Prediction of Diaphragm Wall Deflection in Deep Excavations Using Evolutionary Support Vector Machine Inference Model (ESIM)

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Abstract

Problems in deep excavations are full of uncertain, vague, and incomplete information. In most instances, successfully solving such problems depends on experts' knowledge and experience. The primary object of this research was to propose an "Evolutionary Support Vector Machine Inference Model (ESIM)" to predict wall deformation in deep excavation in Taipei Basin. ESIM is developed based on a hybrid approach that fuses support vector machines (SVM) and fast messy genetic algorithm (fmGA). SVM is primarily concerned with learning and curve fitting; and fmGA with optimization. Fifty-seven wall deformation monitoring database were collected based on monitoring data and compiled from prior projects. Fifty-two of 57 were selected for training, leaving 5 valid cases available for testing. Results show that ESIM can successfully predict the deflection and apply to contractors utilizes the knowledge and experience from past projects to predict wall deformation of new projects. Therefore the construction and foundation construction contractors can update wall deflection monitoring data of different stages during deep excavation process, in order to predict the wall deformation of the next stage and examine whether the max deflection is within the controlled range. The results are used as guidelines on site safety and risk management.
Keywords: SVM, fmGA, Diaphragm Wall; Excavation; Deflection

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.

However, these approaches presented several important difficulties which rendered them inadequate for general application. The construction industry is replete with myriad uncertainties that make management exceedingly complex. Various scientific and engineering specializations have been paying increasing attention in recent years to the fusing of different artificial intelligence (AI) paradigms to achieve greater efficacy in results. A number of studies have demonstrated that performances achieved by fusing different AI techniques are better than those achieved by employing a single conventional technique (Yang and Yau 2000). Fast messy genetic algorithms (fmGA) and the support vector machine (SVM) are two tools that have been applied successfully to solve various construction management problems. Considering the characteristics and merits of each, this paper combines the two to propose a new Evolutionary Support Vector Machine Inference Model (ESIM) (Cheng and Wu 2008). In the ESIM, the SVM is employed primarily to address learning and curve fitting, while fmGA addresses optimization. This model was developed to achieve the fittest C and gamma parameters with minimal prediction error. This study applied diaphragm wall deflection data previously compiled from 18 metropolitan Taipei projects to the ESIM to prediction result accuracy.

2. The Evolutionary Support Vector Machine Inference Model (ESIM)

Support vector machines and fast messy genetic algorithms represent recently developed AI paradigms. SVMs were first suggested by Vapnik (1995) and have recently been applied to a range of problems that include pattern recognition, bioinformatics, and text categorization. An SVM classifies data using different class labels by determining a set of support vectors that are members of the set of training inputs that outline a hyper plane in a feature space. It provides a generic mechanism that fits the hyper plane surface to the training data using a kernel function. The user may select a kernel function (e.g. linear, polynomial, or sigmoid) for the SVM during the training process, which identifies support vectors along the function surface. Using SVMs presents users with the problem of determining optimal kernel parameter settings. Therefore, obtaining SVM parameters must occur simultaneously. Proper parameter settings can improve SVM prediction accuracy, with parameters that should be optimized including penalty parameter C and kernel function parameters such as the gamma of the radial basis function (RBF) kernel. In designing an SVM, one must choose a kernel function, set kernel parameters and determine a soft margin constant C (penalty parameter). The Grid algorithm is an alternative to finding the best C and gamma when using the RBF kernel function. However, this method is time consuming and does not perform well (Hsu and Lin 2002; Huang, Wang 2006). Fast messy genetic algorithms were developed by Goldberg et al. in 1993. Unlike the well-known simple genetic algorithm (sGA), which uses fixed length strings to represent possible solutions, fmGA applies messy chromosomes to form strings of various lengths. Its ability to identify optimal solutions efficiently for large-scale permutation problems gives fmGA the potential to generate SVM parameters C and gamma simultaneously. Considering the characteristics and merits of each, this paper combined the two to propose an Evolutionary Support Vector Machine Inference Model (ESIM). In the ESIM, the SVM is employed primarily to address learning and curve fitting, while fmGA addresses optimization. This model was developed to achieve the fittest C and gamma parameters with minimal prediction error. ESIM structure is illustrated in Figure 1.

The following three steps must be followed to establish an accurate fmGA-based parameter optimization model:

(1) Establish an SVM training model. The SVM trains a prediction model using default parameters and a training dataset.

(2) Obtain average accuracy. A training dataset is used for each chromosome representing C and gamma to train the SVM and calculate accuracy. When said accuracy is obtained, each chromosome is evaluated using a fitness function.

(3) Set termination criteria. The process ends once termination criteria are satisfied. In the absence of such, the model will proceed to the next generation.

(4) Search fmGA parameters. The model searches for better solutions by genetic operations.

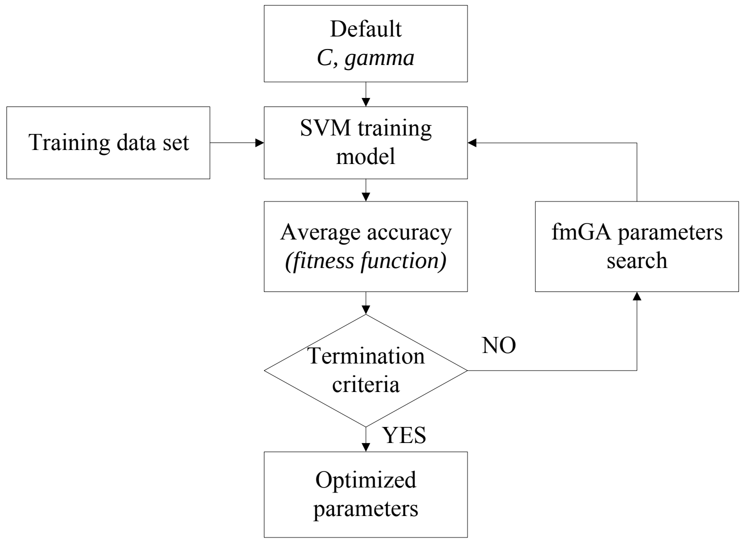

Figure 1. Structure of the ESIM.

3. ESIM for Predicting Diaphragm Wall Deflection

3.1 Knowledge Representation of Diaphragm Wall Deflection in Deep Excavation

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 ESIM 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 2, W represents diaphragm wall thickness; H 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:

Seven Inputs:

(1)Diaphragm wall thickness: *W*.

(2)Excavation depth: *H*.

(3)The equivalent SPT-N value between H+0.25He and H-0.25He: $\overline{N}$.

(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: $D_{i\text{-}1}$.

(6)The deflection of the observation point in the (i-2)-th stage: $D_{i\text{-}2}$.

(7)The deflection of the observation point in the (i-3)-th stage: $D_{i\text{-}3}$.

One Output:

(1)The deflection of the observation point in i-th stage: *Di*.

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

3.2 Historical cases

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.

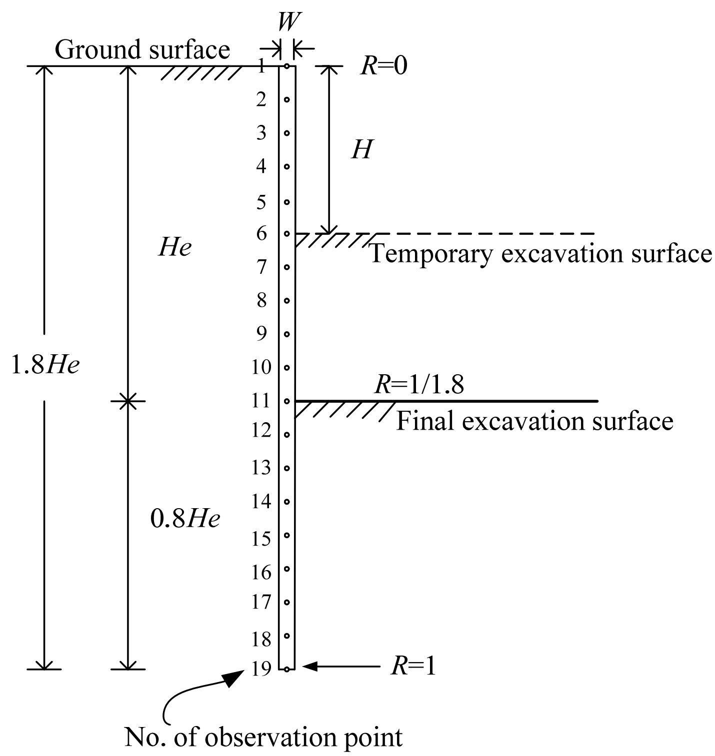

Figure 2. Representation of the Diaphragm Wall Structure

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 ESIM diaphragm wall deflection prediction system. After training, the RMSE (Root Mean Square Error) equaled 3.794%. In Figure 3, 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]). ACCtraining equals 0.8983 and ACCtesting equals 0.8898. Among the 52 training excavation stages, there were 28 cases with relative errors less than 10%; 12 cases with relative errors between 10% and 20%; and 12 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 12 of 52 can be considered to have failed in prediction, i.e., the accuracy of diaphragm wall deflection prediction using this model is 76.9%. 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, 5 of the 5 were qualified. This gives an accuracy of prediction of 100%. 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. In the following section, improvements will be applied to the prediction model to improve results even further.

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

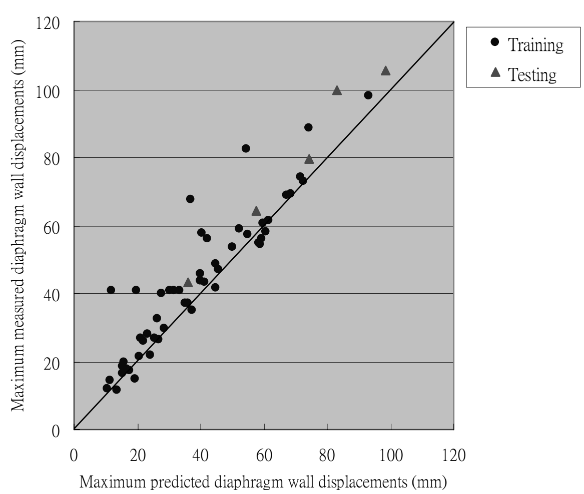

Figure 3. Measured vs. Predicted Maximum Diaphragm Wall Displacements.

4.1 An improvement for a new excavation project

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.

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 reduced and accuracy improved by this modified process. The modified process significant improved ACCtesting compared to the previous result (from 0.8898 to 0.8927). Detailed results on wall deflection at every stage are shown in Figure 4. 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.

Table 2. Results of the Modified Process Applied to the New Excavation Project

Excavation stage	Measured Max. displacement (mm)	Predicted Max. displacement (mm)	Original Error (%)	Modified Max. displacement (mm)	Modified Error(%)
3rd	43.44	35.84	**17.49**	35.84	**17.49**
4th	64.34	57.54	**10.57**	57.72	**10.29**
5th	79.57	73.88	**7.15**	73.89	**7.14**
6th	99.64	84.14	**15.56**	84.14	**15.56**
7th	105.72	101.14	**4.33**	102.42	**3.12**

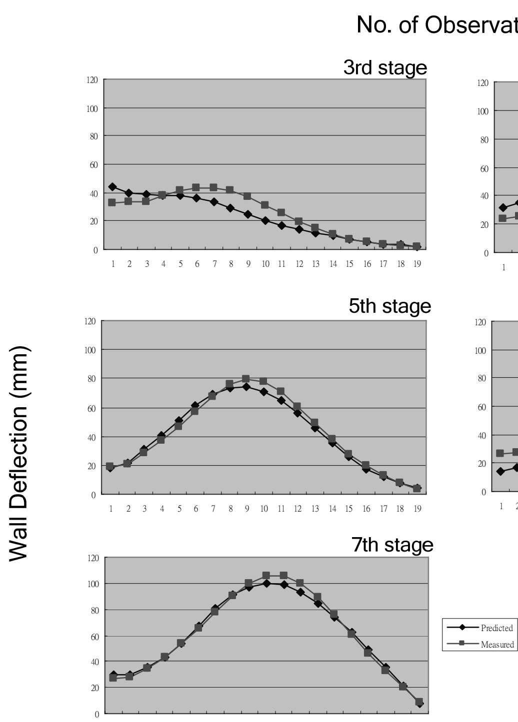

Figure 4. Wall Deflection Prediction Using the Modified Process

5. Conclusions

As useful information is hidden within monitored data, the ESIM 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 ESIM, 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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