strong ability of modeling linear and nonlinear relationship, it has been widely used in optimization, calibration, parameter identification, modeling and pattern recognition [5-6]. The aim of the paper is to propose a new inversion algorithm to estimate model parameters, and to demonstrate the usefulness of the neural network for parameter estimate of nonlinear constitutive model of conditioned soils.

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II. Basic Mechanical Properties Of Conditioned Soils

In order to provide a simple framework encompassing the most important characteristics of conditioned soil stress-strain behaviour using material parameters available from conventional laboratory tests, Duncan and Chang [7] developed a hyperbolic model based on the hyperbolic equation proposed by Kondner [8]. Because of its simplicity and wide applicability, Duncan and Chang's model is adopted herein to define the non-linear stress-strain behaviour of the conditioned soil in chamber of shield machine. The stress-strain behavior of conditioned soil depends on a number of different factors including density, water content, structure, drainage conditions, strain conditions, duration of loading, stress history, confining pressure, and shear stress. The hyperbolic equation proposed by Kondner is expressed as follows

$$(\sigma_1-\sigma_3)=\frac{\varepsilon}{a+b\varepsilon}\,. \tag{1}$$

Where σ_1 and σ_3 are the major and minor principal stresses; ε is the axial strain; a and b are constants whose values may be determined experimentally. By expressing the parameters a and b in terms of the initial tangent modulus value and the compressive strength, Eq. 1 can be rewritten as follows

$$(\sigma_1-\sigma_3)=\frac{\varepsilon}{[\frac{1}{E_i}+\frac{\varepsilon R_f}{(\sigma_1-\sigma_3)_f}]}\,. \tag{2}$$

Where R_f is the failure ratio, which always has a value less than unity, the value of R_f has been found to be between 0.75 and 1.00. $(\sigma_1-\sigma_3)_f$ is the compressive strength. Experimental studies by Janbu have shown that the relationship between initial tangent modulus and confining pressure may be expressed as

$$E_i=Kp_a(\frac{\sigma_3}{p_a})^n\,. \tag{3}$$

Where E_i is the initial tangent modulus; p_a is the atmospheric pressure expressed in the same pressure units as E_i; K is a modulus number; n is the exponent determining the rate of variation of E_i with σ_3. If it is assumed that failure will occur with no change in the value of σ_3, the relationship between compressive strength and confining pressure may be expressed conveniently in terms of the Mohr-Coulomb failure criterion as

$$(\sigma_1-\sigma_3)_f=\frac{2c\cos\varphi+2\sigma_3\sin\varphi}{1-\sin\varphi}\,. \tag{4}$$

Where c and φ are the Mohr-Coulomb strength parameters. Eqs. 3,4, combination with Eq.2, provide a means of relating stress to strain and confining pressure by means of the five parameters K, n, c , φ and R_f. The stress-strain relationship may be employed very conveniently in incremental stress analyses because it is possible to determine the value of the tangent modulus corresponding to any point on the stress-strain curve. If the value of the minor principal stress is constant, the tangent modulus may be expressed as

$$E_t=\frac{\partial(\sigma_1-\sigma_3)}{\partial\varepsilon}\,. \tag{5}$$

Where E_t is the tangent modulus of soil. The values of tangent modulus and Poisson ratio for any stress condition may be expressed as

$$E_t=Kp_a(\frac{\sigma_3}{p_a})^n[1-\frac{R_f(1-\sin\varphi)(\sigma_1-\sigma_3)}{2C\cos\varphi+2\sigma_3\sin\varphi}]^2\,. \tag{6}$$

$$\nu_i=\frac{G-F\lg(\frac{\sigma_3}{p_a})}{1-A^2}\,. \tag{7}$$

$$A=\frac{D(\sigma_1-\sigma_3)}{Kp_a[\frac{\sigma_3}{p_a}][1-\frac{R_f(\sigma_1-\sigma_3)(1-\sin\varphi)}{2c\cos\varphi+2c\sigma_3\sin\varphi}]}\,. \tag{8}$$

This expression for tangent modulus may be employed very conveniently in incremental stress analyses, and constitutes the essential portion of the stress-strain relationship. Laboratory tests were conducted in a tree-dimensional compression machine to study the characteristics of the conditioned soil. Fig. 1 shows the sketch map of laboratory test of conditioned soil for tree-dimensional compression. Fig. 2 demonstrates relationship between stress and axial strain. Fig.3 depicts the variation of radial strain versus axial strain.

Fig 1. Sketch map of laboratory test of conditioned soil for tree-dimensional compression

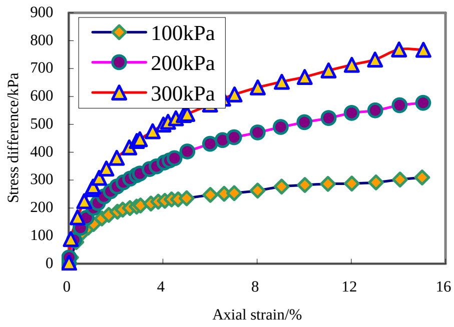

Fig 2. Relationship between stress and axial strain

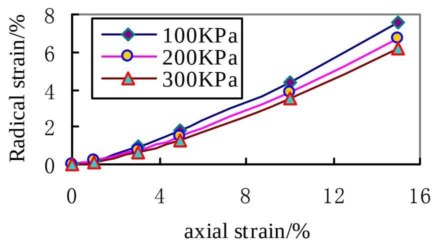

Fig 3. Variation of radial strain versus axial strain

III. Artificial Neural Network Model For Parameter Estimating In Conditioned Soil In EPB Shield

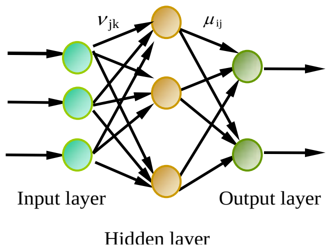

Fig 4. A schematic of neural network model

Least squares are popular for solving inverse problems because they lead to the easiest computations. Their only drawback is the lack of robustness, i.e., their strong sensitivity to a small number of large errors in a data set. An artificial neural network model is a system with inputs and outputs based on biological nerves. The system can be composed of many computational elements that operate in parallel and are arranged in patterns similar to biological neural nets. A neural network is typically characterized by its computational elements, its network topology and the learning algorithm used. The neural networks have such strength as processing large amounts of sensory information, collective and parallel processing capability and adaptation by learning.

The architecture of BP networks, depicted in Figure 4, includes an input layer, one or more hidden layers, and an output layer. The nodes in each layer are connected to each node in the adjacent layer. Notably, Hecht-Nielsen proved that one hidden layer of neurons suffices to model any solution surface of practical interest. Hence, a network with only one hidden layer is considered in this study. Before an ANN can be used, it must be trained from an existing training set of pairs of input-output elements. The training of a supervised neural network using a BP learning algorithm normally involves three stages. The first stage is the data feed forward. The computed output of the i-th node in output layer is defined as follows

$$y_i = f\left(\sum_{j=1}^{N_h}\left(\mu_{ij} f\left(\sum_{k=1}^{N_i} v_{jk} x_k + \theta_j\right) + \lambda_i\right)\right). \quad (9)$$

Where μ_{ij} is the connective weight between nodes in the hidden layer and those in the output layer; v_{jk} is the connective weight between nodes in the input layer and those in the hidden layer; θ_j or λ_i is bias term that represents the threshold of the transfer function f, and x_k is the input of the kth node in the input layer. Term N_i, N_h and N_o are the number of nodes in input, hidden and output layers, respectively. The transfer function f is selected as Sigmoid function:

$$f(\cdot) = 1/[1 + \exp(-\cdot)]. \quad (10)$$

The second stage is error back-propagation through the network. During training, a system error function is used to monitor the performance of the network. This function is often defined as follows

$$E(w) = \frac{1}{2}\sum_{p=1}^{P}\left(\sum_{i=1}^{N_o}(y_i^p - o_i^p)\right)^2. \quad (11)$$

Where y_i^p and o_i^p denote the practical and desired value of output node i for training pattern p, P is the number of sample. Training methods based on back-propagation offer a means of solving this nonlinear optimization problem based on adjusting the network parameters by a constant amount in the direction of steepest descent, with some variations depending on the flavor of BP being used. The optimization algorithm used to train network makes use of the Levenberg-Marquardt approximation. This algorithm is more powerful than the common used gradient descent methods, because the Levenberg-Marquardt approximation makes training more accurate and faster near minima on the error surface. The weight adjustment using Levenberg-Marquardt algorithm is expressed as follows:

$$w(k+1) = w(k) - \frac{J^T(k)e(k)}{[J^T(k)J(k) + \mu I]}. \quad (12)$$

Where w(k) is the vector of network parameters(net weights and element biases) for iteration k, J is the

Jacobian matrix; μ is a constant, I is a unity matrix; e is an error vector. The Levenberg-Marquardt algorithm approximates the normal gradient descent method, while if it is small, the expression transforms into the Gauss-Newton method. After each successful step the constant μ is decreased, forcing the adjusted weight matrix to transform as quickly as possible to the Gauss-Newton solution. When after a step the errors increase the constant μ is increased subsequently. The training sample data are regularized before they are trained. The topology structure of neural network is composed of 31*3=93 input nodes, 100 hidden nodes and 8 output nodes. The node number of input layer is determined by number of observed deformation data. The node number of hidden layer is determined by test, which approaches to double of node number of input layer. The node number of output layer agrees with number of identified parameters. Fig. 5 shows objective function versus training epochs. The estimated parameters for the conditioned soil are listed in Table 1. Fig. 6 shows the comparison of observed axial displacements of test sample with forecasted ones with FEM based on identified parameters.

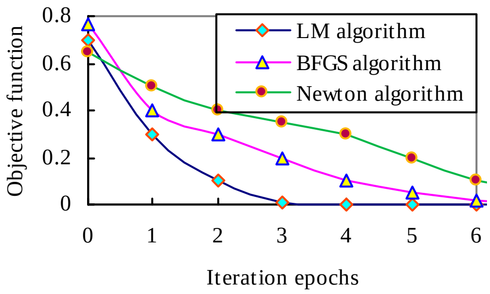

Fig 5. Objective function versus training epochs for different training algorithm

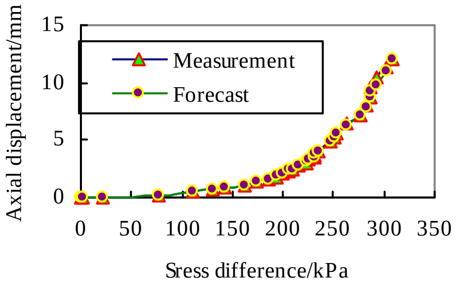

Fig 6. Comparison of observed axial displacements of test sample with forecasted ones

TABLE I.

HYPERBOLIC MATERIAL CONSTANTS OF CONDITIONED SOIL

Parameters	C /kpa	φ	R_f	K	*n*	D	F	G
Value	0.6	35	0.71	82	0.65	0.03	0.04	0.33

IV. CONCLUSION

This work presents a novel procedure for estimating the model parameters of conditioned soils by using neural network approach. The proposed method of estimating the model parameters of conditioned soils has been verified by excellent agreement between the observed deformation of test sample and forecasted ones based on parameter identification.

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