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Real-time modeling prediction for excavation behavior

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Abstract. Two real-time modeling prediction (RMP) schemes are presented in this paper for analyzing the behavior of deep excavations during construction. The first RMP scheme is developed from the traditional $AR(p)$ model. The second is based on the simplified Elman-style recurrent neural networks. An on-line learning algorithm is introduced to describe the dynamic behavior of deep excavations. As a case study, in-situ measurements of an excavation were recorded and the measured data were used to verify the reliability of the two schemes. They proved to be both effective and convenient for predicting the behavior of deep excavations during construction. It is shown through the case study that the RMP scheme based on the neural network is more accurate than that based on the traditional $AR(p)$ model.

Key words: neural network; excavation; real-time modeling prediction; construction.

1. Introduction

Underground excavation is very complicated and is always influenced by various engineering conditions. Currently, the design of excavations relies mainly on empirical roles, assisted by some numerical or theoretical analysis. Even though theoretical and numerical analysis has been

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conducted, engineers still have to rely on in-situ measurements for making their decisions. The dynamic process of excavation is usually depicted by observing changes of items such as stress, deformation and displacement over time. There observations are used to help predict the behavior of the excavation, and to ensure its safety and engineering reliability.

Traditionally three methods are used in geotechnical engineering, namely numerical (e.g. using finite elements), empirical and semi-empirical ones. Of these the finite element method is often used for excavation design (Souley *et al*. 1997, Ou *et al*. 1996, Zhang 1999). However, the dynamic process of deep excavation is a very complicated nonlinear system, because it depends on many factors such as temperature, geology, opening geometry, excavation sequence etc.(Kwon and Wilson 1999). Hence many parameters need to be selected. This makes it difficult for the finite element method (FEM) to be used to predict the dynamic process of deep excavation accurately, despite it being a powerful tool for solving many engineering problems in other fields (Li *et al*. 2001b, Fang *et al*. 1998, Li *et al*. 2001a, 1999a, Luo *et al*. 2002, Yang *et al*. 2001, Luo *et al*. 2001).

Empirical and semi-empirical methods are usually based on the data collected from similar field conditions and are extremely dependent on the range of site conditions represented in the data base. It is difficult to adopt simple empirical formulae and regression curves to describe the complicated dynamic process of excavation.

Because of the difficulties in using numerical or theoretical methods (Xiao *et al*. 2002, 2003), engineers are now paying more attention to field monitoring and real-time prediction of excavation behavior (Ishida and Uchita 2000, Yanagizawa *et al*. 1995) to confirm the safety of excavation during construction and improve the design of subsequent stages of construction. In this paper, two efficient schemes are presented for predicting the precise behavior of excavations.

The stress and strain in the soil is gradually released during construction, and the resulting displacement is related not only to time, but also nonlinearly to the local stress level and to the time the stress is sustained for. In addition, many constitutive relations of soil are complex and their parameters are difficult to determine. Experimental monitoring shows that series of data formed by taking readings at successive time intervals are related to each other, i.e. the present state depends on the previous state (Li and Li 2001). Furthermore, because the construction of excavations is often disturbed by uncertain factors, the measured data often shows various random characteristics. Considering that excavation often progresses by layers and by sections, the model for predicting behavior is usually not available at the commencement of excavation. Therefore the data collecting, modeling and predicting should be done simultaneously. Besides, the model established from previous data cannot show the recent and real-time characteristics of excavation, and the data series of the model will vary with time during the excavation. It is therefore of benefit to develop an efficient real-time modeling and prediction method which accounts for these real characteristics of excavation construction.

Supposing $\{x_t\}(t = 1, 2, 3, \ldots, p)$ is the data series describing the excavation behaviour as time changes. Then in order to carry out real-time modelling and prediction (RMP) of the excavation, a model $\boldsymbol{G}$ is required to describe the relationship between x_j and the previous observed values $(x_{j-1}, x_{j-2}, \ldots, x_{j-k})$, i.e.

$$x_j = G(x_{j-1}, x_{j-2}, \ldots, x_{j-k}), (j = k+1, k+2, \ldots) \tag{1}$$

It is necessary to find a mathematical model to describe $\boldsymbol{G}$. But $\boldsymbol{G}$ is usually a non-linear function and so it is difficult to describe it accurately by means of existing theoretical models and numerical methods. Such modelling should be convenient and simple, to ensure completion of the modelling and prediction in time. In this paper, two efficient RMP schemes are developed for predicting the dynamic behaviour of excavation.

2. RMP scheme based on *AR*(*p*) model

2.1 AR(p) model

A very general class of prediction model is the *ARMA*(p, q) model (Reinsel 1993, Box and Jenkins 1970, Choi 1992, Hamilton 1994, Elman 1990).

$$x_t = \gamma + \sum_{i=1}^{p} \varphi_i x_{t-i} + \sum_{j=1}^{q} \theta_j e_{t-j} + e_t \tag{2}$$

where: x_t is the autoregressive variable; e_t is the moving average variable; φ_i is the autoregressive parameter; θ_j is the moving average parameter; p and q are the orders of the autoregressive and moving average parameters, respectively.

It is usually assumed that $E(e_t / x_{t-1}, x_{t-2}, \ldots) = 0$. For example, this condition is satisfied when e_t is a zero mean, uniformly distributed and independent variable. It is assumed that e_t has a finite value of variance σ^2. For a zero mean process x_t the intercept γ is zero. To simplify Eq. (2), it is assumed that $\gamma = 0$.

An *AR*(p) process model is the special case of an *ARMA*(p, q) process model (Li *et al*. 2000a) for which $q = 0$. Eq. (2) changes to the following form

$$x_t = \varphi_1 x_{t-1} + \ldots + \varphi_p x_{t-p} + e_t \tag{3}$$

Its style is simpler and it is easier to calculate the parameters. Therefore the *AR*(p) model is the preferred model for the real-time modelling and prediction of engineering problems.

There are probably some abnormal points in the observation values and so it is beneficial to do some pre-process work to acquire the stable data series $\{X_t\}$ of the excavation behaviour. We have used the following simple formula to achieve this for the most abnormal values:

$$x_i = (x_{i-1} + 2x_i + x_{i+1}) / 4 \tag{4}$$

2.2 Least squares estimator of parameters

The least squares method is usually used to estimate parameters. Letting $t = n+1, n+2, \ldots, N$ in Eq. (3), this enables the values of the parameters to be expressed as:

$$\boldsymbol{\phi}_N = (\boldsymbol{X}_N^T \boldsymbol{X}_N)^{-1} \cdot \boldsymbol{X}_N^T \cdot \boldsymbol{Y}_N \tag{5}$$

where:

$$\boldsymbol{\phi}_N = [\phi_1, \phi_2, \ldots, \phi_n]^T \tag{6}$$

$$\boldsymbol{Y}_N = [x_{n+1}, x_{n+2}, \ldots, x_N]^T \tag{7}$$

$$\boldsymbol{X_N} = \begin{bmatrix} x_n & x_{n-1} & \dots & x_1 \\ x_{n+1} & x_n & \dots & x_2 \\ \dots & \dots & \dots & \dots \\ x_{N-1} & x_{N-2} & \dots & x_{N-n} \end{bmatrix} \tag{8}$$

$$\sigma_a^2 = \frac{1}{N-n}\sum_{t=n+1}^{N}\left(x_t - \sum_{i=1}^{n}\phi_i x_{t-i}\right)^2 \tag{9}$$

Supposing the new value x_{N+1} is observed, the least squares estimation is:

$$\boldsymbol{\phi_{N+1}} = (\boldsymbol{X_{N+1}^T X_{N+1}})^{-1}\boldsymbol{X_{N+1}^T Y_{N+1}} \tag{10}$$

where:

$$\boldsymbol{Y_{N+1}} = \begin{bmatrix} \boldsymbol{Y_N} \\ x_{N+1} \end{bmatrix} \tag{11}$$

$$\boldsymbol{X_{N+1}} = \begin{bmatrix} \boldsymbol{X_N} \\ \boldsymbol{X_{(S+1)}} \end{bmatrix} \tag{12}$$

$$\boldsymbol{X_{(S+1)}} = [x_N, x_{N-1}, \dots, x_{N-n+1}] \tag{13}$$

Then the expression obtained for the parameter estimation is:

$$\boldsymbol{\phi_{N+1}} = \boldsymbol{\phi_N} + \boldsymbol{K_{N+1}}(x_{N+1} - \boldsymbol{X_{(S+1)}} \cdot \boldsymbol{\phi_N}) \tag{14}$$

where:

$$\boldsymbol{K_{N+1}} = \frac{1}{1 + \boldsymbol{X_{(S+1)}}(\boldsymbol{X_N^T X_N})^{-1}\boldsymbol{X_{(S+1)}^T}} \cdot (\boldsymbol{X_N^T X_N})^{-1}\boldsymbol{X_{(S+1)}^T} \tag{15}$$

2.3 Prediction

According to the $AR(q)$ model and the estimation of the parameters presented above, the prediction for step l is:

$$\hat{X}_t(l) = \sum_{i=1}^{n}\phi_i \hat{X}_t(l-i) \qquad (l > n) \tag{16}$$

As a special case, the one-step prediction is

$$\hat{X}_t(l) = \phi_1 \hat{X}_t(l-1) \tag{17}$$

Because more information is contained in the newly observed data series, the one-step prediction can be sufficiently accurate and so, because it is simpler than the multiple-step prediction, it is adopted in this paper. However, the multiple-step prediction has also been introduced herein as a general approach.

3. RMP scheme based on the recurrent neural network

Neural networks have recently emerged as a successful tool in the field of pattern classification and control of dynamic systems (Kerh and Yee 2000, Goh 1995, Rafiq *et al.* 2001, Li *et al.* 2000b 1999b). This is due to the computational efficiency of the back-propagation algorithm and the versatility of the three-layer feed forward neural network in approximating arbitrary static nonlinearity. One of the early journal articles on neural network application in civil/structural engineering was published in 1989 (Adeli and Yeh 1989). The great majority of civil engineering applications of neural networks are primarily based on the BP algorithm because of its simplicity (Nerrand *et al.* 1994). In this paper, a simple Elman-style architect of recurrent neural network (Pham and Karaboga 1999, Kremer 1995, Adeli 2001) is developed for real-time modelling and prediction of excavation behaviour.

3.1 The architecture of the neural network

The architecture of the neural network applied in this study is illustrated in Fig. 1. The network consists of four layers of nodes: an input layer with one unit, a context with n units, a hidden layer with n units and an output layer with one unit. The input unit is connected to every hidden unit, as every context unit does. Similarly, every hidden unit is connected to the output unit.

A traditional forward feedback neural network lacks the ability of online learning, and training can only be done after enough samples have been accumulated. So, it is actually a static non-linear mapping. In comparison, recurrent neural networks (Nerrand *et al.* 1994) can have nonlinear and dynamic functions in training. In Fig. 1 $x(t)$ and $y(t)$ are respectively the input and output of a network at time t. In contract to forward feedback neural networks, context units are introduced in addition to input nodes, hidden nodes and output nodes. This provides the network with a dynamic memory function by saving the characteristics of hidden nodes at the previous time step and exporting it to context units at the next time step. Therefore, the context units can be considered as

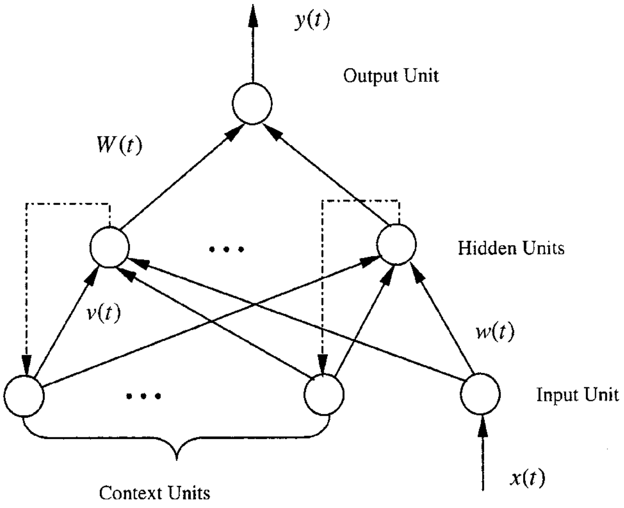


Fig. 1 Architecture of an Elman-style neural network

input units whose input is the output of the hidden units at the previous time step. In a sense, the hidden units are defined as the 'status' of the network, so it is obvious that the input of the network is related to both the present and previous 'status' of the network, as is the case for excavation behaviour. The data for the excavation behaviour at time t, $x(t)$, is not only related to the observation data at previous time, but also depends on the present status of the excavation.

3.2 The network algorithm

The algorithm for the neural network adopted in this study can be expressed as:

$$\begin{cases} y(t) = \sum_{i=1}^{h} W_i(t-1)H_i(t) \\ H_i(t) = f(h_i(t)) \\ h_i(t) = w_i(t-1)x(t) + \alpha\sum_{j=1}^{h} v_{ij}(t-1)H_j(t-1) + \theta_j(t) \end{cases} \tag{18}$$

Here, and Fig. 1, w_i is the weighting between the input unit and the hidden units (i); $W_i(t)$ is the weighting between the hidden units and the output unit; $v_{ij}(t)$ is the feedback weighting between the hidden units and the context units; $H_i(t)$ is the output of the hidden units; h is the number of the hidden units; $\theta_i(t)$ is the threshold value of a hidden unit; $f(\cdot)$ is a nonlinear impulsive function, which is normally Sigmoid. Here the augmentation coefficient of feedback is introduced as α.

Let $y(t)$ and $y_e(t)$ be the actual and expected output of the networks. Then an error function for a training cycle can be defined as

$$E(t) = \frac{1}{2}e^2(t) \tag{19}$$

where:

$$e(t) = y_e(t) - y(t) \tag{20}$$

The weighting in the networks is adjusted by the gradient descent method, i.e.

$$W_i(t+1) = W_i(t) - \eta_1 \cdot \frac{\partial E(t)}{\partial W_i(t-1)} = W_i(t) + \eta_1 \cdot e(t) \cdot H_i(t) \tag{21}$$

$$v_{ij}(t+1) = v_{ij}(t) - \frac{\eta_2 \partial E(t)}{\partial v_{ij}(t-1)} = v_{ij}(t) + \eta_2 e(t) W_i(t-1)\frac{\partial H_i(t)}{\partial v_{ij}(t-1)} \tag{22}$$

$$w_i(t+1) = w_i(t) - \eta_3 \cdot \frac{\partial E(t)}{\partial w_i(t-1)} = w_i(t) + \eta_3 \cdot e(t) \cdot W_i(t-1) \cdot \frac{\partial H_i(t)}{\partial w_i(t-1)} \tag{23}$$

where: η_1, η_2, η_3 are training modulus of W_i, v_{ij}, w_i respectively;
In Eq. (22),

$$\frac{\partial H_i(t)}{\partial v_{ij}(t-1)} = f'(h_i(t))\left(H_j(t-1) + \sum_{j=1}^{h} v_{ij}(t-1)\frac{\partial H_j(t-1)}{\partial v_{ij}(t-2)}\right) \tag{24}$$

In Eq. (23),

$$\frac{\partial H_i(t)}{\partial w_i(t-1)} = f'(h_i(t))\left(x(t) + \sum_{j=1}^{h} v_{ij}(t-1)\frac{\partial H_j(t-1)}{\partial w_i(t-2)}\right) \tag{25}$$

3.3 Pre-processing of input serial

The 'peak' points were deselected before prediction, and then the stability of the input data was checked. If it was not stable, it was smoothed by the difference method. The last value of the input serial expresses the trend of the system in the future and it greatly influences the prediction result, so it must be ensured that it is accurate and trustworthy.

3.4 On-line learning method

Since the model built on previous data cannot describe the characteristics of the system at present absolutely, an online learning method is used here to depict the dynamic characteristics of deep excavation behaviour. It is supposed that the observation values $x(1)$, $x(2)$, ..., $x(k)$ have been obtained as the learning samples of training and they are defined as the learning serial, i.e. they have been observed in advance. The number of values in the learning serial cannot be too small if the accuracy of the prediction is to be ensured.

The learning process can be described as follows. First let $x(1)$ and $x(2)$ be respectively the input and output of the neural network and adjust the weightings to minimize the error function. Then let $x(2)$ be the input and $x(3)$ be the output, and train the network again. At the last step, let $x(k-1)$ be the input and $x(k)$ be the output, and adjust the weightings again. Hence the previous and present information is mostly contained in the weightings of the neural network obtained by this continuous training.

Let $x(k)$ be the input of the neural network and let $y(k)$ be the output obtained from the trained network. Then defining the step $(k+1)$ prediction value as $x'(k+1)$ gives

$$x'(k+1) = y(k) \tag{26}$$

from which the prediction for step $(k+1)$ can be obtained.

For a further prediction, supposing the observation value is close to the prediction value, let

$$x(k+1) = x'(k+1). \tag{27}$$

The newly obtained data $x(k+1)$ can be added to the learning serial, while simultaneously deleting the oldest data in the serial. In this case $x(1)$ is deleted. Then a new input serial, i.e. $x(2)$, $x(3)$, ..., $x(k+1)$ in this case, is constructed to predict the next value $x(k+2)$. Therefore, every time the input serial is updated, its length remains constant. Then the neural network can be trained by the new input serial by adjusting the weightings, and the prediction of the next step can be carried out. Doing this continually, the status of the excavation can be tracked and the trend of its subsequent behaviour predicted.

In fact, the observation values are accumulated during construction. The newly observed data contain more recent information about the excavation. Once the real value of $x(k+1)$ is observed, we may substitute the observed value for the supposed one in order to ensure the prediction will express the new state of the excavation.

4. Engineering case study

4.1 General introduction

The Long Gang Commercial Centre is located in Nanjing, China. The main building has forty storeys above ground and two floors underground. Fourteen horizontal displacement measurement points and fifteen stress measurement points were selected for this study. Some of them are indicated in Fig. 2. The excavation was 11.6 meters deep. The retaining structure was a continuous reinforced concrete wall and three sets of braces were set up vertically. The horizontal distribution of the braces was a symmetrically-supported truss. The elevations of the braces were −2.0 m and −7.8 m, respectively. Fourteen theodolites were placed to monitor the horizontal displacement of the selected measurement points. Clinometers of Model BC-1 strain-measurement were installed in the continuous wall to monitor its deformation during construction. Twenty soil pressure gauges were embedded at different depths to measure stress. Measurements from sine frequency-measurement instruments were converted into the stress values of the reinforcing steel bars.

4.2 Calculation and prediction by the two RMP schemes

Monitoring of the excavation was conducted from Oct. 13 to Dec. 21 in 1999. The observations commenced at 10 a.m. every day and the associated prediction work commenced at 4 p.m., using the two RMP methods presented above.

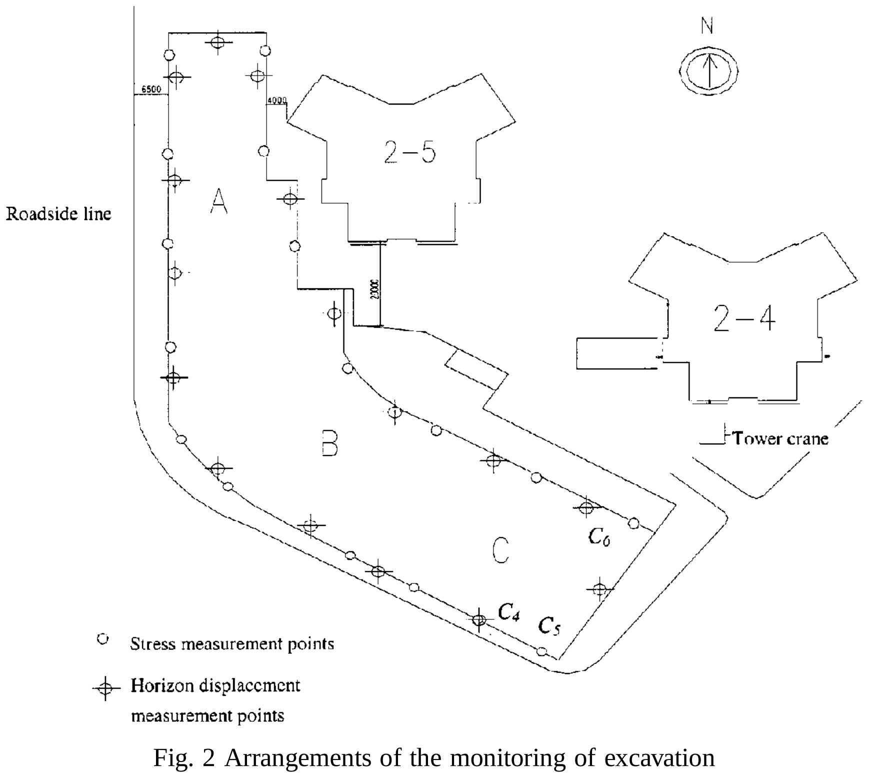
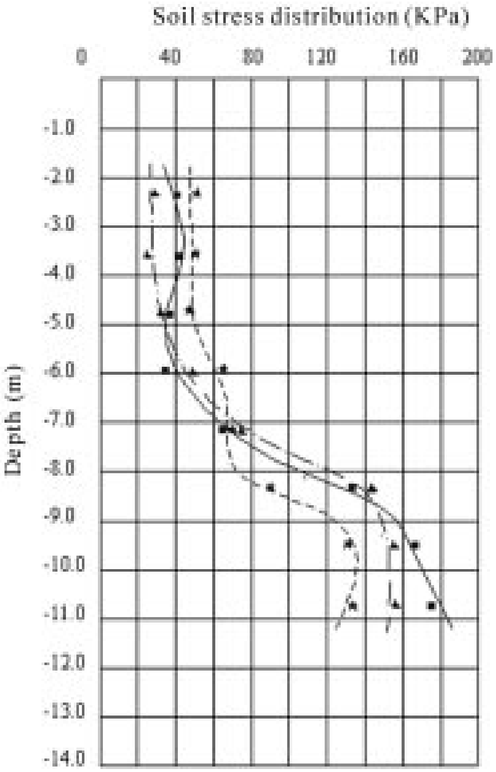


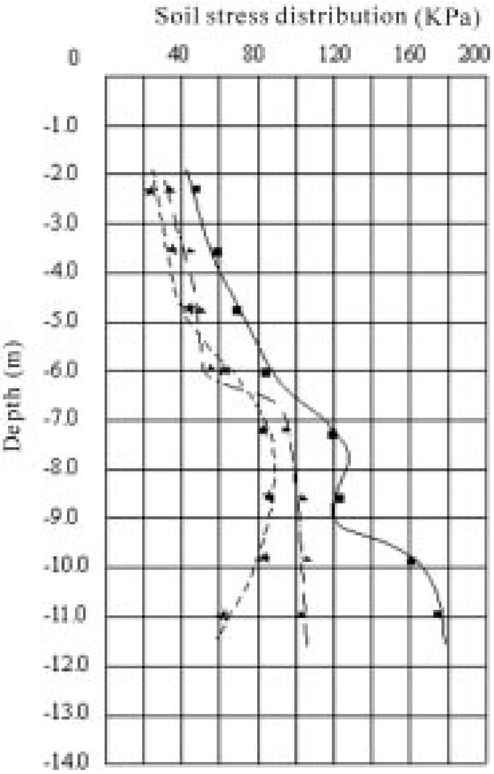
Fig. 2 Arrangements of the monitoring of excavation

A 1-7-7-1 structure recurrent network was established by comparing the theoretical analysis with the field measurement, where 1-7-7-1 means that the numbers of input, hidden, context and output units were 1,7,7 and 1 respectively. The feedback coefficient α was determined mainly from experience as $\alpha = 0.65$ and the predicted results showed this choice to be reasonable. The initial step length for learning was selected as $\eta = 0.65$. The training of the network aimed to adjust the values of the weightings *W*, *v* and *w* and to learn the dynamic behaviour of the system.

The observed values from Oct. 13 to Oct. 22 were used as the initial learning serial $x(1)$, $x(2)$, ..., $x(10)$. The learning process was that described in the paragraph above Eq. (26), with $k = 10$. The trained network contained the information of the previous and present states. By using $x(10)$ as input, the results for Oct. 23 were predicted.

Letting $k = 10$ implies that the number of terms in the learning serial is 10. The newly obtained Oct. 23 data was then added to the input serial, and the oldest data was deleted to obtain a new input serial, retrain the network, adjust the weightings of the network and hence to predict the behaviour of the excavation at Oct. 24. This process was repeated every day until Dec. 21. Modelling and calculation took about twenty minutes.





Excavation depth	−2 m	−4 m	−7.8 m
Soil stress distribution curves	– – –	-----	———
Observed values	★	▲	■

Fig. 3 The soil stress distribution of the measurement point C_4

Fig. 4 The soil stress distribution of the measurement point C_6

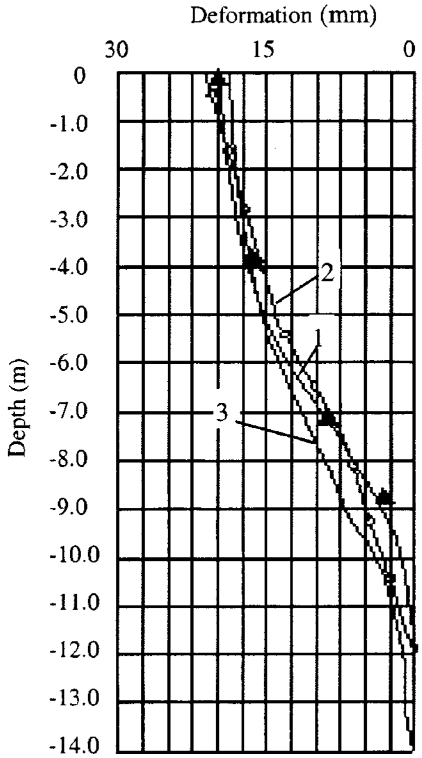


Fig. 5 Horizontal displacement curve at the measurement point C_5

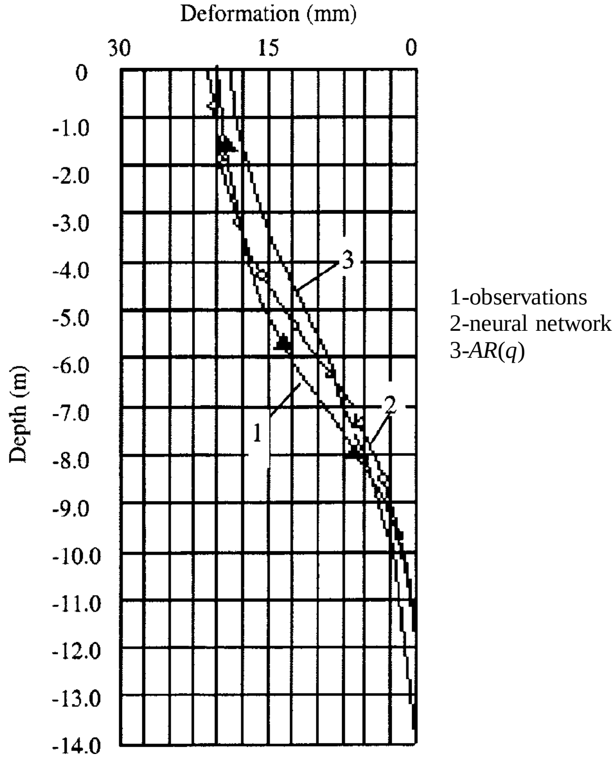


Fig. 6 Horizontal displacement curve at the measurement point C_6

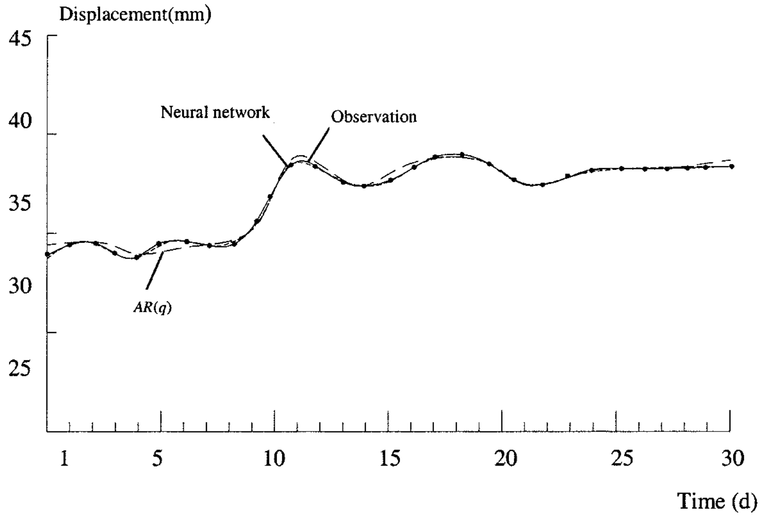


Fig. 7 Horizontal displacements at the measurement point C_4

Fig. 3 shows the soil stress distribution curve at the measurement point C_4 for excavation depths of −2 m, −4 m and −7.8 m, as predicted by the neural network. Fig. 4 repeats these results, but for the measurement point C_6. The points are the observed values. Figs. 5 and 6 show the horizontal displacement curves of the continuous wall at the measurement points C_5 and C_6, respectively. Here curve 1-3 represent, respectively, the observed results, the results predicted by the neural network and those predicted by the $AR(q)$ model. Fig. 7 shows the one-step prediction results of the horizontal displacement for the thirty days from Oct. 23. The observation position was located at elevation −7.8 m and at the measurement point C_4.

4.3 Analysis and comparison of the prediction results

From the monitoring results, it seems that the scheme which is based on the neural network is more accurate than that based on the $AR(q)$ model. In Fig. 7, the maximum error of the prediction given by the neural network is 2.8% which is less than that of the $AR(q)$ model. From Fig. 7, it is seen that at the beginning of the monitoring, the predicted and observed data show a fluctuating trend. This is because the progress of excavation is usually affected by various random factors. Additionally, there is a hysteretic period between the excavation phases and the stability phases. This usually takes about 25 days and reflects the time effect for soft soil.

5. Conclusions

Underground excavation is generally very complicated and always influenced by various factors. It is difficult to adopt a simple empirical formula or regressive curve to describe this complicated dynamic process. An attempt is made in this paper to simulate it by a simplified Elman-style recurrent neural network model and by a one-step traditional $AR(p)$ model. These are both real-time modeling prediction (RMP) schemes. The major conclusions from an engineering case study are that:

(1) Both RMP schemes proved to be effective and convenient for real-time modeling and for prediction of excavation behavior.

(2) The recurrent neural network scheme was able to describe the dynamic behavior of the excavation more accurately than was the traditional $AR(p)$ model scheme.

(3) Hence the recurrent neural network scheme is an effective tool for predicting the behavior of deep excavations during their construction.

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