Geotechnical and Geological Engineering (2006) 24: 1781–1801
DOI 10.1007/s10706-006-6807-6

The displacement computation and construction pre-control of a foundation pit in Shanghai utilizing FEM and intelligent methods

YOU-LIANG CHEN[1,2,★], RAFIG AZZAM[2] and FU-BO ZHANG[1]
[1]*Department of Civil Engineering, Shanghai University, 200072, Shanghai, PR China*
[2]*Department of Engineering Geology and Hydrogeology, RWTH-Aachen University, 52064, Aachen, Germany*

(Received 7 April 2005; accepted 19 January 2006)

Abstract. Controlling the displacements of foundation pit walls and supporting structures is one of the most effective measures for ensuring safety of foundation pit construction. Because of this, the accurate displacement computation of foundation pit walls and supporting structures is paid great attention by geotechnical scientists and engineers. In this paper, the three-dimensional displacement field of Deping Station foundation pit, which is part of Shanghai Track Traffic Line 6 project, is computed by means of ANSYS software. Artificial neural networks (ANNs) are a broad category of computer algorithms which have the ability to learn some target values (desired output) from a set of chosen input data that has been introduced to the network. The ANNs have very excellent ability in simulating nonlinear and complicated problems. In the current paper, the authors try to combine FEM method with ANNs so as to improve the computational accuracy. Basing on the computed results, fuzzy control theory is applied to construction pre-control. The application effect is satisfactory. The research result of current paper is very helpful for geotechnical construction and the development of geotechnical theory.

Key words. foundation pit, FEM method, artificial neural networks, fuzzy logic, construction pre-control.

1. Introduction

Since more than 10 years the designing and constructing techniques of foundation pits have greatly improved, especially the design philosophies and ideas. With the rapid growth of urban population and the lack of building land, more and more superhigh buildings and city track traffic lines are built in some densely populated cities, for example, Shanghai, Beijing, Hong Kong and Tokyo. And many buildings and track traffic lines must be constructed in very complicated environments, for instance, some buildings, municipal pipes and wires are situated closely around the construction site. Under these circumstances, the design philosophies and ideas of foundation pits must be adjusted in order to fit in with the complicated environments.

★ Corresponding author: e-mail: chenyouliang2001@yahoo.com.cn

During design of foundation pit projects, following five aspects should be given importance.

(1) Foundation pit supporting structure design is an independent design stage.
(2) Foundation pit supporting structure design includes two parts, namely plan design and working drawing design. These two parts have close relations with foundation pit construction design.
(3) Foundation pit supporting structure design must meet the requirements on basement construction space, working safety and safeguarding environments.
(4) Foundation pit supporting structure design must meet the standard on deformation and strength. Normally deformation restriction is much more difficult to accomplish than meeting strength standard. So the deformation restriction is very important for safe construction of foundation pits.
(5) Ground water is one of the most decisive factors that decide the safety of foundation pit design and construction.

In the current paper, the above-mentioned aspects will be considered.

The methods of displacement analysis in geotechnical engineering include safety coefficient methodology, empirical formula methodology, numerical methods (forward deduction and inversion), system analysis methodology and intelligent methodology. Up to now, all kinds of above-mentioned methods have been applied to underground projects.

Huang (1991) developed "An expert system for deep and large-scale foundation pit design". Li (1992) adopted incoordinate finite element method with eight nodes to compute three-dimensional stress and displacement fields of some foundation pits, in which continuous underground walls are employed as supporting structures. He obtained the relation between the displacement and dug depth. Wang (1994) employed large-deformation theory to study the displacements of some foundation pits and summed up the applicable scope of large- and small-deformation theory separately. Yu (1995) studied the computer-aided optimum design of deep foundation pit construction. Xu (1997) adopted two-dimensional FEM method to simulate the process of deep foundation pit digging and discussed the influence of digging depth, rigidity of supporting structure, position of supporting structure and the others on the deformation of supporting structure. Yu (1997) computed soil pressure and deformation of supporting structure of soft soil deep foundation pit by means of three-dimensional FEM method. Huang and Xu (1997) and Feng (2000) have applied BP neural networks to displacement analysis and prediction of stability of a few slopes. Gao (1998) studied rheological characteristic of soils and its influence on supporting structure of deep foundation pit by means of three-dimensional FEM method. Wang (1999) has applied ANNs to intelligent control of foundation pit excavation. Deng and Lee (2001) have presented a novel method for displacement back analysis basing on the coupling of BP neural networks and genetic algorithm and applied it to the movement prediction of a steep slope at the Three Gorges Project site. Yuan (2001) have developed a software packet based on utilizing ANNs, fuzzy logic and Matlab 5.2 for predicting and controlling foundation pit construction and applied it to analyzing Metro construction in Shanghai. Yang and Rosenbaum (2002) have adopted artificial neural networks (ANNs) to predict geotechnical properties utilising their Relative Effective Strength (RES) and Potential Relative Effective Strength (PRES). Li et al. (2002) has employed ANNs for predicting the parameters of water-bearing stratum. Chen et al. (2004) have combined ANNs and fuzzy logic theory for predicting the displacements and pre-controlling the construction process of a foundation pit in Shanghai. Basma and Kallas (2004) have employed BP neural networks to model soil collapse. Panigrahi and Sahu (2004) have applied adaptive resonance theory of ANNs to the classification of coal seams with respect to their proneness to spontaneous heating.

FEM method, ANNs and fuzzy logic demonstrate different advantages in solving geotechnical problems, for instance, FEM in computing three-dimensional problems, ANNs in simulating and predicting very complicated nonlinear problems and fuzzy logic in training linguistic data. Nobody has previously solved geotechnical problems by means of the integration of FEM, ANNs and fuzzy logic. In this paper, the displacements of continuous underground wall are computed and the pre-control of foundation pit construction is conducted by means of three-dimensional FEM method, ANNs and fuzzy logic. Firstly, three-dimensional displacements are computed by utilizing FEM method and ANSYS software. Secondly, a displacement prediction model is established based on some of above-obtained results. Finally, the pre-control plan of foundation pit construction is obtained by employing fuzzy logic.

In another paper, the constitutive relation of foundation pit soil will be obtained by employing BP-neural networks. Three-dimensional displacement field will be computed by adopting the obtained BP constitutive model and FEM method. The pre-control plan of foundation pit construction will be suggested by means of fuzzy logic. It will be published later.

2. Project Background

Deping Station of Shanghai Track Traffic Line 6 project is located on the west side of Zhangyang Road. 2 residential buildings with 7 and 6 floors respectively are situated to the north of the station. The distance between the northern buildings and main supporting structure of station foundation pit is about 27 m. A commercial house with 2 floors lies to the south of the station. And the southern house is also about 27 m apart from the main supporting structure of station foundation pit. Zhangyang Road is about 24 m in breadth, with 6 two-way traffic lanes.

The main supporting structure of Deping station foundation pit is continuous underground walls with the thickness of 600 mm (Figure 1). Round lock-mouth pipe is employed to connect the normal part of continuous underground wall and its end pit section. The foundation pit bottom of border between the normal part and end pit section is consolidated by means of grouting. The consolidated depth is 4.0 m. Sixty-seven drilling grouting piles are arranged below the foundation pit bottom for

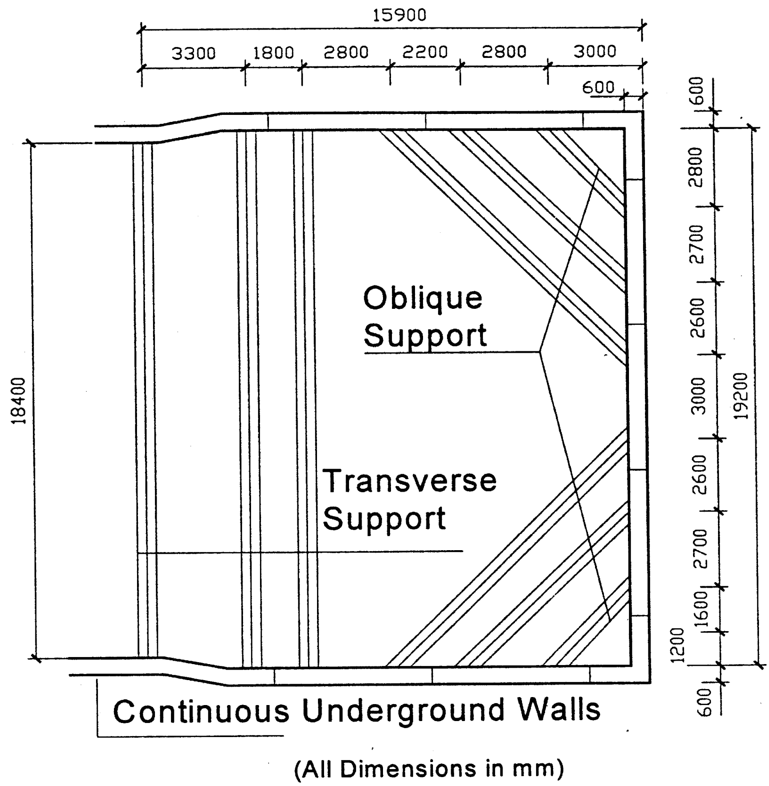


Figure 1. The planar graph for support of end pit section.

anti-floating. The pile diameter is 600 mm and the depth of piles into soil layers is 20 m. The pile top is at the same height as the lower end of bottom beams. The bottom soil of boundary between station and track lane should be consolidated by means of deep stirring piles before the digging of foundation pit. The main project dimensions are listed in Table 1.

Table 1. The main project dimensions (Dimension unit: m)

The total length of Deping station	135
The breadth of normal section	16.2
The breadth of facility section	18.4
The breadth of end pit section	19.2
The depth of foundation pit at the end pit section	15
The depth of foundation pit at the normal section	13
The thickness of continuous underground walls	0.6
The depth of continuous underground walls at the end pit section	27
The depth of continuous underground walls at the normal section	24
The diameter of round lock-mouth pipe	0.6
The depth of piles into soil layers	20

3. The Basic Theory of Back-propagation (BP) Neural Networks

3.1. INTRODUCTION

Artificial neural networks are a broad category of computer algorithms which have the ability to learn some target values (desired output) from a set of chosen input data that has been introduced to the network under both supervised and self-adjusted or unsupervised learning algorithms (Sirat and Talbot, 2001). The learning or training process is achieved by minimizing the error between the desired output and the output computed by the neural network using different learning algorithms. The predictive ability of the trained neural network can be tested by adding observations not included previously (Sirat and Talbot, 2001).

One of the most popular neural networks is the one that uses a BP learning algorithm. A BP neural network consists of a number of neuron-containing layers interconnected in a particular problem-dependant topology (Sirat and Talbot, 2001). In this paper, the BP neural networks are used.

3.2. TOPOLOGY

Topology is the distribution and number of neurons within the layers of a BP network (Figure 2).

The first (input) layer consists of a number of neurons that are interconnected to each of the elements in the input vector to feed external information into the network (Figure 2). One or more hidden layer(s) with arbitrary numbers of neurons are

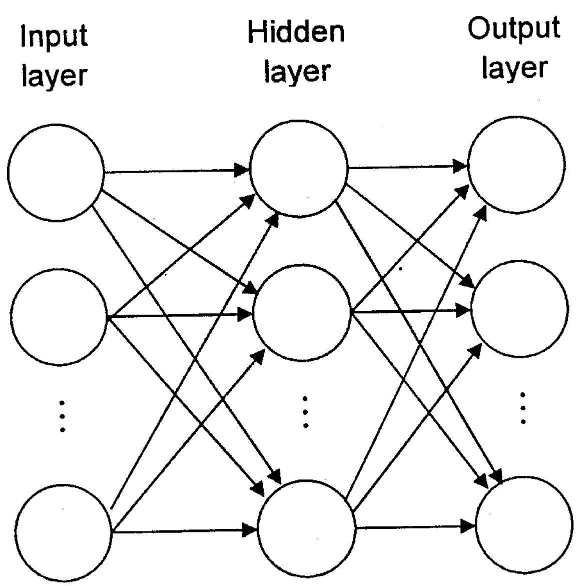


Figure 2. Diagram showing the topology of a back-propagation network with one hidden layer.

interconnected between the first (input) and the last (output) layer. The output layer produces the computed output vectors corresponding to the solution. In the BP network used here, the input consists of time sequence, and the output is displacements of the foundation pit walls. One hidden layer BP network is adopted here.

Interconnections among neurons in different layers are controlled by the weights that represent the type and strength of these connections. Except for the input layer, all neurons in the BP network are associated with a transfer function. The application of these transfer functions depends on the purpose of the neural network. In the BP network used in the trials, the following sigmoid function as follows was used:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

3.3. TRAINING AND TESTING

Neural networks have the ability to learn complex interrelations and their relative importance among input parameters and desired output parameters by using different learning algorithms (Sirat and Talbot, 2001). The training process is repeated until the "sum-square error" of the difference between the desired output and the actually computed output is as low as a pre-set target error. Modifications of the BP process are aiming to enhance the rate and quality of learning including momentum and adaptive earning. The BP learning algorithm is based on the gradient-descent method.

After training, the success of the BP network's prediction can be best determined using a cross-validation technique. The ability of the trained network to reproduce data (output) comparable with the original data (input vector) is tested by inserting additional data (new input vector set) that are not already used in the training process (Sirat and Talbot, 2001).

4. The Basic Theory of Fuzzy Controller

Fuzzy models describe input–output relationships by fuzzy if-then rules (fuzzy propositions). They make use of fuzzy sets and approximate reasoning to find an overall 'good enough' solution to a particular problem domain without using detailed first-principle knowledge of that domain. Fuzzy rules may be formulated on the basis of expert knowledge of the system.

An interesting and attractive characteristic of fuzzy logic compared with other methods commonly used in geotechnical engineering, such as statistics and neural networks, is that the training samples may be both linguistic (symbolic) and numeric ones. An expert may articulate linguistic association. Or a fuzzy system may adaptively infer and modify its fuzzy associations from numerical samples. Fuzzy logic have reasoning and switch functions besides its prediction ability, they can produce both quantitative and qualitative results.

Two most well-known fuzzy modeling methods are the Mamdani method and the Takagi–Sugeno (TS) method Feng (2000).

4.1. THE MAMDANI FUZZY MODEL

As mentioned by Alvarez Grima and Babuska (1999), the Mamdani algorithm is perhaps the most appealing fuzzy method to employ in engineering geological problems. The general "if-then" rule structure of the Mamdani algorithm is given in the following equation:

$$\begin{aligned} R_i : &\text{ if } x_1 \text{ is } A_{i1} \text{ and } x_2 \text{ is } A_{i2} \text{ and } \ldots \text{ and } x_n \text{ is } A_{in}, \\ &\quad \text{then } y \text{ is } B_i \ (\text{for} = 1, 2, \ldots, k) \end{aligned} \tag{2}$$

where k is the number of rules, x_1, x_2... x_n are the input variables (antecedent variables) and y is the output variable (consequent variable).

Although many methods of composition of fuzzy relations (e.g. min–max, max–max, min–min, max–mean etc.) exist in the literatures (Alvarez and Babuska, 1999; Feng, 2000; Sonmez et al., 2004), max–min and max–product methods are the two most commonly used techniques. The basic form of a fuzzy composition process is given by the following expression:

$$B = A \circ R \tag{3}$$

where A is the input or antecedent defined on universe X, B is the output or consequent defined on universe Y, and R is the fuzzy relation characterizing the relationship between specific inputs (x) and specific outputs (y). The stages and components of the Mamdani inference algorithm are given by Alvarez Grima.

4.2. THE TAKAGI–SUGENO (TS) FUZZY MODEL

The TS fuzzy modelling method was proposed by Takagi and Sugeno (1985) as a framework for generating fuzzy "*if then*" rules from numerical data. A TS fuzzy model consists of a set of fuzzy rules, each describing a local linear input–output relationship:

$$\begin{aligned} R_i : &\text{ if } x_1 \text{ is } A_{i1} \text{ and } x_2 \text{ is } A_{i2} \text{ and } \ldots \text{ and } x_n \text{ is } A_{in}, \\ &\quad \text{then } \hat{y} = a_i x + b_i, i = 1, 2, \ldots, k \end{aligned} \tag{4}$$

Here R_i is the ith rule, $x = [x_1 , \ldots ,x_n]^T \in X$ is the input vector (antecedent) variable, A_{i1}, ..., A_{in} are fuzzy sets defined in the antecedent space and $\hat{y}_i$ is the rule output of the model. K denotes the number of rules. The aggregated output of the model $\hat{y} \in Y$, is calculated by means of the weighted average of the rule contributions

$$\hat{y}_i = \frac{\sum_{i=1}^{K} \beta_i(x)\hat{y}_i}{\sum_{i=1}^{K} \beta_i(x)} \tag{5}$$

where $\beta_i,(x)$ is the degree of fulfillment of the ith rule given by

$$\beta_i(x) = \prod_{j=1}^{n} \mu_{A_{ij}}(x_j) \tag{6}$$

and $\mu_{Aij}(x_j) : R \rightarrow [0, 1]$ is the membership function of the fuzzy set A_{ij} in the antecedent R_i.

5. Computation Software

In this paper, Matlab is used as basic software for ANNs and fuzzy logic analysis, and ANSYS is used for three-dimensional FEM computation.

6. Constitutive Equation of Soil

It is considered that the soil is grain-structure material, its compressive yield strength is much greater than its tensile yield strength. Not only hydrostatic pressure, but also the other stress can bring about plastic volume variation. So, in this paper, the nonlinear elastic-plastic Drucker-Prager model is adopted to compute stress field and displacement field, and its yield condition is the extended Von Mises criterion. The formula of effective stress σ_e is

$$\sigma_e = 3\beta\sigma_m + \left[|S|^{\mathrm{T}}[\mathrm{M}]\{s\}/2\right]^{\frac{1}{2}} \tag{7}$$

in which σ_m is normal stress or hydrostatic pressure stress, $\{s\}$ is deviator stress. β is material parameter and can be obtained by formula (8). [M] is given by Equation (9).

$$\beta = \frac{2 \sin \phi}{\sqrt{3}(3 - \sin \phi)} \tag{8}$$

$$[\mathrm{M}] = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 \end{bmatrix} \tag{9}$$

In formula (8), ϕ is the angle of internal friction.

In the extended Von Mises criterion, the influence of hydrostatic pressure stress is considered. The yield strength will go up with the increase of hydrostatic pressure stress. The formula of yield strength is as follows.

$$\sigma_y = \frac{6C \cos\phi}{\sqrt{3}(3 - \sin \phi)} \tag{10}$$

where C is the cohesion intercept and ϕ is the angle of internal friction.

The yielding criterion is expressed as follows.

$$F = 3\beta\sigma_m + \left[\{s\}^{\mathrm{T}}[\mathrm{M}]\{s\}/2\right]^{\frac{1}{2}} - \sigma_y = 0 \tag{11}$$

7. Choice of Contact Surface Elements Between Continuous Underground Wall and Soil Medium

In this paper, Goodman shell contact element is adopted to compute the contact surface between continuous underground walls and soil medium. Goodman shell contact element was suggested by Goodman in 1968 (Xu, 1997) and widely applied to geotechnical engineering computation. It is a sort of 4-node shell elements. On the contact surface, the relation between stress and relative displacement is

$$\begin{Bmatrix} \sigma \\ \tau \end{Bmatrix} = \begin{bmatrix} k_n & 0 \\ 0 & k_s \end{bmatrix} \begin{Bmatrix} \omega_n \\ \omega_s \end{Bmatrix} \tag{12}$$

where ω_n and ω_s, are the normal and tangential relative displacements, respectively. σ and τ are the normal and shear stresses. k_n and k_s, are the normal and shear stiffness coefficients.

In the above-mentioned formula (12), k_n and k_s are important parameters. Which values they take has very great influence on the accuracy of computed results.

8. Three-dimensional FEM Computation

In this paper, 8-node three-dimensional solid element and Druck-prager ideal elastic-plastic model are adopted to compute the stress and displacement fields. 4-node plate element is employed to simulate the reinforced concrete continuous underground walls. Bar element is adopted to imitate the internal steel bar supports. It is assumed that the continuous underground walls are consisted of nonlinear elastic material and internal steel bar supports are composed of linear elastic material. The finite element mesh of soil medium, continuous underground walls and bar supports is shown in Figures 3 and 4.

Here "killing and activating element" method is employed to simulate the process of foundation pit digging and supporting. The so-called "killing element" is to multiply the element rigidity and mass by a small number so that the "killed element" has not important influence on the total computed result. On the contrary, "activating element" is to resume the original rigidity and mass of the "killed elements". For example, the plate elements of continuous underground walls will be "killed" when computing the soil subsidence caused by gravity pressure, but after the computation of soil gravitation subsidence, the above- mentioned killed plate elements will be "activated".

In the current paper, the simulating procedure is as follows.

(1) Modelling the whole site soil medium and supporting structures;

(2) "Killing" all support structure elements and then computing the soil body subsidence caused by gravity pressure;
(3) "Activating" continuous underground wall elements and applying water pressure on the lateral surface of continuous underground walls;

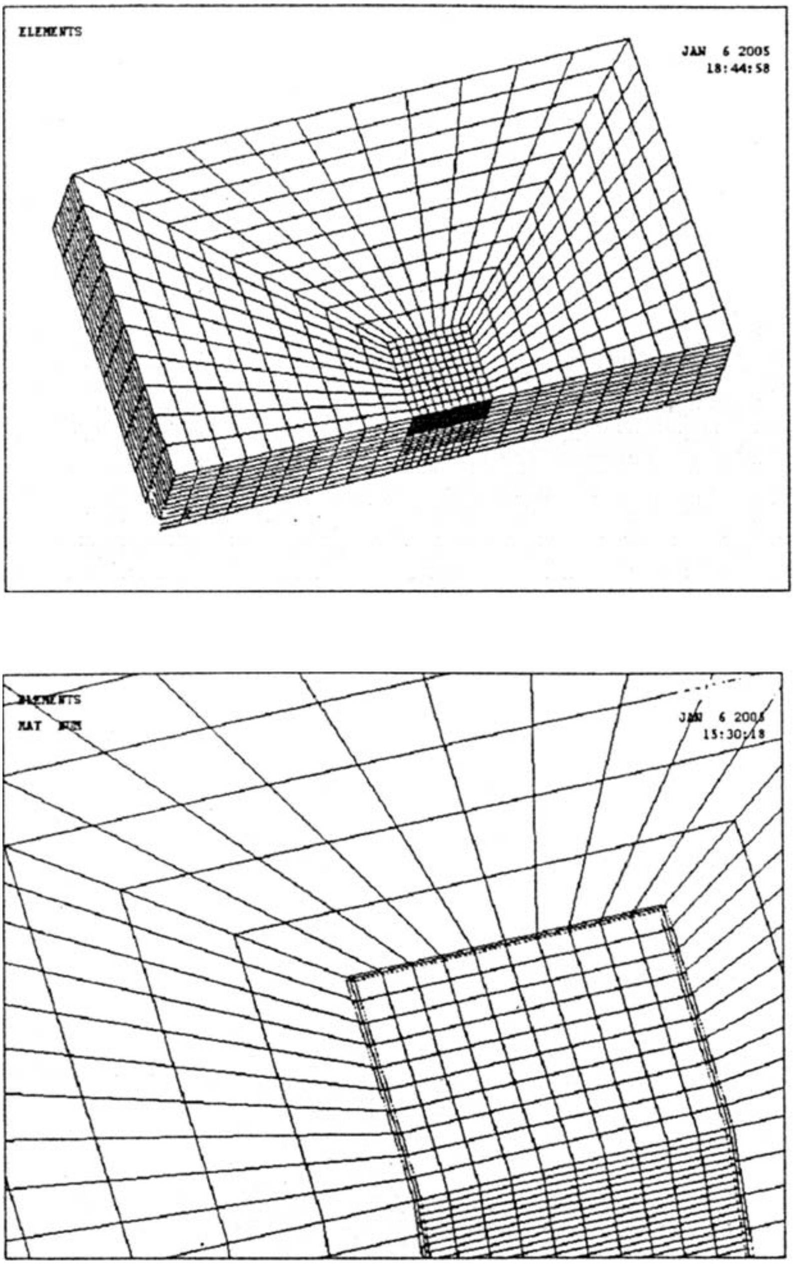
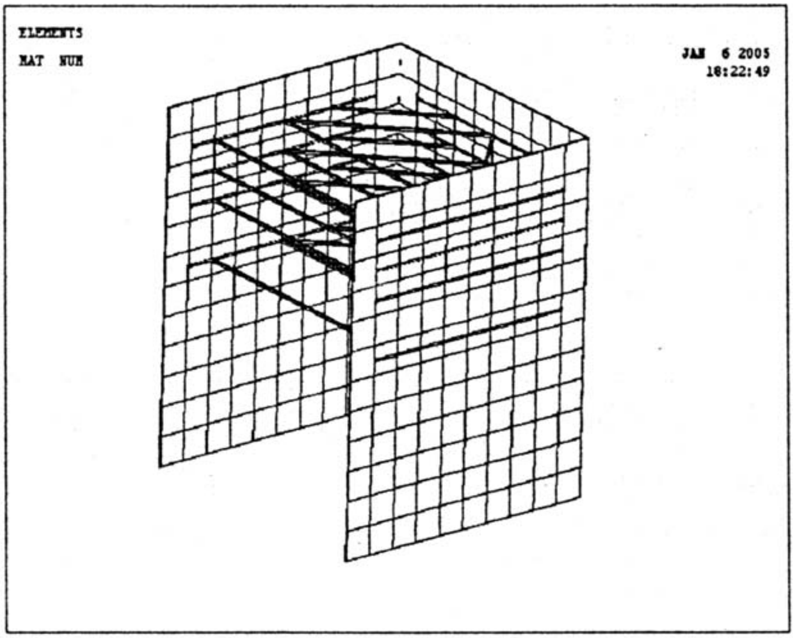


Figure 3. The finite element mesh of soil medium.



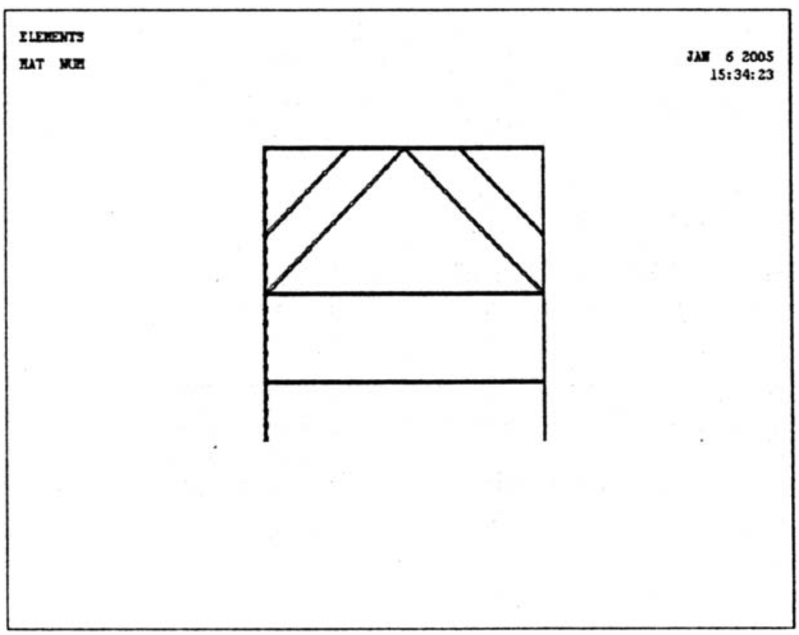


Figure 4. The finite element mesh of continuous underground walls and bar supports.

(4) "Killing" soil elements layer by layer and "activating" the relative internal bar support elements for simulating foundation pit digging and supporting structure constructing;
(5) Repeating (4) until the foundation pit digging and supporting structure constructing have been finished.

8.1. COMPUTATION OF INITIAL STRESS FIELD

The initial stress field is computed by means of Newton iteration method. The computation accuracy is controlled by the error between two adjacent computed results.

8.2. THE DETAILED COMPUTING METHOD AND PROCEDURE

In the current paper, 2~3 times the size of foundation pit is taken as the influence range of foundation pit construction. The computation model is a cuboid of 115×40×30 m. The finite element mesh of soil medium, continuous underground walls and bar supports is shown in Figures 3 and 4. Boolean operation is taken to coordinate the deformation of adjacent soil layers. Newton–Laplace equation is adopted as FEM computing equation. Based on previous experience, 25 are taken as the ideal number of iteration times.

Incremental method is employed to compute the displacement field and stress field. The simulation for the whole process of foundation pit digging and supporting is as follows.

(1) Computing the initial stress field $\{\sigma\}_0$ caused by gravity pressure of soil;
(2) Computing the stress increment $\{\Delta\sigma\}_1$ and displacement increment $\{\Delta\delta\}_1$ produced by first step foundation pit digging. After having finished first step foundation pit digging, the stress field and displacement field are turned into

$$\{\sigma\}_1 = \{\sigma\}_0 + \{\Delta\sigma\}_1 \tag{13}$$

$$\{\delta\}_1 = \{\delta\}_0 + \{\Delta\delta\}_1 \tag{14}$$

where $\{\delta\}_0$ take zero;

(3) Testing if the soil medium has turned into yield state;
(4) Repeating (2) and (3) until the foundation pit digging and supporting structure construction have been finished.

The final stress and displacement fields are

$$\{\sigma\}_1 = \{\sigma\}_0 + \sum \{\Delta\sigma\}_i \tag{15}$$

$$\{\delta\}_1 = \{\delta\}_0 + \sum \{\Delta\delta\}_i \tag{16}$$

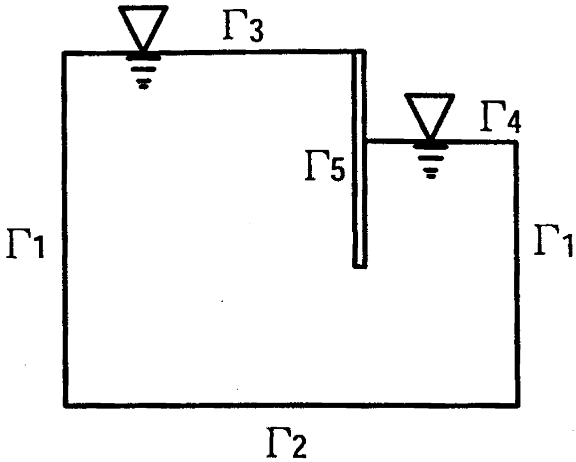


Figure 5. Boundary condition during foundation pit digging.

8.3. BOUNDARY CONDITION

The solid boundary condition is

$$\Gamma_1 + \Gamma_2 : \{\delta\}|_{\Gamma_1+\Gamma_2} = \{\bar{\delta}\} \tag{17}$$

where $\{\bar{\delta}\}$ is the known boundary displacement field. It could be assumed that there is no horizontal displacement on boundary Γ_1 and the boundary Γ_2 when the computing zone is enough large.

There is no constraint on boundaries Γ_3 and Γ_4.

8.4. BASIC SOIL PARAMETERS

The physical parameters of all correlative soil layers are listed in Table 2.

The deformation modulus in Table 2 is obtained from the static ground load-bearing capability test. The computation formula is

$$E_0 = \frac{pb(1-\mu^2)}{s}\omega \tag{18}$$

Table 2. The physical parameters of all correlative soil layers

Serial number of soil layers	Soil density (kg m^3)	Deformation modulus (kpa)	Poisson ratio	Cohesion intercept (kpa)	Angle of internal friction (°)
1	1780	4570	0.35	5	21.5
2	1900	2920	0.37	15	15
3	1750	2210	0.33	11	24
4	1660	3960	0.35	3	23

where E_0 is deformation modulus. b is the width of rectangular pressure-bearing plate or diameter of circular pressure-bearing plate. μ is Poisson ratio. p and s are the pressure stress and precipitation value corresponding to the proportional limit of p (pressure stress)–s (precipitation value) curve. ω is equal to 0.88 for rectangular pressure-bearing plate or 0.79 for circular pressure-bearing plate.

8.5. SOME OF ANSYS-SIMULATED RESULTS

The control of displacement field of continuous underground walls is especially important for ensuring the safety of foundation pit construction. So, in this section, the displacement field of continuous underground walls is discussed. As a tentative work, only the displacements under following states are studied.

State 1: Having finished the second digging step;
State 2: Having finished the third digging step;
State 3: Having finished the fourth digging step and the relative inner supports.

The horizontal displacements of continuous underground walls for the fourth vertical rank of nodes at different depth are computed by means of ANSYS and shown in Table 3. These nodes are situated in the normal section of continuous underground walls. The positive x-direction is perpendicular to the continuous underground wall and from outside to inside. The y-axis is parallel to continuous underground wall.

Table 3. The computed horizontal displacements of continuous underground walls at different depth (Displacement unit: mm)

Depth (m)	State 1		State 2		State 3	
	In x-axis direction	In y-axis direction	In x-axis direction	In y-axis direction	In x-axis direction	In y-axis direction
0	2.7472	−1.2513	4.0118	−1.7255	5.9862	−1.0332
2	5.1498	−2.4253	7.0368	−5.2124	9.8032	−7.8134
4	8.9744	−5.6021	12.246	−10.2131	16.658	−12.2543
6	8.6128	−5.6284	25.77	−10.7159	35.354	−21.6237
8	7.8235	−4.1002	27.455	−10.681	37.724	−23.3538
10	6.6032	−3.3245	25.238	−7.9419	34.667	−20.978
12	5.2134	−3.0235	18.741	−6.1586	25.669	−14.653
14	1.2761	−2.4913	4.3256	−3.8045	5.8249	−5.6149
16	0.226	−1.8167	0.7857	−2.2621	0.8957	−1.9961
18	0.0689	−0.8538	0.4052	−1.1298	0.5024	−1.1867
20	0.3976	−0.1037	0.7794	−0.2082	1.1647	−0.4267
22	0.9988	−0.3447	1.607	−0.352	2.4484	−0.0695
24	0.1797	−0.6904	0.2729	−0.8325	0.4122	−0.1823

9. BP-simulation of the Computed Results

Basing on the data of States 1–2, a BP neural network model is established. The input layer is composed of digging depth of foundation pit, elastic modulus of soil, cohesion intercept and angle of internal friction. The output layer is composed of displacement of continuous underground walls. 3-layer BP neural network model is adopted. The sigmoid function is employed by BP neural network. The displacement of State 3 will be predicted by means of above-obtained BP neural network. And the predicted result is shown in Table 4.

From Figures 6 and 7 it could be found that the error between ANSYS-computed and BPNN-predicted displacements is not large.

10. The Dynamic Fuzzy Pre-control of Foundation Pit Digging

In this section, a fuzzy logic model is set up for pre-control of foundation pit digging. In the fuzzy logic model, the total horizontal displacement and incremental horizontal displacement are adopted as input variables. The output variable is the pre-control measure. The purpose of fuzzy control is to ensure the safety of the foundation pit digging. Following *if-then* rules are adopted in this paper.

For the adopted *if-then* rules, the grade of total and incremental horizontal displacements is defined as follows.

Table 9 can be obtained from Tables 5– 8.

Table 4. The horizontal displacements of continuous underground walls at different depth, which are computed by means of ANSYS and predicted by means of BP neural networks (For State 3)

Depth (m)	Displacement in *x*-axis direction (mm)		Displacement in *y*-axis direction (mm)	
	BPNN-predicted result	ANSYS-computed result	BPNN-predicted result	ANSYS-computed result
0	6.7638	5.9862	−3.3152	−1.0332
2	9.3754	9.8032	−6.6549	−7.8134
4	18.027	16.658	−12.5513	−12.2543
6	34.4759	35.354	−21.4825	−21.6237
8	37.4017	37.724	−23.3538	−23.3538
10	34.3189	34.667	−19.6783	−20.978
12	26.059	25.669	−14.5931	−14.653
14	6.3471	5.8249	−4.9067	−5.6149
16	1.5094	0.8957	−2.8567	−1.9961
18	0.4122	0.5024	−1.8635	−1.1867
20	1.851	1.1647	−1.8103	−0.4267
22	3.1426	2.4484	−0.6495	−0.0695
24	1.1483	0.4122	−0.0705	−0.1823

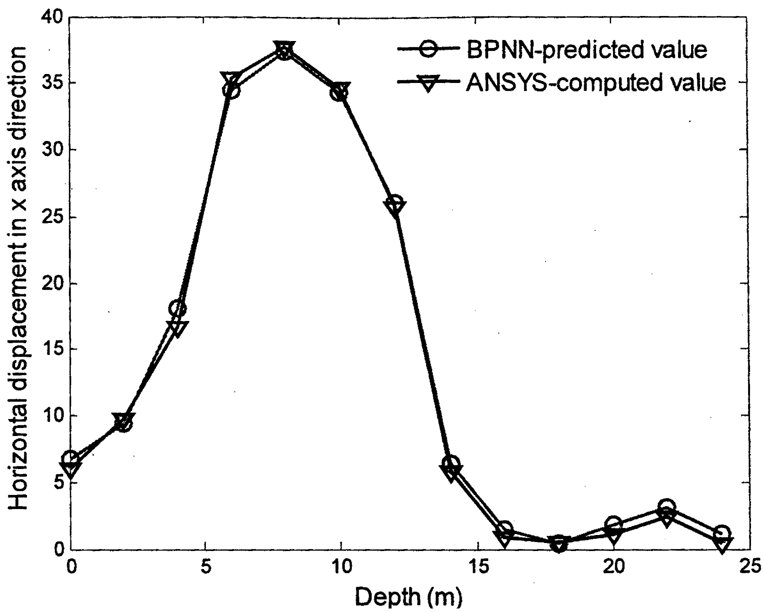


Figure 6. The contrast between ANSYS-computed and BPNN-predicted horizontal displacements in *x*-axis direction (Displacement unit: mm).

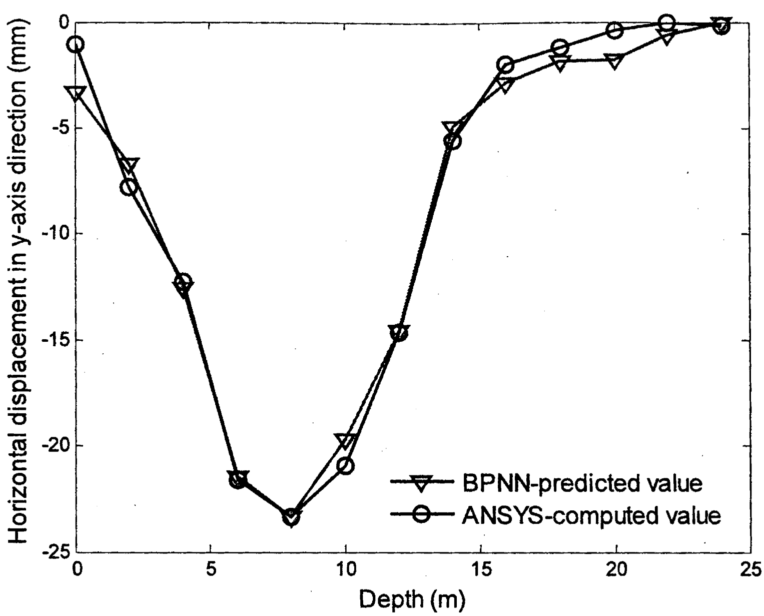


Figure 7. The contrast between ANSYS-computed and BPNN-predicted horizontal displacements in *y*-axis direction.

Table 5. "If-then" rules for fuzzy pre-control of Deping Station foundation pit digging of Shanghai Track Traffic Line 6 project

Rule No.	Definition of if-then rules
1	**If** *the total horizontal displacement is small* and *the incremental displacement is small* **then** *output is normal construction*
2	**If** *the total horizontal displacement is small* and *the incremental displacement is medium* **then** *output is slowdown construction*
3	**If** *the total horizontal displacement is medium* and *the incremental displacement is small* **then** *output is slowdown construction*
4	**If** *the total horizontal displacement is medium* and *the incremental displacement is medium* **then** *output is slowdown construction*
5	**If** *the total horizontal displacement is small* and *the incremental displacement is large* **then***output is suspend construction*
6	**If** *the total horizontal displacement is medium* and *the incremental displacement is large* **then** *output is suspend construction*
7	**If** *the total horizontal displacement is large* and *the incremental displacement is small* **then** *output is suspend construction*
8	**If** *the total horizontal displacement is large* and *the incremental displacement is medium* **then** *output is suspend construction*
9	**If** *the total horizontal displacement is large* and *the incremental displacement is large* **then** *output is reinforce*

Table 10 can be produced by integrating the results in x-axis direction and in y-axis direction.

The result of Table 10 is the same as the measures that employed in practical construction.

Table 6. The total horizontal displacement and incremental horizontal displacement in x-axis obtained by FEM computation

Depth (m)	Total horizontal displacement of State 1	Total horizontal displacement of State 2	Incremental horizontal displacement of State 2	Total horizontal displacement of State 3	Incremental horizontal displacement of State 3
0	2.7472	4.0118	1.2646	5.9862	1.9744
2	5.1498	7.0368	1.887	9.8032	2.7664
4	8.9744	12.246	3.2716	16.658	4.412
6	8.6128	25.77	17.157	35.354	9.584
8	7.8235	27.455	19.632	37.724	10.269
10	6.6032	25.238	18.635	34.667	9.429
12	5.2134	18.741	13.528	25.669	6.928
14	1.2761	4.3256	3.0495	5.8249	1.4993
16	0.226	0.7857	0.5597	0.8957	0.11
18	0.0689	0.4052	0.3363	0.5024	0.0972
20	0.3976	0.7794	0.3818	1.1647	0.3853
22	0.9988	1.607	0.6082	2.4484	0.8414
24	0.1797	0.2729	0.0932	0.4122	0.1393

Table 7. The total horizontal displacement and incremental horizontal displacement in y-axis obtained by FEM computation

Depth (m)	Total horizontal displacement of State 1	Total horizontal displacement of State 2	Incremental horizontal displacement of State 2	Total horizontal displacement of State 3	Incremental horizontal displacement of State 3
0	−1.2513	−1.7255	−0.4742	−1.0332	0.6923
2	−2.4253	−5.2124	−2.7871	−7.8134	−2.601
4	−5.6021	−10.2131	−4.611	−12.2543	−2.0412
6	−5.6284	−10.7159	−5.0875	−21.6237	−10.9078
8	−4.1002	−10.681	−6.5808	−23.3538	−12.6728
10	−3.3245	−7.9419	−4.6174	−20.978	−13.0361
12	−3.0235	−6.1586	−3.1351	−14.653	−8.4944
14	−2.4913	−3.8045	−1.3132	−5.6149	−1.8104
16	−1.8167	−2.2621	−0.4454	−1.9961	0.266
18	−0.8538	−1.1298	−0.276	−1.1867	−0.0569
20	−0.1037	−0.2082	−0.1045	−0.4267	−0.2185
22	−0.3447	−0.352	−0.0073	−0.0695	0.2825
24	−0.6904	−0.8325	−0.1421	−0.1823	0.6502

Table 8. The grade of total and incremental horizontal displacements employed by above-mentioned "if-then" rules

	Small	Medium	Large
Total horizontal displacement	Below 30 mm	30–40 mm	Greater than 40 mm
Incremental horizontal displacement	Below 10 mm	10–20 mm	Greater than 20 mm

11. Conclusions

The research work of the current paper is only an elementary trial to integrate FEM method with ANNs and fuzzy logic to solve geotechnical practical problems. The result computed by FEM method is compared with that predicted by neural networks so as to understand the computational accuracy of these two methods. Fuzzy logic is applied to simulate the pre-control measures of foundation pit digging. Following conclusions could be summarized from these studies.

(1) BP neural networks have a very excellent ability in simulating the result and process of geotechnical FEM computation of the current paper.
(2) An interesting and attractive characteristic of fuzzy logic is that the training samples may be both linguistic (symbolic) and numeric ones. An expert may articulate linguistic association. Or a fuzzy system may adaptively infer its fuzzy associations from numerical samples. The fuzzy logic has reasoning and switch functions besides its predicting ability, it can produce both quantitative and qualitative results. Fuzzy logic has the unique superiority in simulating the pre-control measures of foundation pit digging.

Table 9. The pre-control measures obtained through fuzzy logic operation

Depth (m)	State 2 (in x-axis direction)	State 2 (in y-axis direction)	State 3 (in x-axis direction)	State 3 (in y-axis direction)
0	normal construction	normal construction	normal construction	normal construction
2	normal construction	normal construction	normal construction	normal construction
4	normal construction	normal construction	normal construction	normal construction
6	slowdown construction	normal construction	slowdown construction	slowdown construction
8	slowdown construction	normal construction	slowdown construction	slowdown construction
10	slowdown construction	normal construction	slowdown construction	slowdown construction
12	slowdown construction	normal construction	normal construction	normal construction
14	normal construction	normal construction	normal construction	normal construction
16	normal construction	normal construction	normal construction	normal construction
18	normal construction	normal construction	normal construction	normal construction
20	normal construction	normal construction	normal construction	normal construction
22	normal construction	normal construction	normal construction	normal construction
24	normal construction	normal construction	normal construction	normal construction

Table 10. The pre-control measures obtained through fuzzy logic operation (After integrating the results in x-axis direction and in y-axis direction)

Depth (m)	State 2	State 3
0	normal construction	normal construction
2	normal construction	normal construction
4	normal construction	normal construction
6	slowdown construction	slowdown construction
8	slowdown construction	slowdown construction
10	slowdown construction	slowdown construction
12	slowdown construction	normal construction
14	normal construction	normal construction
16	normal construction	normal construction
18	normal construction	normal construction
20	normal construction	normal construction
22	normal construction	normal construction
24	normal construction	normal construction

(3) It is worthwhile to emphasize that a thorough investigation and study on huge amount of data and the possession of rich experience are very paramount prerequisite for establishing the most efficient BP neural network and fuzzy logic coupling model. Different model establishers may sum up different models because of different levels of understanding for the same process.
(4) The traditional FEM method and intelligent technique should be closely integrated for better solving of geotechnical practical problems.

References

Alvarez, G.M. and Babuska, R. (1999) Fuzzy model for the prediction of unconfined compressive strength of rock samples, *International Journal of Rock Mechanics and Mining Science*, **36**(3), 339–349.

Basma, A.A. and Kallas, N. (2004) Modeling soil collapse by artificial neural networks, *Geotechnical and Geological Engineering*, **22**(3), 427–438.

Chen, Y-L., Azzam, R., Zhang, F-B. and Pan, Z-T. (2004) The prediction of construction control plan of deep foundation pit excavation utilizing back-propagation neural network and fuzzy logical control, *Mitteilungen zur Ingenieurgeologie und Hydrogeologie*, **88**, 81–98.

Deng, J-H. and Lee, C.F. (2001) Displacement back analysis for a steep slope at the Three Gorges Project site, *International Journal of Rock Mechanics and Mining Science*, **38**, 259–268.

Feng, X-T. (2000) Introduction of Intelligent Rock Mechanics, Science Press, Beijing (in Chinese).

Gao, W-H. (1998) The application of visco-elastic thick plate theory in analyzing deformation of deep foundation pit support structure. Thesis for applying doctoral degree, Tongji University (in Chinese).

Huang, R-Q. and Xu, Q. (1997) Principle and application of general systematical scientific analyzing method in geological engineering, Geology Press, Beijing (in Chinese).

Huang, T. (1991) An expert system for deep and large-scale foundation pit design. Thesis for applying doctoral degree, Tongji University (in Chinese).

Li, J-C. (1992) Three-dimensional FEM computation and experimental study of foundation pit digging in soft soil areas. Thesis for applying doctoral degree, Tongji University (in Chinese).

Li, S-J. et al. (2002) The inversion method of rock mass osmotic coefficient and its engineering application, *Chinese Journal of Rock Mechanics and Rock Engineering*, 21(4), 479–483 (in Chinese).

Panigrahi, D.C. and Sahu, H.B. (2004) Classification of coal seams with respect to their spontaneous heating susceptibility – a neural network approach, *Geotechnical and Geological Engineering*, **22**(4), 457–476.

Sirat, M. and Talbot, C.J. (2001) Application of artificial neural networks to fracture analysis at the Aspo HRL, Sweden: fracture sets classification, *International Journal of Rock Mechanics and Mining Science*, **38**, 621–639.

Sonmez, H., Gokceoglu, C. and Ulusay, R. (2004) A mamdani fuzzy inference system for the geological strength index (gsi) and its use in slope stability assessments, *International Journal of Rock Mechanics and Mining Science*, **41**(3), 513–514.

Takagi, T. and Sugeno, M. (1985) Fuzzy identification of systems and its applications to modelling and control, *IEEE Trans Syst Man Cybernet*, **15**, 116–132.

Wang, G-G. (1994) Large-scale deformation theory of foundation pit digging. Thesis for applying doctoral degree, Tongji University (in Chinese).

Wang, X-H. (1999) Studies on intelligent control methods for soil foundation pit digging. Thesis for applying doctoral degree, Tongji University (in Chinese).

Xu Y. (1997) The numerical analysis of deep foundation pit digging in soft soil areas. Thesis for applying doctoral degree, Tongji University (in Chinese).

Yang, Y. and Rosenbaum, M.S. (2002) The artificial neural network as a tool for assessing geotechnical properties, *Geotechnical and Geological Engineering*, **20**(2), 149–168.

Yu, J-L. (1997) Studies on numerical computation of deep soft soil foundation pit. Thesis for applying doctoral degree, Zhejiang University (in Chinese).

Yu, Z-J. (1995) Studies on the mechanism of deep foundation digging and computer-aided design of foundation pit supporting system. Thesis for applying doctoral degree, Tongji University (in Chinese).

Yuan, J-R. (2001) The intelligent prediction and control on displacement of underground engineering construction. Thesis for applying doctoral degree, Tongji University (in Chinese).