Prediction of the Vertical Swelling Percentage of Expansive Clays Using a Two-Stage Artificial Neural Networks Methodology

Shlomo Bekhor[1]* and Moshe Livneh[2]

Abstract: Artificial Neural Networks (ANN), which are used in many different areas, have been applied to predict the vertical swelling percentage of expansive clays. In contrast to previous models that estimated ANN Models in a single phase, this paper proposes an alternative analysis in based on the following two-stage operation: (a) conducting an ANN analysis on the swelling-pressure test results (i.e., the ASTM 4546 Method C test results) to obtain the swelling- pressure model for any given clay characteristics; (b) performing an additional ANN analysis on the swelling-percentage test results (i.e., the ASTM 4546 Method B test results), including the former ones, with the given independent variables of the clay characteristics. This second stage includes 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. Two final ANN Models, each with a different arrangement of the given independent variables, were derived from this two-stage procedure. Their statistical fit was clearly found to be superior in comparison to previous models estimated with the same data set. 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.

Key words: Expansive clay, goodness-of-fit statistics, neural network, prediction, swelling model.

* Corresponding author

[1] Associate Professor, Faculty of Civil and Environmental Engineering, Technion-Israel Institute of Technology. E-mail: sbekhor@tx.technion.ac.il

[2] Professor Emeritus, Faculty of Civil and Environmental Engineering, Technion-Israel Institute of Technology. E-mail: moshliv@tx.technion.ac.il

1. Introduction and Objectives

A predictive model for the vertical swell percentage of expansive clays is used as a tool to estimate 1-D heaves in expansive clays. The technical literature lists several models, among which are (a) the new Israeli model, termed in this paper the W-Model; and (b) the U.S. Corps of Engineers Model, termed in this paper the CE-Model. A list of other vertical swell-percentage models can be found in [1-5], among others. The outputs of the W- and CE-Models are compared in this paper with the predictive models developed in the present paper.

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. This updating operation follows a previous one conducted by the second author for 352 undisturbed specimens existing at that time [6]. As the goodness-of-fit statistics obtained in the second analysis (on the 897 undisturbed specimens) 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, as well as to make complex predictions. These models were estimated in a previous paper written by the authors [7] in a single-stage approach, as performed in common practice of ANN model estimation, 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. This is done in the present paper by applying a two-stage analysis using ANN methodology.

As previously mentioned, the present 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 [5]--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 two-stage operation in ESC 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:

- To present a summary of the latest available local (Israeli) set of predictive models for vertical swell percentage (i.e., the W-Model and the CE-Model) derived by applying the ESC analysis to new test results (the 897 undisturbed specimens).
- To develop a set of swelling-pressure models based on the original W-Models or CE-Models by applying the multi-variable linear regression analysis to the results of 341 of the total 897 undisturbed specimens for which the vertical swelling percentage was kept at zero.
- To develop a set of swelling-pressure models based on the original W-Models or the CE-Models by applying the ANN analysis to the local test results of the aforementioned 341 undisturbed specimens and comparing their outputs with those of the multi-variable linear regression.
- Based on the above 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 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.

The sections to follow will detail the process of attaining these five objectives and then present associated conclusions. In addition, the present paper serves as a supplement to the authors' previous one [7], 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. The main contribution of the present paper is the development of the two-stage ANN methodology to obtain swelling models that exhibit good statistical fit and also the expected geophysical behavior.

2. Summary of Existing Regression-Based Models

Previous studies [7-9] 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 (D) in kN/m^3, and applied vertical pressure (Pp) in kPa. The swelling tests themselves were conducted according to ASTM Designation D 4548-08 [5], and the determination was performed with the Excel-Solver command (ESC), utilizing (a) the first Israeli general swelling-pressure model, which was arrived at in [10] by conducting linear multiple regressions on 125 undisturbed specimens; (b) the basic vertical swelling model given in Wiseman et al.[11] after a series of empirical relationships reported in the technical literature, including that of McDowell [12], was analyzed (though no verification was received from local laboratory tests). This set of models is termed the W-Models to denote their basic formulation following [11].

In the same manner, the aforementioned 897 undisturbed specimens were used by Livneh [9] 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:

For both the W-Models and the CE-Models:

$$\log(Po/98.07)=a_0+a_1\times X_1+a_2\times X_2+a_3\times D/9.81 \quad (1)$$

For the W-Models only:

$$Sp=a_4\times(Po/98.07)\times\log(Pp/Po) \quad (2)$$

For the CE-Models only:

$$Sp=(b_0+b_1\times X_1+b_2\times X_2+b_3\times D/9.81)\times\log(Po/Pp)/(1+e) \quad (3)$$

In Equations 1, 2 and 3, Po denotes the swelling pressure in kPa; Sp denotes the vertical swelling percentage; Pp denotes the induced vertical pressure in kPa; D 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. Table 1, as reproduced from Bekhor and Livneh [7] and Livneh [9], contains (a) the various expressions for two specified arrangements of X_i; and (b) the a_i and b_i values for each of these two specified arrangements.

[Table 1 here]

The goodness-of-fit statistics for Equations 1, 2 and 3 are defined from the well-known equations for determining SE/SY, R^2 and Adjusted R^2. To recall, SE denotes the standard error of the Sp prediction (i.e., standard deviation of error), SY denotes the standard deviation of the measured Sp from its mean value, R^2 denotes the coefficient of determination of the given specified regression and adjusted R^2 denotes the adjusted coefficient of determination of the same given specified regression.

Note that the adjusted R^2 is used to compensate for the addition of variables to the model. As more independent variables are added to the regression model, the unadjusted R^2 will generally increase, but there will never be a decrease. The unadjusted R^2 will increase even when the additional variables do little to help explain the dependent variable. To compensate for this increase, the adjusted R^2 is corrected for the number of independent variables in the model. The result is an adjusted R^2 that can go up or down, depending on whether the addition of another variable adds or does not add to the explanatory power of the model. Therefore, it has become standard practice to report the adjusted R^2, especially when there are multiple models with varying numbers of independent variables. Finally, the adjusted R^2 will always be lower than the unadjusted R^2.

Now, the goodness-of-fit statistics yielded for the regression analyses outputs of Table 1 are given in Table 2. They indicate, as similarly shown by Ceylan et al.[13], how the prediction-accuracy level of a given predictive model varies with the change in independent variables. Table 2 also shows that the best values in terms of goodness-of-fit are those associated with Model CE-1. However, in terms of the correlation criterion specified in Table 3, Model CE-1 can be categorized only as a "fair" correlation product [14]. The second-best model in terms of goodness-of-fit is Model W-2, while Model W-1 is the worst and Model CE-2 the second worst.

[Table 2 here]

[Table 3 here]

Now, it is interesting to compare the predicted swelling curves according to the above two sets of models, based on 897 undisturbed specimens. For the W-1 and the W-2 Models, this comparison is shown, first, in Figure 1, where the following cases of W/PL and D are applied: (a) 0.8 and $1.5\times9.81=14.7$ kN/m^3; (b) 1.0 and 14.7 kN/m^3. In Figure 2, the following cases of W/PL and D are applied: (a) 0.8 and $1.7\times9.81=16.7$ kN/m^3; (b) 1.0 and 16.7 kN/m^3. These two figures indicate that the differences among their solutions for the 897 undisturbed specimens are practically negligible for LL=50% and LL=70%. However, for L=90%, the ESC Model of W-2 leads for the majority of cases to higher Sp values than those of the ESC Model of W-1.

[Figure 1 here]

[Figure 2 here]

[Figure 3 here]

As for the CE-1 and CE-2 ESC Models, the above-mentioned comparison is shown in Figure 3, where again the following cases of W/PL and D are applied: (a) 0.8 and $1.5\times9.81=14.7$ kN/m^3, (b) 1.0 and 14.7 kN/m^3; and in Figure 4, where again the following cases of W/PL and D are applied: (a) 0.8 and $1.7\times9.81=16.7$ kN/m3, (b) 1.0 and 16.7 kN/m^3. These two figures indicate that the differences among their solutions for the 897 undisturbed specimens are practically negligible for all three LL values. In addition, a comparison of the W ESC Models (Figures 1 and 2) with the CE ESC Models (Figures 3 and 4) leads to the conclusion that the W Sp and the CE Sp values are almost the same, but that the CE Po values are higher than those of W Po when D=16.7 kN/m^3.

[Figure 4 here]

Finally, it is worthwhile mentioning that additional solutions of ESC Models are given in [7] and [9]. These other models are not shown here, as their results are very similar to those presented in the four figures above.

3. Proposed Methodology

In the data-mining literature, it is common to include additional variables, or a transformation of these variables, in multi-stage analysis. For example, Lu et al.[15] developed a two-stage neural network that they used to predict ozone concentrations from meteorological conditions. Ahmed and Farag [16] 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. Figure 5 presents a diagram of the proposed approach.

[Figure 5 here]

3.1 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) was 341. The results of the direct linear regression analysis of these 341 undisturbed specimens as formulated by Equation 1 are given in Table 4 [17]. These regression results are termed the DLR Models in this paper. Here, it is worthwhile noting that a similar R^2 value of Table 4 has been reached by Komornik and David [10] for their linear multiple regression on 125 undisturbed specimens (0.360).

[Table 4 here]

Table 4 indicates that in terms of the correlation criterion specified in Table 3, both DLR Models can be categorized as a "poor" correlation product. Thus, they are definitely very questionable for prediction uses. In addition, Figure 6, which presents the predicted swelling pressure versus the ratio of moisture content to plasticity limit obtained from these two DLR Models, indicates that the two solutions are almost the same, but yield lower Po values than those obtained from Figures 1a and 1b, both for D=14.7 kN/m^3, and higher Po values than those obtained from Figures 2a and 2b, both for D=16.7 kN/m^3, but only for LL=90%. As for Figures 3a and 3b, both of them for D=14.7 kN/m3, again lower Po values are obtained for Figure 6a than for those two figures. Finally, in regard to Figures 4a and 4b, both for D=16.7 kN/m^3, lower Po values are obtained for Figure 6b than for those figures, but only for LL=90%.

[Figure 6 here]

More important, however, is that Figures 6a and 6b lead to the conclusion that the variation in the predicted swelling pressure with the variation in moisture content is more pronounced with the outputs of the DLR W-1 Model. As this type of variation complies with the geophysical behavior of the clay, this model can be regarded as preferable. This conclusion complies with the fact that the R^2 value of the DLR W-1 Model is somewhat higher than that of the DLR W-2 Model.

In order to enhance the goodness-of-fit statistics of Table 4, 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 "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 [18, 19]. The use of neural networks is considered by some to be much easier than incorporating regression techniques because, as previously mentioned, there is no need to specify the type of functions that present the relationships among the various parameters involved [18].

Similar to other studies in geophysical 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 multi-layered, 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 5. Similar to Table 4, Table 5 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. Note that 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 "good" criterion. (see Table 3).

[Table 5 here]

To illustrate the predicted results provided by the ANN analysis of Table 5, Figure 7 depicts the predicted swelling pressure versus the ratio of moisture content to plasticity limit for (a) D=14.7 kN/m^3 and (b) D=16.7 kN/m^3 as obtained from the first stage of ANN Models W-1 and W-2. This figure indicates that, similar to Figure 6, the variation in the predicted swelling pressure with the variation in moisture content is more pronounced with the outputs of the first stage of the ANN W-1 Model. Again, as this type of variation complies with the geophysical behavior of the clay, this latter model can be regarded as preferable, although its R^2 value is somewhat lower than that of the first stage of the ANN W-2 Model (see Table 5).

[Figure 7 here]

It should be noted at this point that another check of the geophysical validity of the outputs given in Figure 7 should be made by comparing the predicted swelling-pressure values of Figure 7a with those of Figure 6b. This comparison shows, as expected, that for a higher density rate and the same moisture content, the predicted swelling pressure is higher. However, the variation in the LL=90% of Figure 7b seems to lead to unexpectedly high swelling-pressure values compared to those of Figure 6b. Inspection of the dataset reveals that there are relatively few observations for high swelling-pressure values. In accordance with the literature, data-mining models perform when there are sufficient observations for the training phase. Most observations were extracted for lower swelling pressure, and therefore the application of the model is an extrapolation of the results rather than an interpolation.

3.2 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 Equation 2 with a single parameter to estimate. However, after several tries, no satisfactory models were estimated, both in terms of statistical fit and physical 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 Equation 3. The best combinations found were (a) Model W-1 with Model CE-1 and (b) Model W-2 with Model CE-2. The following explanatory variables were used for the second stage: W, LL, D, and Po×log(Pp/Po) for Model 1; and W/PL, log(LL), D, and Po×log(Pp/Po) for Model 2. In both models, Po was calculated from the first stage.

At this juncture, it is important to mention that 12 observations were excluded from the training phase of the second stage because the Po values calculated according to the first-stage ANN Model were negative.

The outcome of the second stage ANN analysis is given in Table 6. Similar to Tables 4 and 5, Table 6 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., Equations 1, 2, and 3. Note that Model WCE-2 seems to be the best, with a correlation rating in the middle range of the "good" criterion (see Table 3). It should be noted, furthermore, that 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 [7]); i.e., R^2=0.695 for the ANN W-1 Model and R^2=0.671 for the ANN W-2 Model.

[Table 6 here]

To illustrate the statistical results provided in Table 6, Figure 8 compares the predicted ANN Sp values with the measured Sp values of the 897 observations. This figure also summarizes the overall Sp value bias statistics for the two models. The unconstrained trend lines all have a positive intercept, ranging between 0.378% for the ANN WCE-1 Model and 0.438% for the ANN WCE-2 Model. In partial compensation, the slope values of the unconstrained trend are all less than 1, ranging from 0.731 for ANN WCE-1 to 0.795 for ANN WCE-2. Overall, ANN WCE-1 exhibits the smallest prediction bias. Furthermore, when the goodness of-fit-statistics given in Table 6 are compared with those in Table 2, the two ANN Models comply with the good correlation criterion. This finding indicates that implementation of the ANN methodology really enhances the accuracy of the swelling models derived from the 897 undisturbed specimens.

[Figure 8 here]

The performance of the ANN models was also checked by calculating the distribution of the Scaled Percent Error (SPE). This measure is defined as the difference between the predicted and observed swelling pressures divided by the range of the observed swelling pressure. In the 897 undisturbed specimens, the swelling pressure ranges between -2.2 and 27.1, so the denominator is equal to 29.3.

Kanibir et al. [20] suggested that a good model should provide predictions within ±10% SPE. Table 7 shows the distribution of the SPE for both ANN models developed in this paper.

[Table 7 here]

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. Figures 9 and 10 are constructed, respectively, in a similar manner to Figures 1 and 2 or Figures 3 and 4. Figure 9 shows the predicted vertical swelling Sp as a function of the vertical pressure Pp, given the assumption that D equals 14.7 kN/m^3 and W/PL equals 0.8 (Figure 9a) and 1.0 (Figure 9b). In Figure 10, the curves are computed for D equals 16.7 kN/m^3 and W/PL equals, again, 0.8 (Figure 10a) and 1.0 (Figure 10b).

[Figure 9 here]

Figures 9a, 9b, 10a and 10b 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.

[Figure 10 here]

[Figure 11 here]

On the other hand, Figures 9a, 9b, 10a and 10b 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. Note that in general, the Po derived from these figures are different from those derived in the first stage of the ANN analysis; i.e., from Figure 7.

At this juncture, it is important to note that 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. Figures 11a and 11b 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) D=14.7 kN/m^3 and for (b) D=16.7 kN/m^3. These figures indicate that these ratio values can sometimes be very far from the value of 1. Note that the lines in these figures represent (a) only positive values of predicted Sp as obtained from the two models under discussion, (b) Sp values are higher than 0.5% as obtained from the ANN WCE-1 Model, and (c) the range of Pp starts from the minimum practical in-situ value of 30 kPa. For the Pp range in which the above ratio is less than 1, its relevant predicted Sp values are small.

Finally, as a result of the above findings, it is important to emphasize that although the second-stage ANN WCE-1 Model yields a lower value for the coefficient of determination than that does the second-stage ANN WCE-2 Model (see Table 6), the former is to be preferred for routine prediction purposes. Consequently, the recommendation given in a previous publication [7] for the use of one-stage ESC Models should be replaced by the recommendation given in the present paper.

5. Discussion of the Best Model

The significant outcome from the previous sections of this paper is the remarkable influence of the choice of regression model on the final predicted values. This choice constitutes the most important decision in the analyzing procedure. As pointed out in the literature, and specifically for estimating swelling pressure and vertical swelling percentage [7], statistical fit is not the only criterion for choosing the best model. Thus, variable selection plays a crucial role here, since there is no single procedure or model that fits all needs.

This paper used well-known statistical techniques to analyze vertical swelling percentage of expansive clays, namely regression analysis and artificial neural networks. Regression analysis requires a priori assumption of the functional form of the independent variables, while ANN provides greater flexibility with respect to variable selection. However, the application of ANN Models cannot be performed in a push-button fashion, as discussed in the literature and specifically for the given dataset in [7].

The literature presents an extensive discussion of regression and ANN Models. Smith and Mason [20] comment that "an artificial neural network may be an attractive substitute for regression if the model commitment step (functional form selection, interaction selection and data transformation) of regression cannot be accomplished successfully." They listed some important issues other than model accuracy to be considered when using regression versus neural networks to estimate cost functions. One of these, which is also found in the present study, relates to the replication of model results.

According to Smith and Mason [20], "training a neural network is an algorithmic procedure and the results can most certainly be replicated as long as one uses the identical computer code, the same initial weights, the same training data, and the same deterministic method of presenting the data during training. However, if one of these parameters is altered, the resulting neural network would almost certainly be different from the original one." The present study found that producing near optimal neural network models involves identifying iteratively good combinations of network architecture, training methods and stopping criteria.

In this study, as has been seen in similar studies in the engineering field, both regression and ANN Models predict a value of the dependent variable, given known values of the explanatory variables. Prediction within the range of values in the dataset used for model-fitting is known informally as interpolation. Prediction outside this range of data is known as extrapolation. Performing extrapolation relies strongly on the regression's assumptions. The further the extrapolation goes outside the data, the more room there is for the model to fail because of differences between the assumptions and the sample data or the true values.

In particular with respect to the ANN Models estimated in this paper, one should, when performing extrapolation, accompany the estimated value of the dependent variable with a prediction interval that represents uncertainty. Such intervals tend to expand rapidly as the values of the independent variable(s) move outside the range covered by the observed data. Tokar and Johnson [21] comment that "ANN Models do not perform well when they extrapolate beyond the range of the data used for calibration. Unlike conventional statistical models, ANN Models generally have a large number of parameters (connection weights), and therefore they can overfit the training data, especially if the training data are noisy." A properly conducted analysis will include an assessment of how well the assumed form is matched by the observed data, but it can only do so within the range of values of the independent variables actually available. This means that any extrapolation is particularly reliant on the assumptions being made about the structural form of the regression relationship.

Finally, in cases in which the geophysical significance of the regression model choice is regarded as one of the major criteria for defining a preferred model, the second-stage ANN WCE-1 Model should be implemented in the process of predicting vertical swelling percentages. This conclusion leads to predicting higher vertical swelling percentages than those of the ESC Models (see Figure 11) for moderate and high values of liquid limits. However, this conclusion should be restricted to the range of input data similar to that of the central range of the tested data given in Figure 4 of [7].

6. Summary and Conclusions

In order to improve the prediction accuracy of statistical models given in a previous paper by the authors [7], 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 geophysical 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 as well as ESC Models did, in particular when it came to values whose range was near (or outside) the dataset 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: (a) 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; (b) performing an additional ANN analysis of the swelling-percentage test results (i.e., the ASTM 4546 Method B test results), 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 earlier 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 to 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.

In addition, 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 non-routine ways of analyses as was done in the present paper.

Finally, mention should be also made of the discrepancy that still exists in this paper between the measured and the predicted values by the new ANN models . This divergence may be attributed to additional influential parameters that were not considered, which might have a significant impact on soil swelling potential. Therefore, further enhancements to the models developed here can be achieved if some more influencing parameters, such as clay content, mineral clay proportion, mineral clay type and the free swelling rate, are considered. On this matter, see also [22].

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Table 1: Summary of the regression coefficients of Equations 1, 2 and 3 for the ESC Models

Model No.	X_1	X_2	a_0	a_1	a_2	a_3	a_4	b_0	b_1	b_2	b_3
W-1	LL	W	-0.753	0.014	-0.018	0.258	-2.217	---	---	---	---
W-2	log(LL)	W/PL	-4.234	2.110	-0.399	0.604	-2.191	---	---	---	---
CE-1	LL	W	-1.560	0.011	-0.012	0.903	---	-4.322	0.282	-0.368	0.082
CE-2	log(LL)	W/PL	-3.954	1.585	-0.361	1.074	---	-33.685	24.143	-7.156	1.547

Table 2: Summary of goodness-of-fit statistics obtained from Equations 1, 2 and 3 for the ESC Models

Model No.	X_1	X_2	SE/SY	R^2	Adjusted R^2
W-1	LL	W	0.653	0.576	0.574
W-2	log(LL)	W/PL	0.631	0.604	0.602
CE-1	LL	W	0.627	0.609	**0.606**
CE-2	log(LL)	W/PL	0.649	0.581	0.578

Table 3: Correlation criterion, rated by goodness-of-fit statistics of SE/SY, R^2 and adjusted R^2 [14]

Correlation Criterion	Excellent	Good	Fair	Poor	Very Poor
R^2	≥0.90	0.70-0.89	0.40-0.69	0.20-0.39	≤0.19
SE/SY	≤0.35	0.36-0.55	0.56-0.75	0.76-0.90	≥0.91

Table 4: Summary of the regression coefficients of Equation 2 and the goodness-of-fit statistics of SE/SY, R^2 and adjusted R^2 for the DLR Models

Model No.	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 5: Summary of the goodness-of-fit statistics of SE/SY, R^2 and adjusted R^2 for the first-stage ANN Models

Model No.	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 6: Summary of the goodness-of-fit statistics of SE/SY, R^2 and adjusted R^2 for the second-stage ANN Models

Model No.	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

Table 7: Scaled percent error of the swelling pressure predicted from the ANN models

Model No.	Cumulative Frequency -15%	-10%	-5%	0%	5%	10%	15%
WCE-1	2%	6%	15%	46%	91%	98%	100%
WCE-2	1%	4%	12%	42%	89%	97%	100%

Figure 1: Predicted vertical swelling versus vertical pressure for D=14.7 kN/m^3 and for (a) W/PL=0.8 and (b) W/PL=1.0 as obtained from ESC Models W-1 and W-2

Figure 2: Predicted vertical swelling versus vertical pressure for D=16.7 kN/m^3 and for (a) W/PL=0.8 and (b) W/PL=1.0 as obtained from ESC Models W-1 and W-2

Figure 3: Predicted vertical swelling versus vertical pressure for D=14.7 kN/m3 and for (a) W/PL=0.8 and (b) W/PL=1.0 as obtained from ESC Models CE-1 and CE-2

Figure 4: Predicted vertical swelling versus vertical pressure for D=14.7 kN/m^3 and for (a) W/PL=0.8 and (b) W/PL=1.0 as obtained from ESC Models CE-1 and CE-2

Figure 5: Diagram of the proposed approach of the two-stage ANN analysis

Figure 6: Predicted swelling pressure versus ratio of moisture content to plasticity limit for (a) D=14.7 kN/m^3 and (b) D=16.7 kN/m^3 as obtained from DLR Models W-1 and W-2

Figure 7: Predicted swelling pressure versus ratio of moisture content to plasticity limit for (a) D=14.7 kN/m^3 and (b) D=16.7 kN/m^3 as obtained from the first-stage ANN W-1 and W-2 Models

Figure 8: Predicted vertical swelling values versus measured vertical swelling values of the 897 tested specimens for the independent variables of (a) ANN WCE-1 Model and (b) ANN WCE-2 Model

Figure 9: Predicted vertical swelling versus vertical pressure for D=14.7 kN/m^3 and for (a) W/PL=0.8 and (b) W/PL=1.0 obtained from second-stage ANN Models WCE-1 and WCE-2

Figure 10: Predicted vertical swelling versus vertical pressure for D=16.7 kN/m^3 and for (a) W/PL=0.8 and (b) W/PL=1.0 as obtained from second-stage ANN Models WCE-1 and WCE-2

Figure 11: Ratio of predicted vertical swelling, ANN WCE-1 Model to ESC W-1 Model, versus vertical pressure for (a) D=14.7 kN/m^3 and (b) D=16.7 kN/m^3

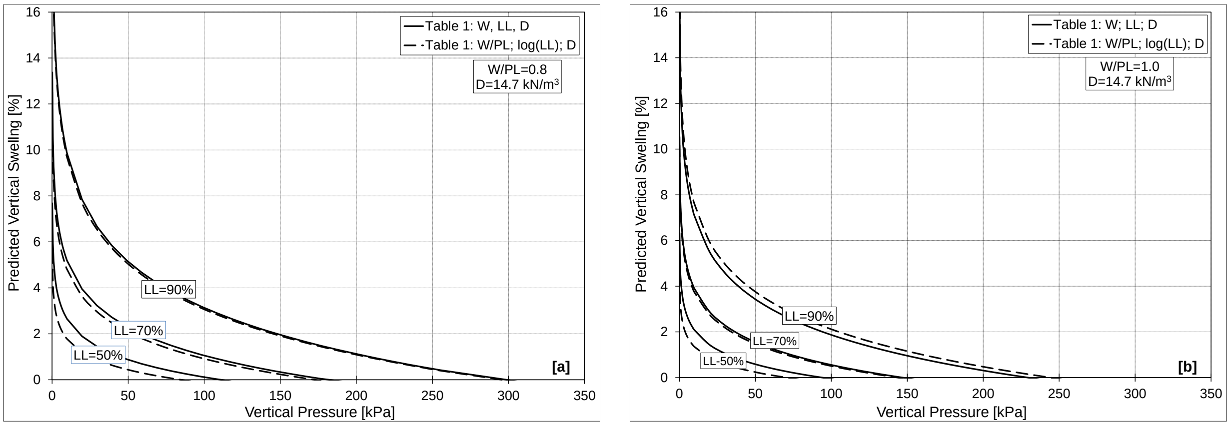

Figure 1: Predicted vertical swelling versus vertical pressure for D=14.7 kN/m³ and for (a) W/PL=0.8 and (b) W/PL=1.0 as obtained from ESC Models W-1 and W-2

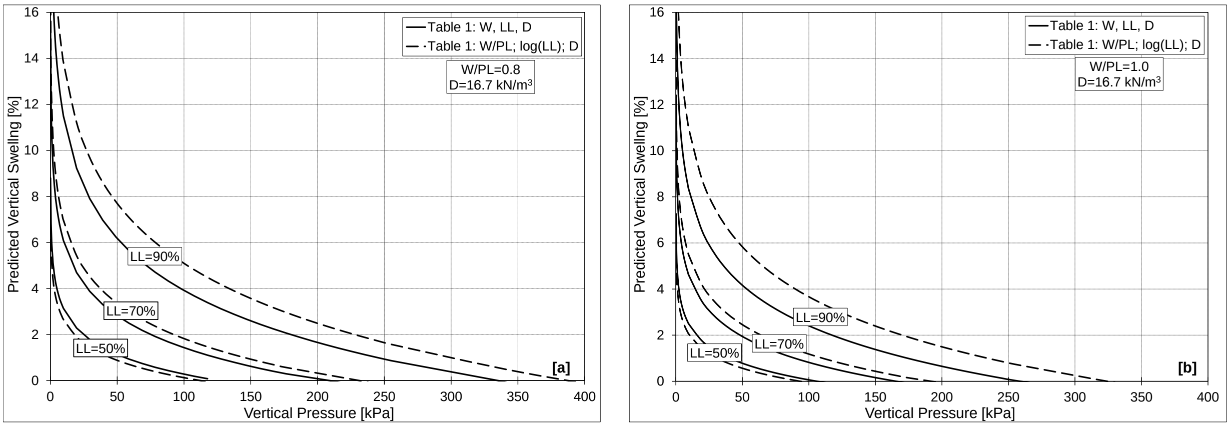

Figure 2: Predicted vertical swelling versus vertical pressure for D=16.7 kN/m³ and for (a) W/PL=0.8 and (b) W/PL=1.0 as obtained from ESC Models W-1 and W-2

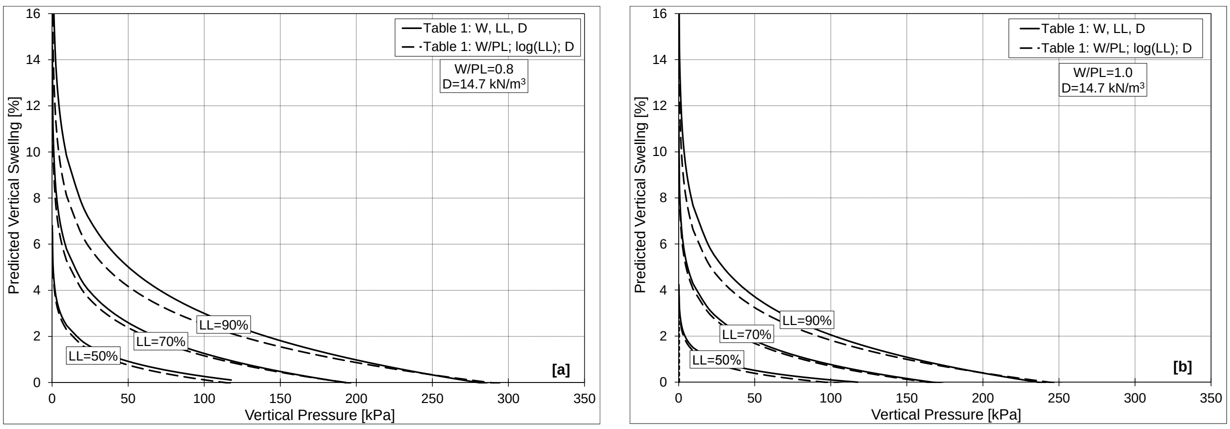

Figure 3: Predicted vertical swelling versus vertical pressure for D=14.7 kN/m3 and for (a) W/PL=0.8 and (b) W/PL=1.0 as obtained from ESC Models CE-1 and CE-2

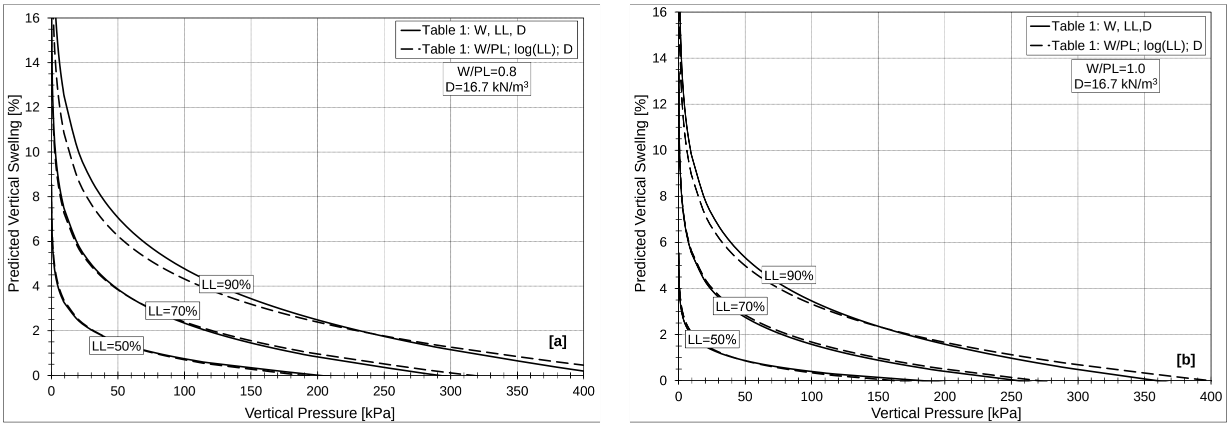

Figure 4: Predicted vertical swelling versus vertical pressure for D=14.7 kN/m^3 and for (a) W/PL=0.8 and (b) W/PL=1.0 as obtained from ESC Models CE-1 and CE-2

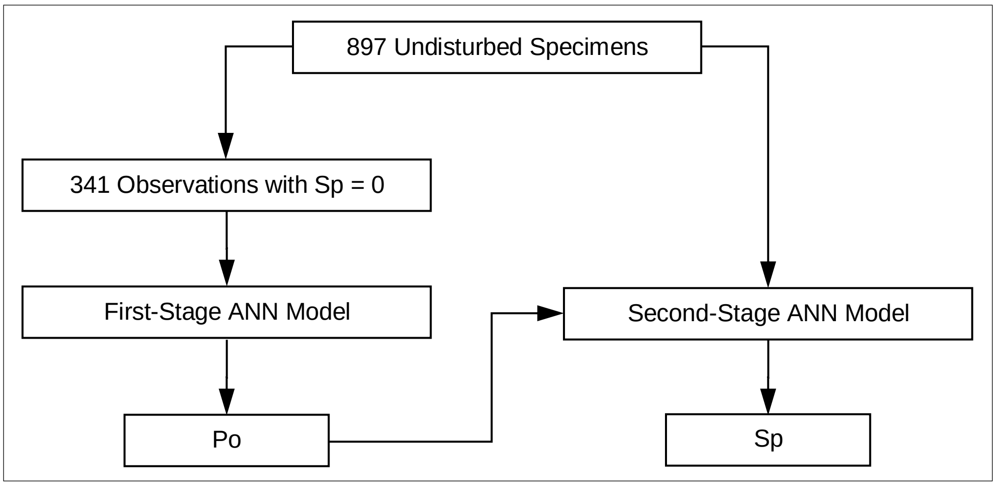

Figure 5: Diagram of the proposed approach of the two-stage ANN analysis

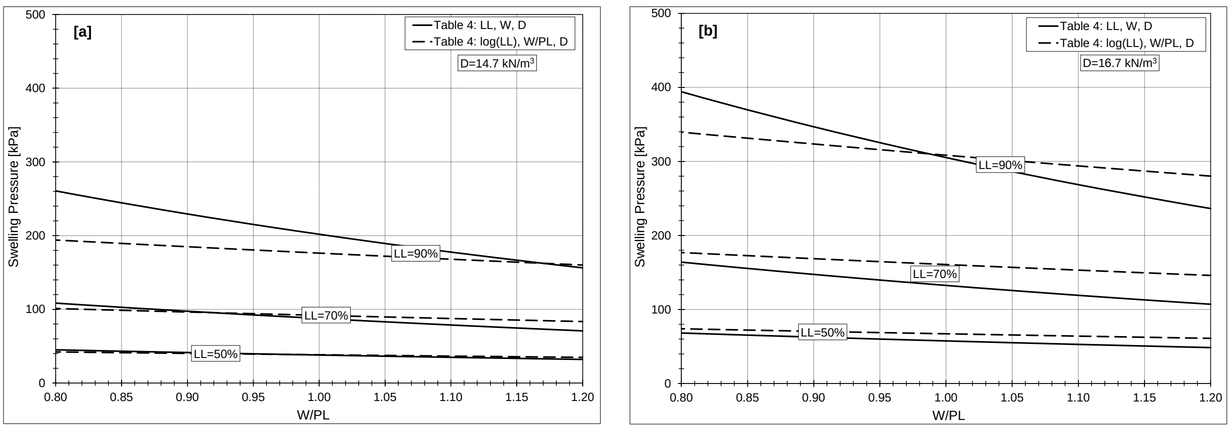

Figure 6: Predicted swelling pressure versus ratio of moisture content to plasticity limit for (a) D=14.7 kN/m^3 and (b) D=16.7 kN/m^3 as obtained from DLR Models W-1 and W-2

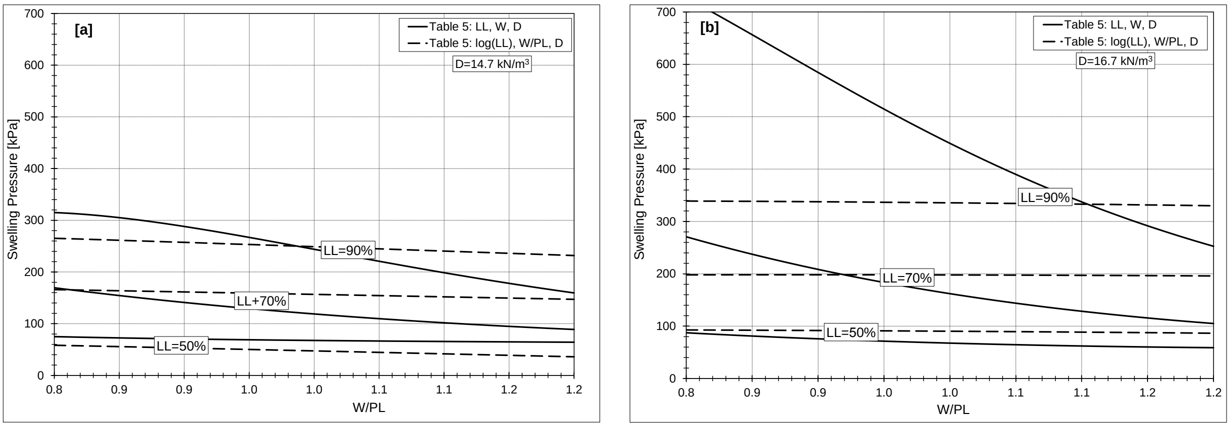

Figure 7: Predicted swelling pressure versus ratio of moisture content to plasticity limit for (a) D=14.7 kN/m^3 and (b) D=16.7 kN/m^3 as obtained from the first-stage ANN W-1 and W-2 Models

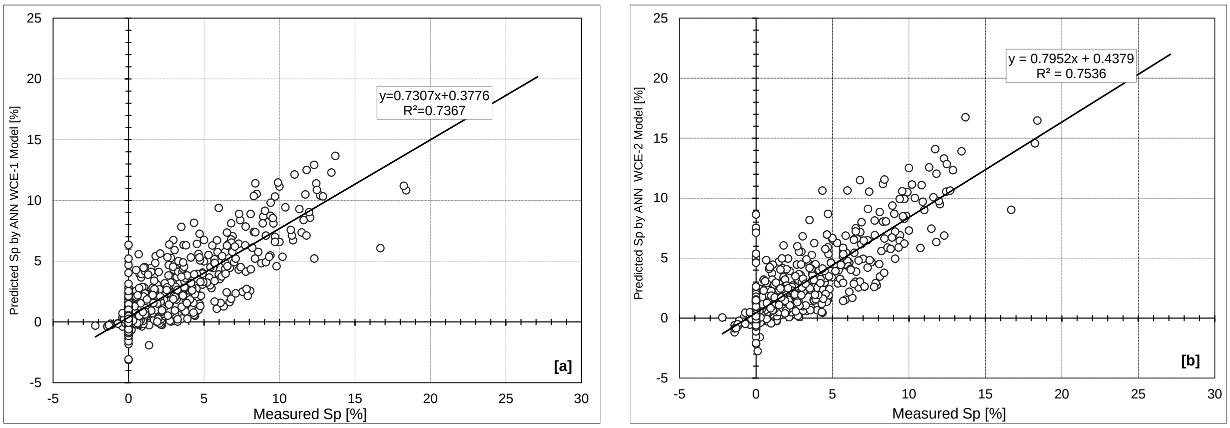

Figure 8: Predicted vertical swelling values versus measured vertical swelling values of the 897 tested specimens for the independent variables of (a) ANN WCE-1 Model and (b) ANN WCE-2 Model

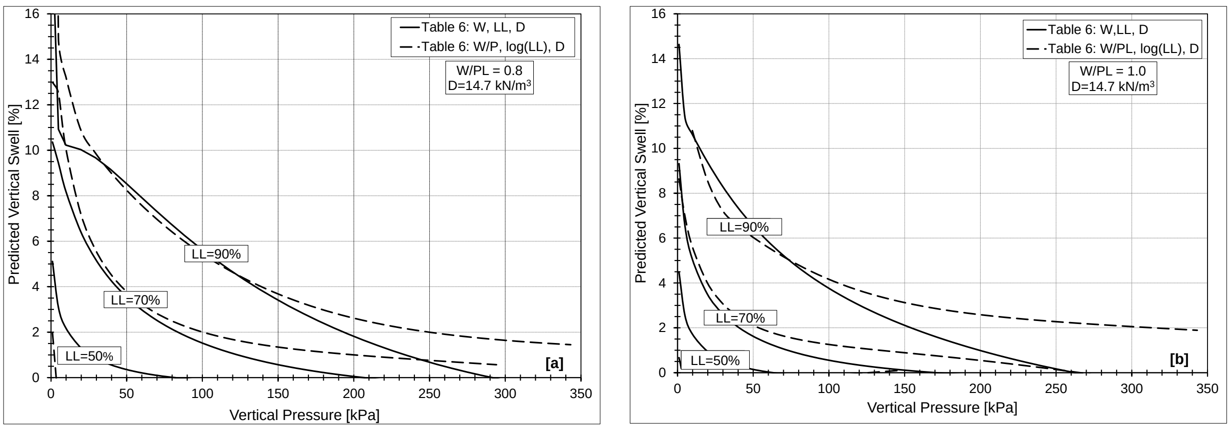

Figure 9: Predicted vertical swelling versus vertical pressure for D=14.7 kN/m^3 and for (a) W/PL=0.8 and (b) W/PL=1.0 obtained from second-stage ANN Models WCE-1 and WCE-2

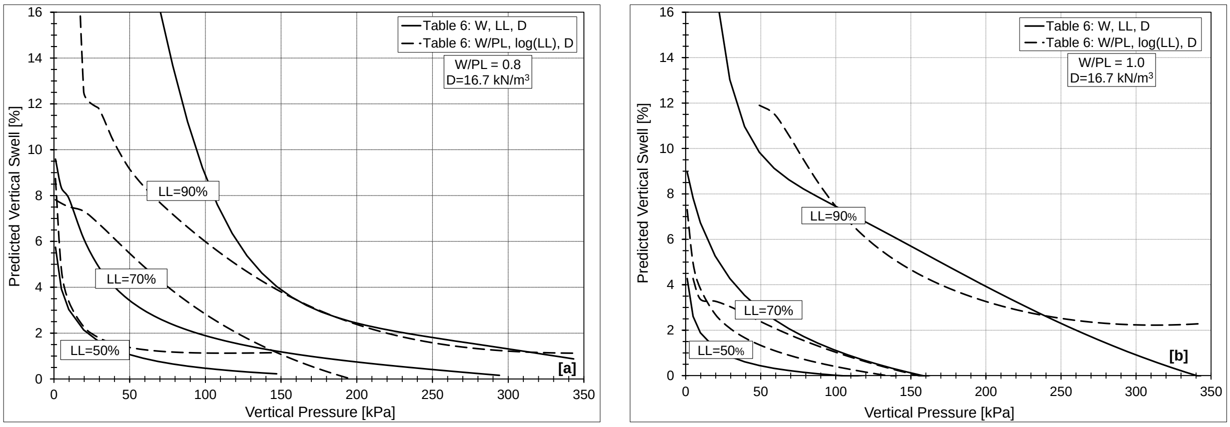

Figure 10: Predicted vertical swelling versus vertical pressure for D=16.7 kN/m^3 and for (a) W/PL=0.8 and (b) W/PL=1.0 as obtained from second-stage ANN Models WCE-1 and WCE-2

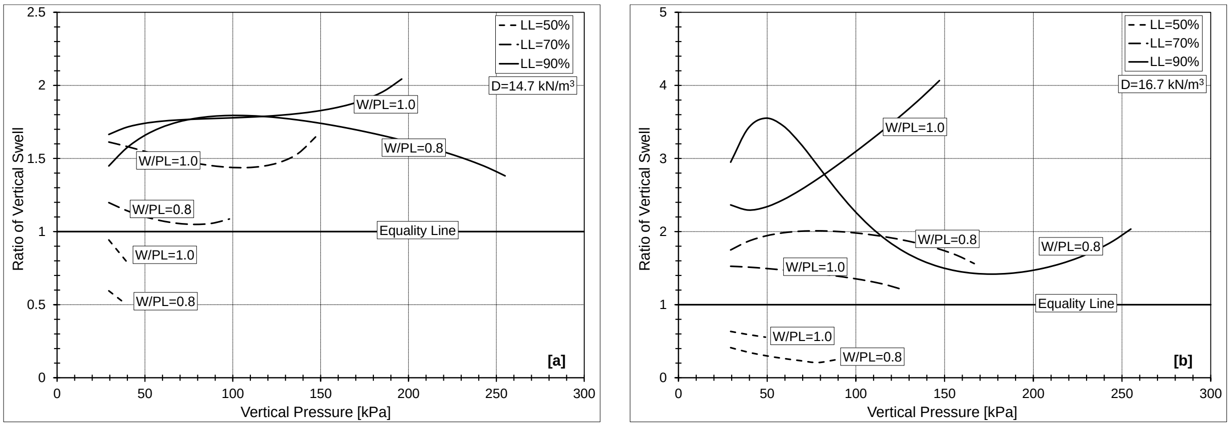

Figure 11: Ratio of predicted vertical swelling, ANN WCE-1 Model to ESC W-1 Model, versus vertical pressure for (a) D=14.7 kN/m^3 and (b) D=16.7 kN/m^3