Prediction of Diaphragm Wall Deflection in Deep Excavation Using Evolutionary Fuzzy Neural Inference Model

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Abstract: In deep excavation, diaphragm wall deflection is an important field measurement that directly affects construction performance, site/adjacent building safety and project risk management. This paper applies historical data to forecast diaphragm wall deflection and proposes a new methodology, the "Evolutionary Fuzzy Neural Wall Deflection Prediction System", to predict deep excavation wall deformation. At the core of this system is the Evolutionary Fuzzy Neural Inference Model (EFNIM), which joins together Genetic Algorithms (GAs), Fuzzy Logic (FL) and Neural Networks (NNs). This research established a historical database of wall deflection statistics from prior projects. The FL reasoning process and NN learning mechanism were then used to generalize a fuzzy rule. Finally, GAs were applied to optimize both FL's and NN's parameters coincidence. By inputting monitored wall deflection data from preceding deep excavation stages, the system developed in this paper helps users predict wall deformation in the upcoming stage and determine whether maximum allowable deflection has been exceeded. Simulation results demonstrated that past project data and experience can be utilized to predict wall deformation with a high level of precision in new projects.
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1. Introduction

Braced diaphragm wall structures are commonly used in deep excavation projects to improve the safety and quality of construction. Therefore, how to use monitored data effectively to predict diaphragm wall deflection, ensure project safety and prevent costly damage represents a critical issue. Data on diaphragm wall deflection is regularly monitored to ensure construction quality and the safety of adjacent buildings - particularly in high density urban settings. However, the complexity of geotechnical parameters and variety of construction factors make the behavior of the soil/wall/prop structures difficult to determine. Peck (1969), Goldberg et al. (1976), Long (2001) have previously identified the key factors in deep excavation to include soil type and properties, excavation depth, and wall stiffness, among others. The first task for this study was to compile historical data from relevant and reliable deep excavation cases. Afterward, approaches to estimate retaining wall support system defection, e.g., finite element analysis, were evaluated and applied.

Finite element analysis has previously been employed to simulate the braced diaphragm wall system (Clough and Hansen 1981; Powrie and Li 1991). However, results are heavily dependent upon the constitutive behavior of soil. As model parameters are usually obtained from laboratory tests, they are unable to fully represent in-situ soil properties due to sample disturbance, in-situ environmental conditions, the diverse effects of construction, and so on. Feedback analysis is commonly applied to field measurements to determine soil parameters (Gioda and Sakurai 1987). Whitted et al. (1993) applied finite element analysis to model the top-down construction of a seven-story, underground parking garage at Post Office Square in Boston. By using optimization approaches, factors were modified to improve agreement with the measured data without recourse to parametric iteration. Ou and Tang (1994) proposed a nonlinear optimization technique to determine soil parameters for deep excavation finite element analysis and studied a hypothetical excavation case under a variety of ground conditions. Chi et al. (2001) obtained optimized parameters by applying an optimization technique for back-analysis that produced results in good agreement with field measurements.

Neural Networks (NNs) represents an alternative numerical analysis procedure. Using compiled historical data and the selected significant parameters, NNs have proven a powerful tool for various modeling requirements, including geotechnical engineering applications. Civil engineering researches employ NNs to define complicated problems in which the governing equation is difficult to form (Flood and Kartam 1994a;

Flood and Kartam 1994b; Elkordy et al. 1993). In geotechnical engineering, Juang et al. (1999) used NNs to evaluate the liquefaction resistance of sandy soils; Neaupane and Adhikari (2006) used NNs to predict ground movement around tunnels; Nawari and Liang (2000) developed a system involving NNs and Fuzzy Logic (FL) to address uncertainties of pile foundations; Goh et al. (1995) demonstrated that NNs can capture the nonlinear interactions between variables and synthesize the finite element results in braced excavations; Hashash et al. (2003) developed an NNs-based constitutive model of soil with outputs defined as wall lateral deflection and ground surface settlement; Jan et al. (2002) applied NNs to eighteen historical deep excavation projects in metropolitan Taipei to predict diaphragm wall deflection; Chua and Goh (2005) used the hybrid evolutionary Bayesian back-propagation neural network and utilized genetic algorithms and the gradient descent method to determine optimal parameters for estimating wall deflection in deep excavation.

This study applied the Evolutionary Fuzzy Neural Inference Model (EFNIM) (Chen and Ko 2003), which joins together Genetic Algorithms (GAs), Fuzzy Logic (FL) and Neural Networks (NNs) to predict deep excavation diaphragm wall deflection. Within the EFNIM, GAs optimize the topology/weightings of NNs and distribute FL membership functions (MFs) (Jagielska et al. 1999); FL is used as the fuzzy inference mechanism to describe inputs/outputs (Gorzalczany and Gradzki 2000); and NNs are applied to tune the shapes of MFs and to extract the fuzzy rules from training data (Ghezelayagh and Lee 1999). This study applied diaphragm wall deflection data previously compiled from 18 metropolitan Taipei projects to the EFNIM to improve prediction result accuracy relative to that achieved by the methodology of Jan et al. (2002), which employed only NNs.

2. The Evolutionary Fuzzy Neural Inference Model (EFNIM)

Knowledge and experience helps us overcome uncertainty, learn and adapt in order to deal with complex problems. Artificial Intelligence (AI), an approach to data management that allows computers to execute tasks normally done by humans, is frequently applied to the resolution of geotechnical engineering problems that have numerous uncertainties inherent in their parameters. GAs, FL and NNs, all popular methods applied to various kinds of problems, each present distinct advantages and drawbacks, and complement the effectiveness of the others. This paper applied EFNIM (a model that fuses GAs, FL and NNs) to predict deep excavation diaphragm wall deflection and prevent the occurrence of illegal and sub-optimal solutions, which usually occur when only NNs are employed.

Although FL can be effectively employed to describe highly complex, ill-defined or difficult-to-analyze subjects, MF distribution and composition operators are difficult to define. Therefore, NNs are employed to infuse self-learning capabilities for solving non-linear and ill-structured problems. Using a Fuzzy Neural Network more effectively imitates the human brain's decision-making processes than using FL alone. In order to meet global optimization, GAs should be used to determine optimal MF distribution and NN parameters necessary to evolve the model toward an ideal adaptation. EFNIM architecture is shown in Figure 1.

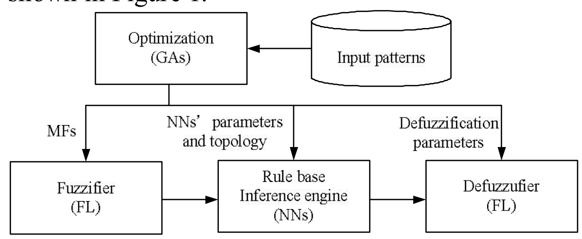

Figure 1. EFNIM Architecture

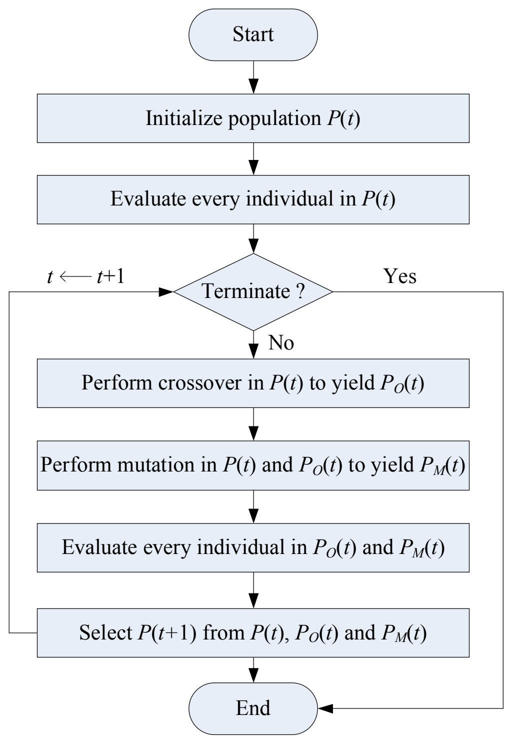

Figure 2. EFNIM Adaptation Process

Figure 2 illustrates the EFNIM adaptation process, where P(t) is used to represent ξ individuals in generation t; PO(t) means that performing crossover ξ individuals yield σ individuals; and PM(t) denotes a mutation population of τ individuals. Initially (t=0), a population of ξ individuals, is randomly generated. Each solution encodes model variables (such as distributions of MFs, NN topology, interconnections, synaptic weights, etc.) into a binary string that simulates a natural chromosome. EFNIM then evaluates chromosome fitness.

3. EFNIM for Predicting Diaphragm Wall Deflection

Diaphragm wall systems are widely used in deep excavation, and significant amounts of data are collected to monitor their safety. As such large amounts of data have been accumulated, how to use such to improve the safety of current and future projects represents an important area of potential development. The EFNIM has been adopted to solve this problem, employing historical data to predict diaphragm wall deflection during excavation. The key initial issue faced is how to configure data into a useable format. In Figure 3, *W* represents diaphragm wall thickness; *D* the temporary depth of excavation; *Ri* the observation point factor where 18 segments are set; and *He* the final depth of excavation. Embedment depth is typically set as 0.8 *He*. However, in cases where embedment depth is less than 0.8 *He*, deflection between the bottom of the diaphragm wall and 19th observation point is assigned as linear and converges to zero and the total depth of diaphragm wall is set as 1.8 *He*. Referring to Jan et al. (2002), seven important factors were selected as inputs and one output was set. Each observation point can be regarded as an individual case, with related parameters illustrated as follows:

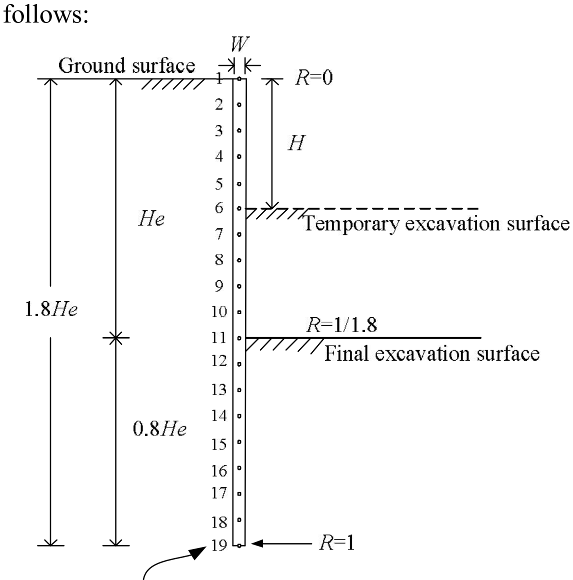

Figure 3. Representation of the Diaphragm Wall Structure

Seven Inputs:
(1)Diaphragm wall thickness: *W*.
(2)Excavation depth: *H*.
(3)The equivalent SPT-N value between *H*+0.25*He* and *H*-0.25*He*: .
(4)The factor of an observation point factor linearly interpolated by the depth: *R*.
(5)The deflection of the observation point in the last stage, i.e., the (*i*-1)-th stage in the current *i* stage in excavation: D_{i-1}.
(6)The deflection of the observation point in the (*i*-2)-th stage: D_{i-2}.
(7)The deflection of the observation point in the (*i*-3)-th stage: D_{i-3}.
One Output:
(1)The deflection of the observation point in *i*-th stage: D_i.

To prevent the absence of fifth to seventh inputs, *i* has to be greater than or equal to three. When *i*=3, the D_{i-3} is set as zero.

Eighteen historical cases from metropolitan Taipei, Taiwan were collected. These cases are listed in Table 1, which provide information on the number of excavation stages, excavation depth and construction method used (top-down or bottom-up). The number of stages in these cases varied from four to seven. As each stage was treated individually, these cases comprised 93 stages in total. Excluding the first and second stages of construction, 57 stages of valuable data were collected. The first seventeen construction cases, including 52 stages total, were used for training. The remaining five stages of the 18th case were employed in testing. Nineteen observation points were set, although excavation depths were not uniform. Therefore, 19 sets of data were collected in each stage. Based on the above, 52×19 = 988 training data sets and 5×19 = 95 testing data sets were collected.

Table 1. 18 Historical Excavation Projects in Metropolitan Taipei.

No.	Stages	Depth (m)	Construction method	No.	Stages	Depth (m)	Construction method
1	5	12.30	Top-down	10	6	14.05	Top-down
2	4	13.90	Bottom-up	11	4	13.60	Top-down
3	6	16.00	Top-down	12	5	17.35	Bottom-up
4	5	12.60	Top-down	13	5	13.15	Top-down
5	5	12.30	Top-down	14	5	23.85	Top-down
6	5	12.25	Top-down	15	6	19.40	Top-down
7	4	10.00	Top-down	16	6	19.40	Top-down
8	6	18.95	Top-down	17	5	13.70	Top-down
9	4	9.30	Top-down	18	7	19.70	Bottom-up

4. Comparison of Results

Training data (988 sets from 52 excavation stages) and testing data (95 sets from 5 excavation stages) were used to develop the EFNIM diaphragm wall deflection prediction system. The crossover rate was adopted as 0.9 and the mutation rate as 0.025. After training 11,000 generations, network interconnections numbered 31 and the RMSE equaled 3.794%. In Figure 4, the accuracy of maximum diaphragm wall displacements is demonstrated by comparing results with actual measurements and the average correlated coefficient (ACC) between the maximum predicted wall displacement and the maximum measured wall displacement (average of [predicted/measured]). $ACC_{training}$ equals 1.0077 and $ACC_{testing}$ equals 0.7943. Among the 52 training excavation stages, there were 28 cases with relative errors less than 10%; 13 cases with relative errors between 10% and 20%; and 11 cases with relative errors exceeding 20%. If we define the criterion of failed prediction as an error of maximum predicted displacement that exceeds 20%, then 10 of 52 can be considered to have failed in prediction, i.e., the accuracy of diaphragm wall deflection prediction using this model is 80.77%. The data of project No. 18 (the project reserved for use in testing data) and its 5 stages with 5×19=95 sets of testing data were calculated and, while the same criterion was taken, only 3 of the 5 were qualified. This gives an accuracy of prediction of 60%. While this result is still applicable, it is certainly not ideal. To sum up training and testing data results, 12 of 57 sets of results fail to meet the criterion, i.e. the model achieves an accuracy of 78.94%. This result is an improvement one than done by Jan et al., which used NNs only. In the following section, improvements will be applied to the prediction model to improve results even further.

The typical deep excavation project has many stages and the deflection observed in any given stage is highly correlated to deflection parameters in previous stages. Therefore, diaphragm wall deflection data from prior stages are important inputs to help predict the values of deflection variables in succeeding stages of an excavation project. As diaphragm deflections accumulate during an excavation, data from previous stages can be employed to predict deflection in the following stage with improved accuracy. Based on the above, project No. 18 data shown in Table 1 are treated as a new excavation project. In this project, the depth of the diaphragm wall is 35 meters and the total excavation depth is 19.7 meters. Seven excavation stages are adopted as follows: 1st stage: 2.8 meters; 2nd stage: 4.9 m; 3rd stage: 8.6 m; 4th stage: 11.8 m; 5th stage: 15.2 m; 6th stage: 17.3 m and 7th stage: 19.7 m. Monitored data from preceding stages can be adding into the training data as a new excavation project progresses from stage to stage. As long as the initial model had been trained, the mutation rate is reduced from 0.025 to 0.001, and 5000 iterations are adopted (reduced from 11,000) to economize on computational time.

For each excavation stage after the 2nd, data compiled from previous stages were added into the training data to present the individual characteristics of this particular project instantaneously. As shown in Table 2, errors have been greatly reduced and accuracy improved by this modified process. The modified process significantly improved $ACC_{testing}$ compared to the previous result (from 0.7943 to 0.9277). Detailed results on wall deflection at every stage are shown in Figure 5. According to the results, the improvement works due to the adding of previous stages' data from the current project. Such data may be highly related with the prediction target based on a project's discrete characteristics.

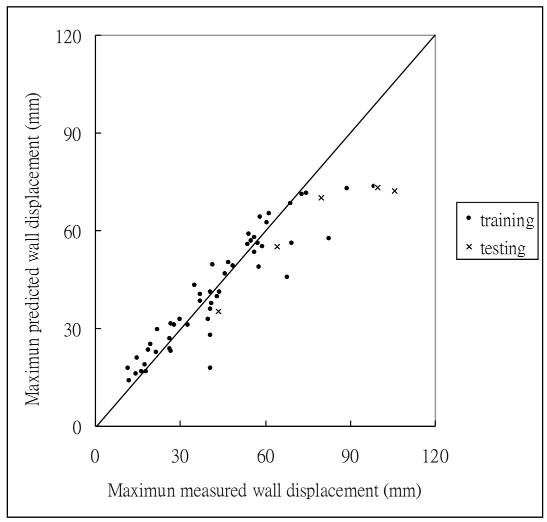

Figure 4. Measured vs. Predicted Maximum Diaphragm Wall Displacements

Table 2. Taxonomic distribution of species (G, Genus; S, Species)

Excavation stage	Measured Max. displacement (mm)	Predicted Max. displacement (mm)	Original Error (%)	Modified Max. displacement (mm)	Modified Error(%)
3rd	43.44	35.23	**18.90%**	51.16	**17.77%**
4th	64.34	55.26	**14.11%**	59.77	**7.10%**
5th	79.57	70.23	**11.74%**	68.19	**14.30%**
6th	99.64	73.33	**26.41%**	76.89	**22.83%**
7th	105.72	72.23	**31.68%**	95.47	**9.70%**

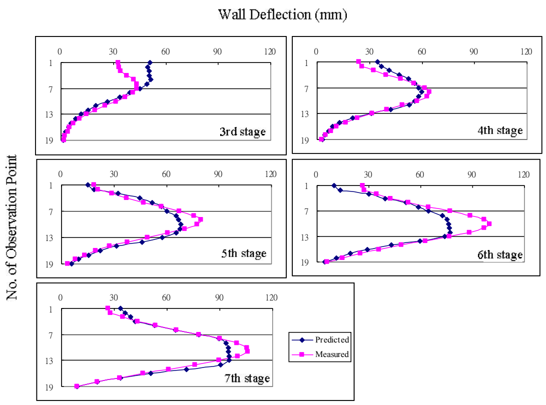

Figure 5. Wall Deflection Prediction Using the Modified Process

4. Discussions

In the EFNIM, FL handles soil parameter uncertainties; NNs form the complicated mapping relationships; and GAs handle global optimization for FL and NN parameters. As useful information is hidden within monitored data, the EFNIM may be employed to extract the critical effects of diaphragm wall deflection. Diaphragm wall deflection predictions not only employ historical case data, but also the data of previous stages in the training sets in order to reflect in-situ particularities. By applying EFNIM, a strict understanding of parameters or their effects is not required. The magnitude of deflection and the position where the maximum displacement occurs in deep excavation diaphragm walls can, therefore, be predicted to ensure safety during the construction process. Deflection in the embedded position can also be performed. This permits engineers to make highly accurate appraisals of the diaphragm wall structure prior to starting the next excavation stage.

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