Using the Artificial Neural Networks Methodology to Predict the Vertical Swelling Percentage of Expansive Clays

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Abstract: Regular use of artificial neural networks (ANN) analysis for predicting the vertical swelling percentage of expansive clays may lead to inappropriate results in terms of their geophysical behavior. This paper presents two new ANN Models derived from a two-stage procedure. The models were estimated using the same data set from the previous paper, and their statistical fit was clearly found to be superior in comparison to the previous models. Furthermore, one of these two models exhibited the expected geophysical behavior. As this new ANN Model yields higher predicted swelling-percentage values, it can definitely be regarded as a preferable one in the sense of enlarging the safety margin in heave calculations. **DOI:** 10.1061/(ASCE)MT.1943-5533.0000931.

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Introduction and Objectives

A predictive model for the vertical swell percentage of expansive clays is used as a tool to estimate one dimensional (1D) heaves in expansive clays. The technical literature lists several models, among which are (1) the new Israeli model, termed the W-Model in this paper and (2) the U.S. Corps of Engineers Model, called the CE-Model in this paper. A list of other vertical swell-percentage models can be found in U.S. Corps of Engineers (1983, 1990), Ortega et al. (2010), Vanapalli et al. (2010), and Vanapalli and Adam (2012), among others.

Both these predictive models for vertical swell percentage (i.e., the W-Model and the CE-Model) are based on local Israeli research. The W-Model has recently been updated by applying the Excel-Solver command (ESC) analysis to new local test results from 897 undisturbed specimens. As the goodness-of-fit statistics obtained in this analysis classify the associated regressions only as fair, it became essential to explore the possibility of enhancing the outputs of these two models by applying the artificial neural networks (ANN) methodology to the same 897 undisturbed specimens.

ANN models are used in many different areas because of their ability to learn and adapt to many different tasks, and to make complex predictions. These models were estimated in a previous paper written by the authors (Bekhor and Livneh 2013) and led to somewhat better goodness-of-fit statistics; however, their outputs were unacceptable in terms of their expected geophysical behavior. Therefore, there was still a need to enhance the accuracy of the prediction tools of the vertical swell percentage.

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The original formulations of the W-Model and the CE-Model are each based on a two-stage operation. The first stage of this operation consists of seeking the variation in the swelling pressure, i.e., the induced vertical pressure that leads to a zero vertical swelling percentage according to the ASTM 4546 Method C, with the indicative properties of clayey specimens, including their moisture content and density values. In the same manner, the second stage of this operation consists of seeking the final variation in the vertical swelling percentage with the induced vertical pressures for the same clayey specimens, which are governed in the first stage by variation in swelling pressures.

As a result of using the aforementioned two-stage operation in the original analyses, it seems logical to suggest the usage of a comparable two-stage operation for the development of new ANN Models based on the same 897 undisturbed clayey specimens. In light of all the foregoing, the objectives of this paper are as follows:

- On the basis of the ANN analysis of the swelling-pressure models, to develop the final vertical swelling percentage by utilizing the second stage of the ANN analysis.
- To compare the existing new Israeli set of W-Models and CE-Models with the set of the newly developed ANN models and to recommend the preferable swelling model for final, routine heave calculations.

This paper serves as a supplement to the authors' previous paper (Bekhor and Livneh 2013), which demonstrated that the regular use of ANN analysis for predicting the vertical swelling percentage of expansive clays may lead to inappropriate results in terms of their geophysical behavior.

Summary of Existing Regression-Based Models

Livneh (2012b), Bekhor and Livneh (2013), and Livneh (2013) used 897 undisturbed specimens to determine the direct dependence of vertical swelling, in percentage terms, on the following basic independent variables that characterize undisturbed clay specimens: liquid limit (LL) in percentage, plastic limit (PL) in percentage, moisture content (W) in percentage, dry density (γ) in kN/m^3, and applied vertical pressure (Pp) in kPa. The swelling tests themselves were conducted according to ASTM Designation

D 4546-06 (ASTM 2011), and the determination was performed with the Excel-Solver command (ESC), utilizing (1) the first Israeli general swelling-pressure model, which was arrived at in Komornik and David (1969) by conducting linear multiple regressions on 125 undisturbed specimens; and (2) the basic vertical swelling model given in Wiseman et al. (1985) after a series of empirical relationships reported in the technical literature, including that of McDowell (1956), was analyzed (although no verification was received from local laboratory tests). This set of models is termed the W-Models to denote their basic formulation following Wiseman et al. (1985).

In the same manner, the aforementioned 897 undisturbed specimens were used by Livneh (2013) to determine the direct dependence of vertical swelling, in percentage terms, on the basic independent variables that characterize undisturbed clay specimens by following the formulation of another existing model, that of the U.S. Corps of Engineers (termed the CE-Model). This was done, again, by applying the ESC analysis to the 897 local test results. To sum up, the existing ESC equations are the following:

$$\text{For both the W-Models and the CE-Models: } \log(\text{Po}/98.07) = a_0 + a_1 \times X_1 + a_2 \times X_2 + a_3 \times \gamma/9.81 \quad (1)$$

$$\text{For the W-Models only: Sp} = a_4 \times (\text{Po}/98.07) \times \log(\text{Pp}/\text{Po}) \quad (2)$$

$$\text{For the CE-Models only: Sp} = (b_0 + b_1 \times X_1 + b_2 \times X_2 + b_3 \times \gamma/9.81) \times \log(\text{Po}/\text{Pp})/(1+e) \quad (3)$$

In Eqs. (1)–(3), Po denotes the swelling pressure in kPa; Sp denotes the vertical swelling percentage; Pp denotes the induced vertical pressure in kPa; γ denotes the dry density of the clayey specimen in kN/m^3; X_i (where $i = 1$ and 2) denotes an additional independent variable (i.e., W in percentage or W/PL, where PL is the plasticity limit in percentage, and LL or log(LL), where LL is the liquid limit in percentage); a_i (where $i = 0$, 1, 2, 3, and 4) and b_i (where $i = 0$, 1, 2 and 3) denote the regression coefficient obtained from the ESC analysis; and, finally, e denotes the void ratio of the clayey specimen. The values the aforementioned regression coefficients are given in the previous paper (Bekhor and Livneh 2013).

Proposed Methodology

In the data mining literature, it is common to include additional variables, or a transformation of these variables, in multistage analysis. For example, Lu et al. (2006) developed a two-stage neural network that they used to predict ozone concentrations from meteorological conditions. Ahmed and Farag (1997) developed a two-stage neural network for the volume segmentation of medical images. In both examples, some variables were used in both stages. Following this approach, ANN methods were applied to model swelling pressure by testing different explanatory variables in a single stage. The present paper mimics the regression approach in performing a two-stage analysis in an attempt to obtain both a good statistical fit and the expected geophysical behavior.

First-Stage Analysis for Po

For the swelling-pressure (Po) analysis, the number of available undisturbed specimens of the total of 897 undisturbed specimens, the testing procedure for which dictated the vertical swelling percentage to be kept at zero [i.e., with the application of the ASTM 4546 Method C testing procedure (ASTM 2011)] was 341. The results of the direct linear regression analysis of these 341 undisturbed specimens as formulated by Eq. (1) are given in Table 1 (Livneh 2012a). These regression results are termed the direct linear regression (DLR) models in this paper. Here, it is worthwhile noting that a similar R^2 value of Table 1 has been reached by Komornik and David (1969) for their linear multiple regression on 125 undisturbed specimens (0.360).

Table 1 indicates that in terms of the correlation criterion. Both DLR models can be categorized as a poor correlation product. Thus, they are definitely very questionable for prediction uses. To enhance the goodness-of-fit statistics of Table 1, it has been previously suggested that the ANN methodology be implemented with the 341 undisturbed specimens. To recall, ANN models are computational methodologies that perform multifactorial analyses. These models contain layers of simple computing nodes that operate as summing devices. The nodes are richly interconnected through weighted connection lines, and the weights are adjusted when data are presented to the network during a so-called *training* process. Successful training can result in an ANN that performs such tasks as predicting output value, classifying an object, approximating a function, recognizing a pattern in multifactorial data, and completing a known pattern. Many ANN applications have been reported in different fields. Specifically, several authors employed ANN for estimating swelling percentage and swelling pressure (Najjar et al. 2000; Ersin and Güneş 2011). The use of neural networks is considered by some to be much easier than incorporating regression techniques because, as previously discussed, there is no need to specify the type of functions that present the relationships among the various parameters involved (Najjar et al. 2000).

Similar to other studies in geotechnical engineering, the present study has modeled the determination of swelling pressure by using back-propagation network architecture. The term *back-propagation network* refers to a multilayered, feed-forward neural network, using an error back-propagation algorithm. The Levenberg-Marquardt back-propagation learning algorithm in the Matlab environment was used to train the network.

The outcome of this ANN analysis is given in Table 2. Similar to Table 1, Table 2 summarizes the goodness-of-fit statistics for the first stage of the two ANN models. Overall, the ANN models produced a better fit than did the DLR models. In contrast to the DLR findings, model W-2 seems to be the better of the two W-Models, with a correlation rating in the middle range of the so-called *good criterion*.

Table 1. Summary of the Regression Coefficients of Eq. (2) and the Goodness-of-Fit Statistics of SE/SY, R^2, and Adjusted R^2 for the DLR Models

Model number	X_1	X_2	a_0	a_1	a_2	a_3	SE/SY	R^2	Adjusted R^2
W-1	LL	W	−2.525	0.023	−0.019	0.898	0.785	0.389	0.384
W-2	log(LL)	W/PL	−6.427	2.594	−0.208	1.215	0.816	0.340	0.334

Table 2. Summary of the Goodness-of-Fit Statistics of SE/SY, R^2, and Adjusted R^2 for the First-Stage ANN Models

Model number	X_1	X_2	SE/SY	R^2	Adjusted R^2
W-1	LL	W	0.498	0.755	0.750
W-2	log(LL)	W/PL	0.454	0.797	0.793

Table 3. Summary of the Goodness-of-Fit Statistics of SE/SY, R^2, and Adjusted R^2 for the Second- Stage ANN Models

Model number	X_1	X_2	SE/SY	R^2	Adjusted R^2
WCE-1	LL	W	0.515	0.735	0.732
WCE-2	log(LL)	W/PL	0.449	0.751	0.748

Second Stage Analysis for Sp

The second stage of the analysis involves an estimation of the vertical swelling percentage Sp for given values of Pp and Po (obtained from the first stage). The simplest way to do this is to use Eq. (2) with a single parameter to estimate. However, after several tries, no satisfactory models were estimated, both in terms of statistical fit and geophysical swelling behavior. Therefore, additional variables were included in the estimation of Sp in an attempt to better explain the variance.

Several combinations of variables were tested, similar to Eq. (3). The best combinations found were (1) model W-1 with model CE-1, and (2) model W-2 with model CE-2. The following explanatory variables were used for the second stage: W, LL, γ, and Po $\times$ log(Pp/Po) for model 1; and W/PL, log(LL), γ, and Po $\times$ log(Pp/Po) for model 2. In both models, Po was calculated from the first stage.

The outcome of the second stage ANN analysis is given in Table 3. Similar to Tables 2 and 3, it summarizes the goodness-of-fit statistics for the two second-stage ANN models. Overall, the ANN models produced a better fit than did the ESC models, i.e., Eqs. (1)–(3). Model WCE-2 seems to be the best. These goodness-of-fit statistics are better than those achieved by the previous, straight ANN analysis of the given 897 undisturbed specimens (as described in Bekhor and Livneh 2013), i.e., $R^2 = 0.695$ for the ANN W-1 model and $R^2 = 0.671$ for the ANN W-2 model.

Now, it is necessary to check the geophysical validity of the two models, ANN WCE-1 and ANN WCE-2. In addition, it would be interesting to compare the predicted swelling curves according to these two sets of models. Fig. 1 shows the predicted vertical swelling Sp as a function of the vertical pressure Pp, given the assumption that γ equals $14.7\ \mathrm{kN/m^3}$ and W/PL equals 0.8 [Fig. 1(a)] and 1.0 [Fig. 1(b)]. In Fig. 2, the curves are computed for γ equals $16.7\ \mathrm{kN/m^3}$ and W/PL equals, again, 0.8 [Fig. 2(a)] and 1.0 [Fig. 2(b)].

Figs. 1(a and b) and 2(a and b) indicate that the second-stage ANN WCE-1 model exhibits the necessary geophysical mode of variation in the predicted vertical swelling percentage with vertical pressure. This is true in both the absolute sense, for which higher vertical pressure values should always lead to lower predicted swelling-pressure values, and in the relative sense, for which higher liquid-limit values or lower moisture-content values or higher density values should always lead to higher predicted swelling-pressure values, when the vertical pressure is kept the same.

In contrast, Figs. 1(a and b) and 2(a and b) do not indicate that the second-stage ANN WCE-2 model exhibits the necessary geophysical mode of variation in predicted swelling pressure with the variation in vertical pressure. For the liquid-limit lines of 90%, the Po value obtained is almost infinite, and for the 50% lines, an inconsistent variation exists in both the absolute and the relative senses. In general, the Po derived from these figures are different from those derived in the first stage of the ANN analysis.

For moderate and high values of liquid limits, the swelling percentage derived from the second-stage ANN WCE-1 model is higher than that derived from the ESC W-1 model or the ESC CE-1 model. Figs. 3(a and b) show the variation in the ratio of predicted vertical swelling derived from ANN WCE-1 to that derived from ESC W-1, with the variation in vertical pressure for (a) $\gamma = 14.7\ \mathrm{kN/m^3}$ and for (b) $\gamma = 16.7\ \mathrm{kN/m^3}$. These figures indicate that these ratio values can sometimes be very far from the value of one. The lines in these figures represent (1) only positive values of predicted Sp as obtained from the two models under discussion, (2) Sp values are higher than 0.5% as obtained from the ANN WCE-1 model, and (3) the range of Pp starts from the minimum practical in situ value of 30 kPa. For the Pp range in which the previous ratio is less than one, its relevant predicted Sp values are small.

Finally, as a result of the previously discussed findings, it is important to emphasize that although the second-stage ANN WCE-1

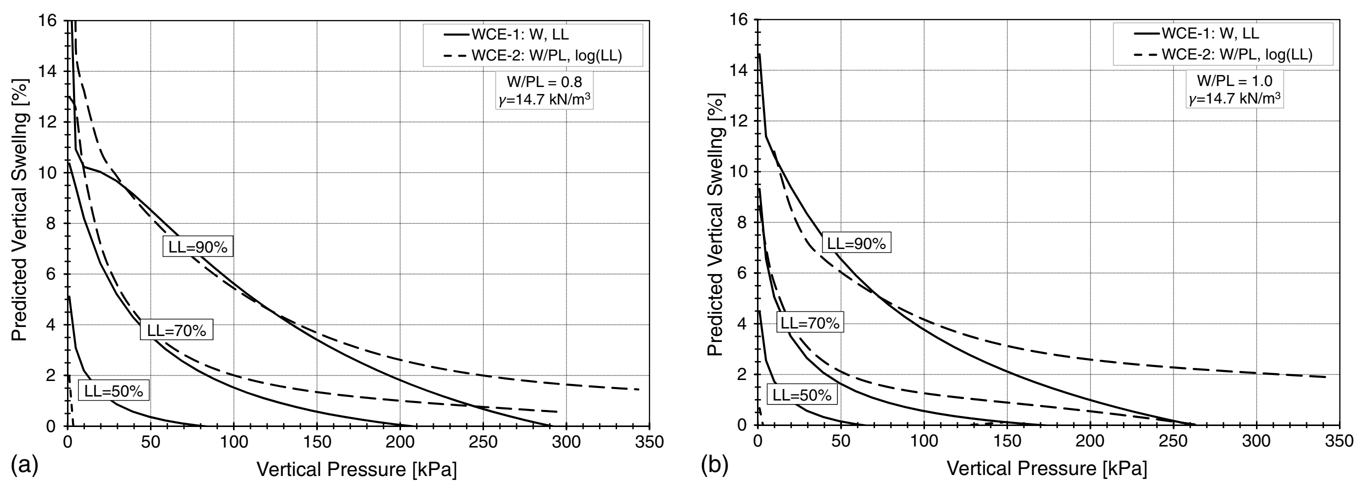

Fig. 1. Predicted vertical swelling versus vertical pressure for $\gamma = 14.7\ \mathrm{kN/m^3}$ obtained from second-stage ANN models WCE-1 and WCE-2 for (a) W/PL = 0.8; (b) W/PL = 1.0

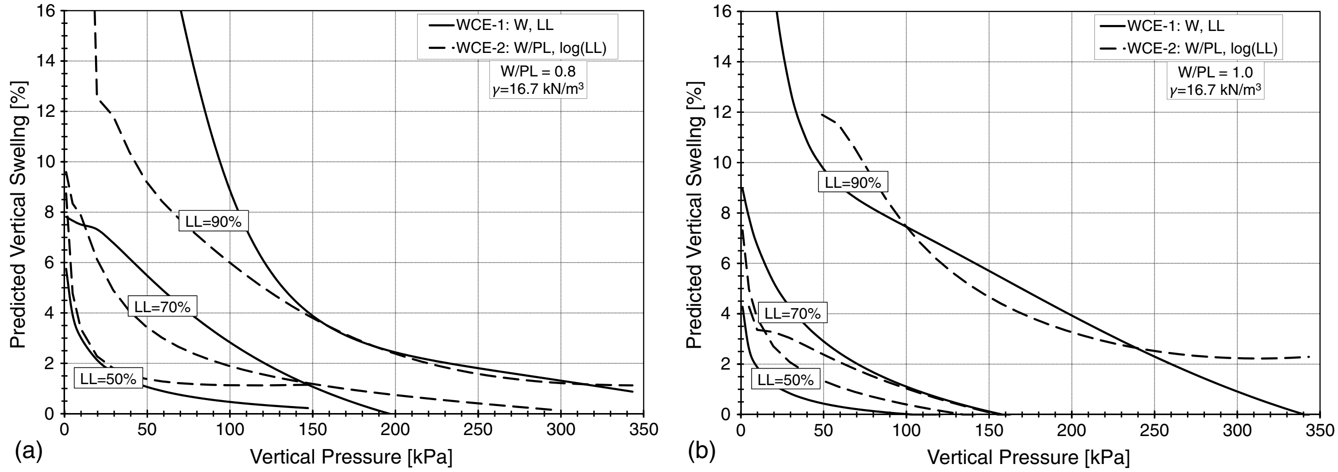

Fig. 2. Predicted vertical swelling versus vertical pressure for $\gamma = 16.7\ \mathrm{kN/m^3}$ as obtained from second-stage ANN models WCE-1 and WCE-2 for (a) $\mathrm{W/PL} = 0.8$; (b) $\mathrm{W/PL} = 1.0$

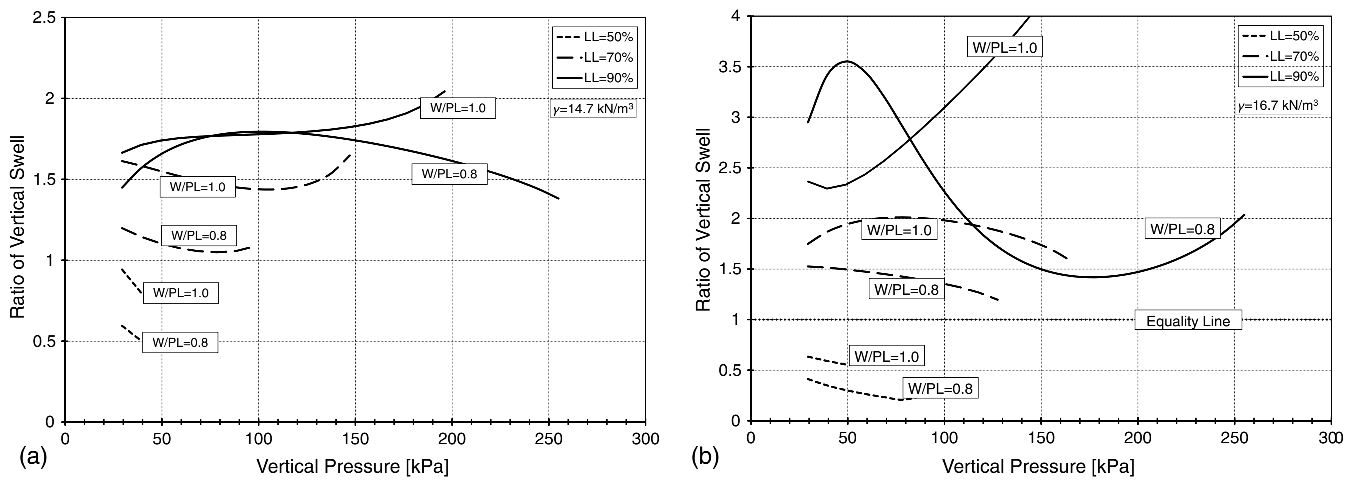

Fig. 3. Ratio of predicted vertical swelling, ANN WCE-1 model to ESC W-1 model, versus vertical pressure for (a) $\gamma = 14.7\ \mathrm{kN/m^3}$; (b) $\gamma = 16.7\ \mathrm{kN/m^3}$

model yields a lower value for the coefficient of determination than that does the second-stage ANN WCE-2 model (Table 3), the former is to be preferred for routine prediction purposes. Consequently, the recommendation given in a previous publication (Bekhor and Livneh 2013) for the use of one-stage ESC models should be replaced by the recommendation given in the present paper.

Summary and Conclusions

To improve the prediction accuracy of statistical models given in a previous paper by the authors (Bekhor and Livneh 2013), neural networks were implemented to develop a more reliable and robust methodology for assessing swelling potential. The ANN methodology applied in the previous paper is similar to that in geotechnical engineering studies. Different models were tested, using the same database formed by 897 field specimens. The statistical fit of the ANN models are clearly superior to the ESC models. However, in terms of the required geophysical behavior, the ANN models did not predict swelling-percentage values and ESC models did, in particular when it came to values whose range was near (or outside) the data set boundaries.

As a result of the authors' previous findings, an additional alternative ANN analysis of these 897 local test results was carried out in this paper. This alternative analysis was based on the following two-stage operation: (1) conducting an ANN analysis of the swelling-pressure tests results (i.e., the ASTM 4546 Method C test results) to obtain the swelling-pressure model for any given clay characteristics; (2) performing an additional ANN analysis of the swelling-percentage test results [i.e., the ASTM 4546 Method B test results [ASTM 2011)], including the former ones, with the given independent variables of the clay characteristics. The latter involves a defined expression containing the given surcharge pressure and the predicted value of the swelling pressure as obtained from the model of the previous stage.

The statistical fit of two final ANN models derived in this two-stage procedure was clearly found to be better than all the previous models reported previously by the authors. Also, in sense of the expected geophysical behavior, one of these two models, i.e., the ANN WCE-1 model was found to be very much acceptable. As this new ANN model yields higher predicted swelling-percentage values compared with ESC W-1 model or ESC CE-1 model, it can definitely be regarded as preferable for predicting the swelling-percentage values of a given clay based on its geophysical characteristics, namely liquid limit, plasticity limit, in situ moisture content in situ density and induced vertical pressure. This conclusion derives from the sense of enlarging the safety margin in heave calculations.

Finally, mention should be made of the fact that different regression models and different methods of data analysis lead to different end results, so far as the required predicted values are concerned. The differences in these end results may sometimes be very critical as demonstrated by the preferred ANN WCE-1 model. The present study demonstrates the fact that higher values of coefficient of determination do not always indicate the achievement of a better statistical model. What is more essential is the achievement of a statistical model that complies with the geophysical behavior of the swelling process of the clay. To this end, effort should always be made to seek nonroutine ways of analysis as was done in the present paper.

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