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MODELING OF SOIL SWELLING VIA REGRESSION AND NEURAL NETWORK APPROCHES

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16. Abstract

Damage due to swelling soil is very noticeable in a wide spectrum of structures such as roads, buildings, canal linings, landfill liners, etc. In order to control or overcome such damage, swelling soils are commonly stabilized either mechanically or chemically. To evaluate the severity of swelling and to design for the best and most economical stabilization strategy, an accurate assessment of the swell potential is required. This report uses reasonable-sized database representing 413 soils retrieved from 45 different projects covering 28 counties in Kansas to develop prediction models. Neural network-based models and various statistical models were developed and compared for their prediction accuracy. Additionally, the reliability of model predictions were examined using an additional 101 data sets.

In the second phase, predictions obtained using the developed neural network models along with the experimental database were used to produce a reliability (probability of success) factor matrix. This matrix is used to assign a specific confidence level to predictions obtained from the developed neural network models in order to classify the soil under consideration as a swelling or non-swelling type. Results obtained from this study showed that neural network-based swelling potential prediction models provide significant improvements in prediction accuracy over statistical counterparts.

A software program was developed to calculate soil swell from three and five input parameters (Liquid Limit (LL), Plastic Limit (PL), Percent Clay (%C), Optimum Moisture Content (OMC), and Maximum Dry Density (MDD)).

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FINAL REPORT

To

Kansas Department of Transportation

By

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January 1998

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ABSTRACT

Damage due to soil swelling is very noticeable in wide spectrum of structures such as roads, buildings, canal linings, landfill liners, etc. In order to control or overcome such damage, swelling soil are commonly stabilized either mechanically or chemically. To evaluate severity of swelling and to design for the best and most economical stabilization strategy, an accurate assessment of the swell potential is required. This report uses reasonable-sized database representing 413 soils retrieved from 45 different projects covering 28 counties in Kansas to develop prediction models. Neural network-based models and various statistical models were developed and compared for their prediction. Additionally, the reliability of model predictions were examined using an additional 101 data sets. In the second phase, predictions obtained using the developed neural network models along with the experimental database were used to produce a reliability (probability of success) factor matrix. This matrix is used to assign a specific confidence level to predictions obtained from the developed neural network models in order to classify the soil under consideration as of swelling or non-swelling type. Results obtained from this study showed that neural network-based swelling potential prediction models provide significant improvements in prediction accuracy over statistical counterparts.

CHAPTER ONE

PREVIEW

1.1 INTRODUCTION

Swelling of soils is of major concern in geotechnical engineering applications where foundations are constructed on soils that have high potentials to undergo swelling. Such structures includes residential buildings, highway pavements, canal linings, clay liners, etc. In the United States, $9 billion are lost each year from the damages to buildings, roads, pipelines, airports, and other facilities caused by expansive soils (Coduto 1994). This cost of damage is more than twice the combined damage from the natural disasters, viz. earthquakes, floods, tornados, and hurricanes (Jones 1987). The amount of swelling and the magnitude of the swelling pressure that is exerted against the foundations of these structures is affected by a large number of parameters pertaining to clay minerals present in soil, soil fabric and structure, and several physicochemical soil-related factors such as intraparticle electrical forces, particle surface structure, pore fluid composition, surface tension properties of the water, cation valence, salt concentration, cementation, and presence of organic matter. The amount of swell to be anticipated from a particular type of soil in the subgrade of a pavement, for instance, depends also on compaction-related parameters and other factors such as dry density, water content, and method of compaction. Since swelling extent and magnitude are also affected by the existing surcharge pressure, it is known to severely damage lighter structures such as small residential buildings, canal linings, and highway pavements. Therefore, it is essential that a soil at a site be identified for its potential for swelling so that soil stabilization (such as lime or cement stabilization) will be carried out before construction. The main objective of the present study is to develop a model that enables prediction of swell potential by evaluating a number of geotechnical parameters that can easily be determined in most soil laboratories. A standard swelling potential test is usually performed by subjecting a soil sample placed into an odometer (consolidometer) to a small surcharge pressure of about 6.89 kN/m^2 (1 psi). Water is then added to the specimen and the expansion of the volume of the specimen is measured when the equilibrium is reached. The percent swell is expressed as $(\Delta H/H)*100$ where ΔH is the height of swell due to saturation, and H is the original height of the soil specimen. Depending on soil type, and composition, surcharge pressure, method of preparation (undisturbed sample or remolded), initial moisture content, the time to equilibrium may vary significantly from one sample to another, thus may range from one to several days (Coduto 1994). Since no specific set of operating conditions are available, no one standardized test is usually followed. Hence, significant variation in the swelling behavior of soils can be expected. Soil specimens are usually prepared at the optimum moisture content and maximum dry density (Seed et al 1962). As can be seen, conducting swelling tests are time consuming when the construction on the site is in progress and soil borrows imported to the site have to be checked for the swelling potential. Moreover, many project areas (especially the remote ones) lack advanced laboratories which requires transporting soil samples to other laboratories. However, it should be understood that any predicted value of swell potential using any prediction model should not be an end by itself. In other words, prediction models should be understood to provide preliminary guidance about the potential magnitude of swelling. However, reliable estimation of swelling and swelling pressure should only be based on results obtained from tests conducted on undisturbed samples tested under appropriate conditions of confinement and water chemistry (Mitchell 1993).

In the present investigation, swell potential of 413 soils covering 51 Kansas Department of Transportation (KDOT) projects from 28 different counties in Kansas (see Table 1[a]) were used to develop the swell potential prediction models. Because of the huge database used in developing the neural network-based models, it is expected that such models can be safely applied to predict swell potential of soils from other states as well. Moreover, statistical models to predict swell potentials based on the activity and clay content of the soil were developed. Furthermore, results obtained using the developed neural network-based models were compared with those obtained from the developed regression equations. As another validation step, additional 101 swell-test data sets conducted on soils obtained from various projects were used to examine the prediction accuracy of the developed models.

1.2 SWELL-TEST EXPERIMENTAL PROCEDURE

Currently, there is no one standardized procedure for testing the swelling potential of soils (Coduto 1994). The KDOT has developed its own testing procedure for determining the percent swell which is defined as the percent change in volume (due to water absorption) of soil sample molded at standard Proctor optimum moisture content (OMC). A brief description of the swell-test experimental procedure used by KDOT for measuring percent swell is presented in this section.

For a given soil, the moisture content-density compaction curve based on standard Proctor is first determined. The swelling tests are performed on two soil specimens: one mixed at OMC+3% and another at OMC-3% moisture contents. Both specimens are compacted at 92% of their standard Proctor maximum dry density (MDD) in the Proctor compaction mold to a height of 2 in. In order to achieve this specimen height and to satisfy at the same time the prespecified dry density and water content, the required amount of oven-dry soil is initially calculated based on the desired dry density and then mixed with the desired amount of water. The two compacted soil specimens are then allowed to stand overnight to allow for full rebound. For each mold, a loading pistons (providing an approximately 1 psi pressure) equipped with dial gauge is placed on top the of specimen and the initial height of the specimen is then recorded. While placed in a pan full of water, the molded specimen rests on perforated base that allows water to seep into it. Readings on the dial gauge are recorded at the end of 4 and 8 hour periods for the first day of saturation and only once a day thereafter for a total period of not less that 96 hours. The specimen is ejected from the mold and dried in an oven, thus allowing determination of initial as-molded moisture content. The percent swell due to absorption of water is calculated as the increase in height of specimen divided by the initial height. The values of percent swell for the two specimens at approximately +3% and -3% from OMC are then used to determine the percent swell at optimum moisture content.

CHAPTER TWO

METHODS OF SWELL PREDICTION

2.1 GENERAL

Several methods are usually used to determine the degree of expansion of natural soils. A wide variety of testing and evaluation methodologies have also been proposed by many researchers, but none of them is widely accepted. Coduto (1994) classifies these methods into three groups. The qualitative methods classify the swell of soil with terms such as *low, medium, or high.* This category of evaluation is based on correlations with common soil tests such as the Atterberg limits and percent of colloids (Holtz 1969), liquid limit, percent passing sieve 200, SPT number, swelling pressure (Chen 1988). Such correlations should be considered approximate and only useful as preliminary assessment of swelling. The other group represents semi-quantitative methods of describing soil swelling is terms of the most commonly used method of measuring the swell potential as discussed before. The final group is the quantitative methods of soil swelling which include measurement of fundamental physical properties. Although this approach has not yet been fully developed, it is considered to form the basis for a rational design procedure.

Swell potential have been frequently used to quantify the swelling behavior of soils. A large number of correlations are available in the literature which relate the swell potential to a number of easily measured properties of tested soils. A most widely used correlation is that of Seed et al. (1962) which relates the swell potential to the percentage of clay size particle (finer than 0.002 mm) present in the soil and the plasticity index, PI, of the soil. Seed et al. (1962) correlation equation which was developed for compacted mixtures of sand and clay is expressed as

$$S = 3.6\times10^{-5} A^{2.44} C^{3.44} \tag{1}$$

where S is the percent swell value under 1 psi, C is the percent of clay fraction, and A is the activity defined as A=PI/C.

2.2 PERFORMANCE MEASURES

Two forms of prediction accuracy measures for model performance were utilized in this study. The first performance measures is the coefficient of determination (R^2) which can be computed from

$$R^2 = \frac{S_{yy'}}{SS_{yy}\ SS_{y'y'}} \tag{2}$$

where $SS_{yy'}$ represents the summation over all sets of the product of deviations of actual values of the dependent variable y from its mean and the deviations of the predicted values y' from their mean. Similarly, SS_{yy} similar summation of the squared values of deviations of actual values y from their mean, and $SS_{y'y'}$ is the summation of squared deviations of predicted values from their mean. The second performance measure is the Mean of the Absolute values of the Relative Error (MARE) which is mathematically expressed as

$$MARE\ (\%) = \frac{\sum_{i=1}^{n} \left| \frac{y_i - y'_i}{y_i} \right|}{N} \times 100 \tag{3}$$

where N is the total number of data sets involved.

2.3 STATISTICAL MODELING

In the present work, the database contains estimates of swell potential (conducted under 1 psi of surcharge pressure and equilibration time of 96 hrs) for a large number of soils from Kansas along with some geotechnical properties of the tested soil. These geotechnical properties are the plastic limit, PL, liquid limit, LL, percent clay, C, and the standard Proctor optimum moisture content and maximum dry density, OMC and MDD, respectively. Since Seed et al. (1962) equation was developed from tests conducted on clay/sand mixtures, this equation (Eq. 1) can not be used in its present form. However, a similar equation is developed using the data of the natural soils of Kansas. As shown from Eq. 1, the swell potential can be generally expressed as

$$S = b\,A^{a}\,C^{c} \tag{4}$$

where b is constant and a and c are exponents. In the development of the Eq. 2, the exponent c is assumed to be equal to 3.44 as given by Eq. 1. Moreover, the activity (A) is modified to be computed as [A=PI/(C-5)] (Holtz and Kovacs 1981). In order to obtain both b and a, Eq. 2 was linearized as

$$Y = b1 + aX \tag{5}$$

where $Y=\ln(S/C^{3.44})$, $X=\ln(A)$, $b1=\ln(b)$. Using the 413 swell-test data, the constants b and a are obtained by performing linear regression between Y and X to yield b=2.20 and a=0.0000217 with coefficient of determination (R^2) of 0.563. Therefore, the swell potential correlation for Kansas soils can be expressed as

$$S = 2.17\times10^{-5}\left[\frac{PI}{C-5}\right]^{2.20} C^{3.44} \tag{6}$$

Figure 1 shows a comparison between the measured percent swell values for the 413 soils tested and those predicted using the developed regression equation. The wide scatter in the data (and the appreciable deviation from the line of equality) may partly reflect the inadequacy of the statistical model to represent the variation in the swell potential of the tested soils. The measured values of swell potential were plotted against the PI and C as shown in Fig. 2. The presence of humps in the middle region of the 3D plot may also emphasize the deficiency in the statistical model to accurately map such behavior.

It is worth mentioning that R^2 reported herein is based on linearized (i.e. transformed) version of Eq. 4 as expressed in Eq. 5. However, when R^2 was evaluated based on actual percent swell values (i.e. no transformation) R^2 dropped to 0.350 with a corresponding MARE of 66.6%. Due to this discrepancy in measuring performance of the models and in order to provide uniform and fair comparison for all prediction models including neural network models, MARE and R^2 values reported from this point and after will be calculated using the actual measured and predicted percent swell values.

Gisi and Bandy (1980) developed a set of four regression equations for determination of percent swell where each equation is applicable for a specified range of PI. The model utilizes a set of four equations obtained from linear regression analysis which combine effect of activity and percent clay on predicted percent swell values. The resulting relationships are expressed as follows:

$$\begin{gathered} S\ (\%) = a\ A^{b}\ \%C^{3.44}\ \textit{where} \\ a = 3.28x10^{-5},\ b = 2.259\ \textit{for}\ PI \leq 20 \\ a = 2.40x10^{-5},\ b = 2.573\ \textit{for}\ 21 \leq PI \leq 30 \\ a = 1.14x10^{-5},\ b = 2.559\ \textit{for}\ 31 \leq PI \leq 40 \\ a = 0.72x10^{-5},\ b = 2.669\ \textit{for}\ PI > 40 \end{gathered} \tag{7}$$

Figure 3 depicts a comparison between the predicted and measured percent swell values using these four relationships for the 413 swell-test data sets. Comparison between Fig. 1 and Fig. 3 reveals that by splitting the model into four equations each applicable for specific PI range has improved the accuracy of the prediction. With this modification, the overall MARE decreased to 41%.

2.4 OVERVIEW OF NEURAL NETWORK MODELING

2.4.1 Neural Networks

Neural networks are evolving efficient techniques for modeling a large number of phenomena in wide spectrum of fields in science, engineering, economy, etc. In all of these fields, large databases are available, yet, theoretical models are not quite known or being successfully developed. It is therefore vital to analyze the available data in order to extract knowledge from them. Nevertheless, data analysis is not a new subject; mainly based on use of statistical (laborious!) methods. Yet, it has been clear for long time that knowledge acquisition by the human brain is not performed by statistical methods! (Zupan and Gateiger 1993). Advances in neurophysiology and the related new experimental techniques have greatly enhanced our understanding of the anatomy of the human brain and the physical and chemical processing occurring within it. Based on this little understanding (if correct!) mathematical models and algorithms have been designed to mimic the processing of information and the acquisition of knowledge in the human brain. These models are called artificial neural networks (ANN) that perform in a massively parallel processing fashion.

Generally, ANN are designed to map a set of m-input variables into n-output variables. The number of input and output variables (i.e., the size of the input and output vectors) is limited only by the available hardware capacity and the associated computation time. The various problems ANN have shown to handle successfully spans over an extremely wide domain. These problems can be classified into four basic categories: association, classification, transformation, and modeling (Zupan and Gasteiger 1993). Of more importance to geotechnical applications is modeling. It is used to develop a model that is being able to relate an input vector to an output vector (a solution) based on learning from given database of a reasonable size. This ANN modeling application elegantly replaces any effort to derive mathematical models that are based on identifying the physical phenomenon involved in the problem. Therefore, the advantage of ANN is that they do not require the knowledge (or assumption) of the involved mathematical functions.

There is a large number of variations of neural networks available in the literature (Zupan and Gasteiger 1993; Hassoun 1995). The backpropagation algorithm (backpropagation of error) is a learning method that is most frequently used in the field of parallel computing. Its popularity can be observed as reflected by the common use of the term "artificial neural networks" to refer to backpropagation by quite large number of authors. The backpropagation neural network was applied with great success to model many phenomena in the fields of transportation, geotechnical and geoenvironmental engineering. Among these are the modeling of durability of aggregate used in pavement construction (Najjar et al. 1997), prediction of clay permeability in the field (Basheer et al. 1994), determination of compaction characteristics (Najjar et al. 1996), assessment of groundwater contamination (Najjar and Basheer 1995), landfill siting (Basheer et al. 1996), modeling constitutive behavior of fine-grained soils (Basheer 1997), modeling of groundwater treatment by adsorption (Basheer et al. 1996). A backpropagation neural network (BPNN) is usually constructed of a number of layers each containing a specified number of units (also called neurons). The input layer consists of those parameters (units) that are presumed to influence the outcome (output) of the phenomenon at hand. The output layer consists of those units that represent the output or the solution of the problem. Between these two layers, there exist a number of layers (called the hidden layers) that permit the flow of the data from the input to the output and *vice versa* through connecting links. The hidden layers are not designed to have any direct contact with the outside environment and can have any number. However, most applications of the BPNN incorporated network architectures with only one hidden layer. A schematic of a-one hidden layer BPNN is shown in Fig. 4. Compared to other learning paradigms, the backpropagation neural network constitutes a well-defined and explicit set of equations for weight corrections. These equations are applied throughout the network starting from the last layer and moving backward towards the input layer. In the forward pass (from the input layer and up) the output is calculated using the optimized connection weights resulting from the training phase. Upon reaching the output layer level, the calculated outputs are compared to the target (actual or measured) values. The residual error is propagated backward (hence the name of the algorithm). Generally, these two passes (forward and backward) are repeated for a large number of times over all data sets involved in the training phase until the residual errors fall below a pre-specified tolerance. The final connection weights are then stored to represent the network topology which can be later used to predict outputs when presented with new data sets where actual values are not available.

In the present work, the BPNN algorithm was coded into a FORTRAN program. The BPNN program was made adaptive such that the number of hidden nodes need not to be determined a priori. The program starts with one hidden node and then adding one additional hidden node at a time till the convergence criteria are met or no further improvements are likely to be achieved. Therefore, the weights of the connections between the various nodes need not be initialized each time a new network structure (varying in number of hidden nodes) is trained. Accordingly, the weights corresponding to a trained neural network with a number of hidden nodes, NH, are also used by the next neural network with number of hidden nodes of NH+1. The weight utilization-nodal addition procedure adopted here can yield a set of optimum weights that minimizes the residual error at a less number of iterations (shorter training and computational time). Also, such a procedure enables the network to escape from a local minimum.

2.4.2 Neural Modeling of Swelling

The development of a neural model requires completion of two phases. The first phase is the training phase where a larger part of the data is used to train the network to generalize from the examples given to it. In the second phase; testing phase, part of the data which were not used in developing the neural model is used to test the validity of the model to generalize on cases other than those used in the training phase. To develop the neural model for predicting swell potential, 310 data sets (examples) where used to train the network and the remaining 103 (25%) sets were kept aside for testing the accuracy and the generalization ability of the trained network. In this paper, two neural models varying in the number of input parameters were developed. The first neural model was developed to compare its prediction accuracy with the statistical models developed earlier. The first neural network consisted of 3 input nodes representing the LL, PL, and C while the output layer consists of the single output; the swelling potential. As can be seen herein, the PI was replaced by its components (LL and PL) to provide for more flexibility in mapping the inputs to the output. It is clear that two soils with similar PI may have different swelling potential. Hence, identifying the first end (PL) or the last end (LL) of the plasticity index length may assist understanding the pattern associated with the data. The second network, on the other hand, is an expansion of the first one with the inclusion of two more geotechnical properties of the tested soil. These are the standard Proctor molding moisture content (OMC) and maximum dry density (MDD). Hence, the structure of the second neural model is composed of 5 input nodes in the input layer and one node in the output layer. In both networks, the number of hidden nodes in the hidden layer was determined experimentally by observing the change in the accuracy of the network to predict the testing examples for a number of networks varying in their number of hidden nodes.

2.4.2.1 The 3-2-1 neural model

Upon training on 310 data sets, this network was found to yield the lowest error in prediction for both the training and the testing data sets at 2 hidden nodes. Hence, this network is denoted by its architecture as 3-2-1 (referring to number of nodes in each layer). For the recall, the Mean of the Absolute value of the Relative Error (MARE) for all sets used in training was calculated as 34.3% and R^2 of 0.41. Similarly, the MARE based on predicting the testing sets was calculated as 37.1% and R^2 of 0.35. For the 101 validation data sets, MARE and R^2 obtained were 43% and 0.35, respectively. Figure 5-a depicts the results of recall for the data used in training as compared to the measured values. The results of the prediction for the 103 testing data sets by the 3-2-1 neural model is shown in Fig. 5-b.

To compare the prediction accuracy of the 3-2-1 neural model with that of the statistical equation, the measured values of the swell potential for both the training and testing data were compared to predictions obtained from Eq. 6. As can be observed, Fig. 6-a and Fig. 6-b show less agreement as compared to corresponding predictions via the neural model (Figures 5-a,b). The

MARE for the prediction obtained using Eq. 6 is calculated as 65.9% for the training data and 68.7% for the testing data sets. The overall measures of performance for the training and testing data sets were MARE=66.6% and R^2=0.35. For the validation set of 101 data sets, the MARE=62.3% and R^2=0.36. With the four-equation model of Bandy and Gisi (1980) the overall MARE=41.0% and R^2=0.29 for both the training and test data sets. Additionally, for the 101 validation sets, the MARE=53.2% and R^2=0.30. It can be seen herein that although both MARE and R^2 are accuracy measures, their relative increase or decrease using the various models was not parallel. It is worthy to mention herein that unlike the neural model, the testing data sets were also used in developing the statistical model. Clearly, neural modeling provides significant improvement for prediction of soil swelling potential over that obtained from regression-based models.

2.4.2.2 The 5-2-1 neural model

In order to improve the prediction accuracy of the 3-2-1 neural model, the OMC and MDD parameters were also included in the input layer. Upon training on the 310 examples , it was found that 2 hidden nodes were also sufficient to yield the best generalization for both the training and the subsequent testing of the 103 data sets. For this developed 5-2-1 neural model, the obtained MARE for the recall data was calculated as 30.4% and the corresponding R^2 of 0.52. Again, for the testing data, these measures were computed as MARE=35.5% and R^2=0.39. These accuracy measures indicate that the 5-2-1 NN only provided slight improvement in prediction over the 3-2-1 neural model. Figure 7-a and 7-b illustrate such improvements as compared to Fig. 5-a and 5-b, respectively. Further comparison between results obtained using this network and those obtained using the one-regression equation model and the four-equation model are presented in Table 2.

2.5 IMPROVING THE MODELS

2.5.1 The Extended Five-Parameter Network

In this network 5 input parameters were used to activate the input layer of the network. These parameters are the consistency limits LL and PL, the (standard) compaction characteristics OMC and MDD, and the percentage of clay (C). In addition to these 5 input parameters, two other input variables PI and A were included. The PI was determined as PI=LL-PL, and the activity was calculated from A=PI/(C-5). The input layer of the network, therefore, included 7 input variables. The output layer contained the percent swell (S). An adaptive type of training using backpropagation paradigm with both training and momentum coefficients of 0.8 were used. Training was run by expanding the hidden layer size one node at a time accompanied by training for 2000 iterations or until convergence is achieved. The optimized network was found at an architecture of 14 hidden nodes with the following accuracy measures: R^2=0.701 for training and 0.517 for testing data, and MARE=25.51% for training and 32.24% for test data. The optimum architecture (7-14-1) was achieved after 1100 iterations in the 14 hidden-noded network. The use of MDD was justified by the fact that all soil specimens were compacted to 92% of this optimum value. Figure 8 shows the comparison between predicted and measured swell percentages for the 413 soils tested. It is observed that including the PI and A in the network input layer has dramatically improved network prediction as observed form the higher R^2 for both training and test sets (compare to 0.52 and 0.39 previously obtained for network 5-2-1). It is worth mentioning that although A and PI are derived from the basic variables LL, PL, and C, these additional transformations have improved the mapping of the network.

2.5.2 The Extended Three-Parameter Network

In this network the compaction characteristics OMC and MDD were dropped. The input layer receives 5 input variables LL, PL, PI, C, and A. Upon adaptive training to as high as 20 hidden nodes, the network was found to be optimum at 20 hidden nodes after 1100 training iterations for the 20-hidden node architecture. The performance measures for this 5-20-1 network were as follows: R^2=0.46 for training and 0.36 for test data, and MARE=32.7% and 37.6% for training and test data, respectively. Figure 9 shows comparison between the predicted and measured percent swell for all soils. This network also outperformed the previously 3-2-1 network given in section 2.4.2.1. However, this network shows a degradation in prediction performance as compared to the 7-14-1 implying that compaction characteristics are sensitive parameters to the measured percent swell.

2.5.3 Summary of Accuracy Measures for Various Models

Table 4 summarizes the accuracy measures MARE and R^2 obtained for the various models attempted. Note that TRN indicates training data of 310 data sets, TST is testing data of 103 data sets, and VAL is validation sets consisting of 101 data sets. It is apparent from Table 2 that the last model (i.e. extended 5-variable NN) provides the best performance among other models.

CHAPTER 3

RELIABILITY OF SWELLING PREDICTION

3.1 GENERAL

In this phase reliability tables which determine the confidence in the predicted values of swelling are developed. All trials for network development were based on 413 data sets. These data were split into 310 data sets for training and 103 sets for testing. An additional newly obtained 101 sets were also used to validate the accuracy of the networks in discriminating swelling from non-swelling soils by assigning reliability factors for the predicted swelling parameter.

3.2 RELIABILITY MODELING

Using KDOT specification for swelling we classified the soils according to their measured percent swell as: $S<2.0\%$ is non swelling soil, and $S\geq2.0\%$ is swelling soil. The obtained numeric predictions for the percent swell were used to classify the soils into these two categories. The two extended-parameter networks described in section 2.5.1 and 2.5.2 were used in obtaining the reliability coefficients matrices of the predictions. A confusion matrix analysis was used in which this matrix shows the agreement between predicted and measured values for four different scenarios. These scenarios are 0 predicted as 0, 0 predicted as 1, 1 predicted as 1, and 1 predicted as 0, where 0 indicates nonoccurrence of an event and 1 implies its occurrence. For the 7-14-1 network, the confusion matrix was determined as follows

$$C = \begin{bmatrix} 0 \rightarrow 0 & 0 \rightarrow 1 \\ 1 \rightarrow 1 & 1 \rightarrow 0 \end{bmatrix} = \begin{bmatrix} 57/413 & 59/413 \\ 275/413 & 22/413 \end{bmatrix} = \begin{bmatrix} 0.138 & 0.143 \\ 0.666 & 0.053 \end{bmatrix}_{NN\,7\text{-}14\text{-}1} \quad (8)$$

where 0→0, for instance, implies that the measured 0 is predicted as 0. Here, we use 0 to indicate non-swelling soil and 1 for swelling soil. The elements in the second matrix denote the number of each category out of the total number of available sets. The overall hit (i.e. successful) rate for the network is calculated as (0→0)+(1→1)=80%, and the overall misses=(0→1)+(1→0)=20%. Note that the element 0→1 represents the overall false alarm rate (=14%) in which a non-swelling soil is predicted as swelling soil.

Utilizing the 5-20-1 network, the following confusion matrix (C) was obtained

$$C = \begin{bmatrix} 0 \rightarrow 0 & 0 \rightarrow 1 \\ 1 \rightarrow 1 & 1 \rightarrow 0 \end{bmatrix} = \begin{bmatrix} 48/413 & 68/413 \\ 278/413 & 19/413 \end{bmatrix} = \begin{bmatrix} 0.116 & 0.165 \\ 0.673 & 0.046 \end{bmatrix}_{NN\,5\text{-}20\text{-}1} \quad (9)$$

This indicates a network prediction accuracy with an overall hit (success) rate=79% and an overall miss rate=21%. Also, C given in Eq. 9 show an overall false alarm rate of 17%.

Because the confusion matrix deals with all data regardless of their distribution with respect to the input variables, we used another approach for estimating reliability of prediction in which the reliability was determined based on distribution of data according to predicted percent swell (S). This procedure increases the reliability of prediction in regions far away from the cut-off S of 2.0%. Table 3 shows reliability factors obtained for both predictive networks. Table 3 can be used as follows: Given a soil with all data belonging to the ranges used in model development [which are LL=23-81, PL=2-56, OMC=11-32%, MDD=86-117 pcf (13.5-18.5 kN/m^3), C=6-62%], the network (say 7-14-1) can be used to determine a numeric value for S. Using Table 3, the predicted value of S is then used to identify the region it belongs to as well as the model-prediction reliability associated with the specified region. For example, assume that you were provided with new soil to determine its reliability to be used as subbase in pavement construction project. The soil had the following properties: LL=65, PL=28, OMC=26%, MDD=92 pcf, and C=28%. Using the 7-14-1 network, the percent swell is predicted as 3.04. Because this value falls in range $S \geq 2.8$ of Table 3, there is 95% probability that this soil is a swelling soil. As another example, consider soil with LL=42, PL=25, OMC=22%, MDD=96 pcf, and C=36%. The 7-14-1 network prediction for S was obtained as 1.37. Therefore, according to Table 3, there is only 15% chance that the soil will be a swelling soil upon testing. In other words, this soil may be regarded with 85% probability as a good (non-swelling) soil for use as subase material.

3.3 RELIABILITY VALIDATION FOR NEURAL NETWORK MODELS

In order to validate the reliability factors obtained for the two networks, an additional number of data sets comprising validation sets were used. A total of 101 sets were run by the two networks and their predicted percent swell (S) values were compared with measured values using the Swell-No-swell criterion. The results of this validation phase yielded the reliability factors as summarized Table 4. Comparison between Table 3 and Table 4 indicates that the reliability (probability) factors developed using the 413 data sets are almost similar to those obtained from the 101 validation data sets. This implies that no further changes to the probability factors is needed.

3.4 PRACTICAL UTILIZATION OF THE MODELS

A neural network-based model is simply a set of connection weights and thresholds as discussed earlier. Using the values of weights and thresholds obtained for the two networks developed herein, the two neural models were encoded into a computer program that furnishes a friendly interface with the user. The program asks the user to enter the values of all the input parameters available and then runs either the extended three-parameter or the five-parameter network depending on the availability of data and preference of user. Along with predicting the numeric values of percent swell, the program provides the reliability (probability of success) of prediction which describes the degree of confidence for the given soil to be classified as swelling or non-swelling soil.

CHAPTER 4

CONCLUSIONS AND RECOMMENDATIONS

For troublesome soils, determination of the best preventive measure to control or avoid swelling of such soil can be made possible through using systematic methods for identifying, testing, and evaluating the swelling potential of the soil at the construction site. Although an experienced engineer can visually identify potentially expansive soil (those soils containing significant amount of clay and specifically those classified as CL and CH), any such visual identification can not be considered final. In such case, additional prediction and experimental testing become a necessity to obtain more information about the swelling behavior of the soil under study. Determining the degree of swelling of a soil is more difficult because of the availability of a wide variety of testing and evaluation methods. The correlation equations available in the literature are specific for soil and testing method used. Therefore, using correlations from the literature to determine the swell potential may incorporate significant errors if several precautions were not considered. In order to develop a swell potential predictive model for Kansas soils, percent swell values of 413 soil samples retrieved from 45 projects covering 28 counties were used to build a reasonable database. Initially, the database was used to develop statistical models that are analogous to the commonly used model of Seed et al. (1962). In order to improve the prediction accuracy of statistical models, neural networks were used to develop a more reliable and robust methodology for swell potential assessment. Two neural network-based models varying in the number of input parameters were developed. The five-input parameters model requires that LL, PL, OMC, MDD, and percentage of clay be available for the given soil. The three-input parameters model does not require the availability of compaction characteristics. Besides these parameters, the two models use additional two variables which are the activity A and the PI in their input layer. Both neural models were able to predict percent swell with higher accuracy than those obtained using correlation equations. The use of neural networks was found to be much easier than incorporating regression techniques because one does not have to specify the type of the functions that represent the relationships between the various parameters. This is more pronounced for cases where a large number of parameters are presumed to influence the swell potential. The discrepancy observed between the measured and predicted values may be attributed to the negligence of some other influential parameters which might have significant impact on the soil swell potential. Therefore, further enhancements to the models developed herein can be achieved if more influential parameters are considered.

The reliability of models predictions was also determined for both models. The reliability provides an additional piece of information which associates the model classification of a given soil with degree of confidence.

CHAPTER 5

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Table 1: The Kansas counties included in the swell potential study.

Allen	Atchison	Bourbon	Brown
Butler	Cowley	Dickinson	Doniphan
Finney Ford	Franklin	Jackson	Johnson
Linn	Labette	Leavenworth	Marion
Miami	Mitchell	Neosho	Osage
Phillips	Sedgwick	Shawnee	Sumner
Wilson	Woodson	Wyandotte	

Table 2: Summary of performance measures for the various predictive models.

Predictive Model	TRN		TST		VAL		OVERALL (TRN+TST)	
	R^2	*MARE*	R^2	*MARE*	R^2	*MARE*	R^2	*MARE*
1-Eq. Model (Eq. 6)	N/A	65.9	N/A	68.7	0.36	62.3	0.35	66.6
4-Eq. Model (Eq. 7)	N/A	N/A	N/A	N/A	0.30	53.2	0.29	41.0
3-Variable NN (original)	0.41	34.3	0.35	37.1	0.35	43.0	0.40	34.9
3-Variable NN (extended)	0.46	32.7	0.36	37.6	0.39	40.6	0.43	33.9
5-Variable NN (original)	0.52	30.4	0.39	35.5	0.37	42.7	0.49	31.7
5-Variable NN (extended)	0.70	25.5	0.52	32.2	0.41	36.5	0.66	27.2

No. training sets=310, No. testing sets=103, No. validation sets=101. The MARE is in percent.

Table 3: Reliability factors for the 413 training and testing data

NN 5-20-1			Range of %Swell (Predicted)	NN 7-14-1		
Prob. of swelling (%)	Number of observations	% from total cases		Number of observations	% from total cases	Prob. of swelling (%)
85	211	51	$S \geq 2.8$	202	49	95
75	50	12	$2.5 \leq S < 2.8$	58	14	76
60	85	21	$2.0 \leq S < 2.5$	74	18	53
45	52	13	$1.5 \leq S < 2.0$	46	11	37
15	15	3	$S < 1.5$	33	8	15
Total	*413*	*100*	------	*413*	*100*	--

Table 4: Reliability factors for the 101 validation data

NN 5-20-1			%Swell (Predicted)	NN 7-14-1		
Prob. of swelling (%)	Number of observations	% from total cases		Number of observations	% from total cases	Prob. of swelling (%)
84	19	19	$S \geq 2.8$	17	17	100
91	11	11	$2.5 \leq S < 2.8$	9	9	78
46	39	38	$2.0 \leq S < 2.5$	36	35	37
38	21	21	$1.5 \leq S < 2.0$	20	20	35
9	11	11	$S < 1.5$	19	19	21
Total	*101*	*100*	------	*101*	*100*	--

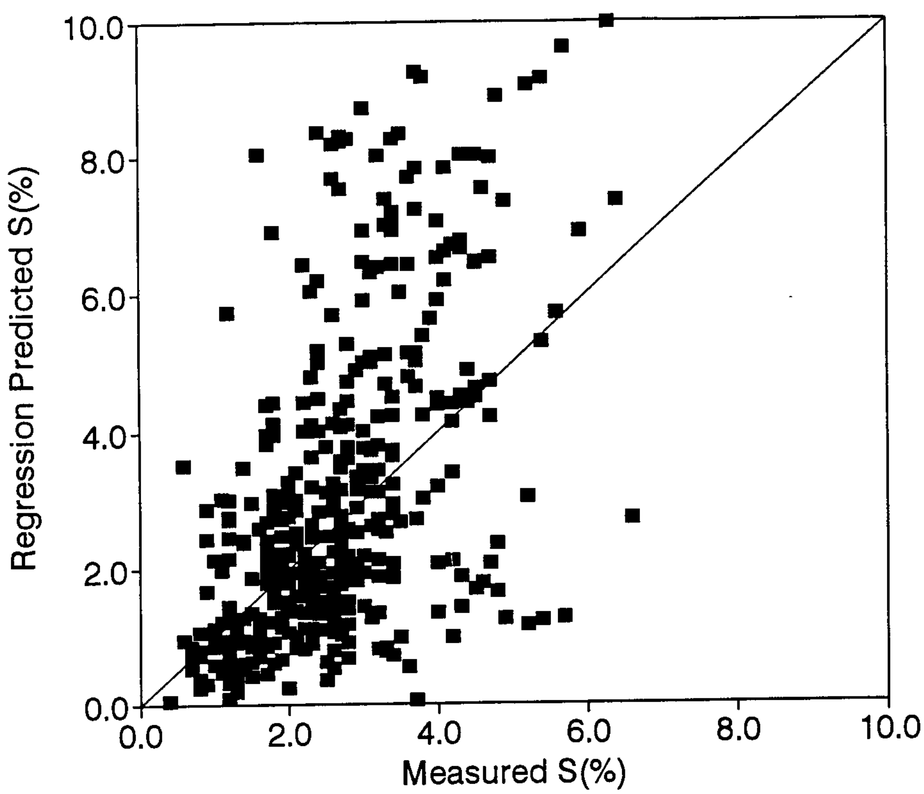


Fig. 1: Comparison between measured and predicted percent swell using one-regression prediction equation.

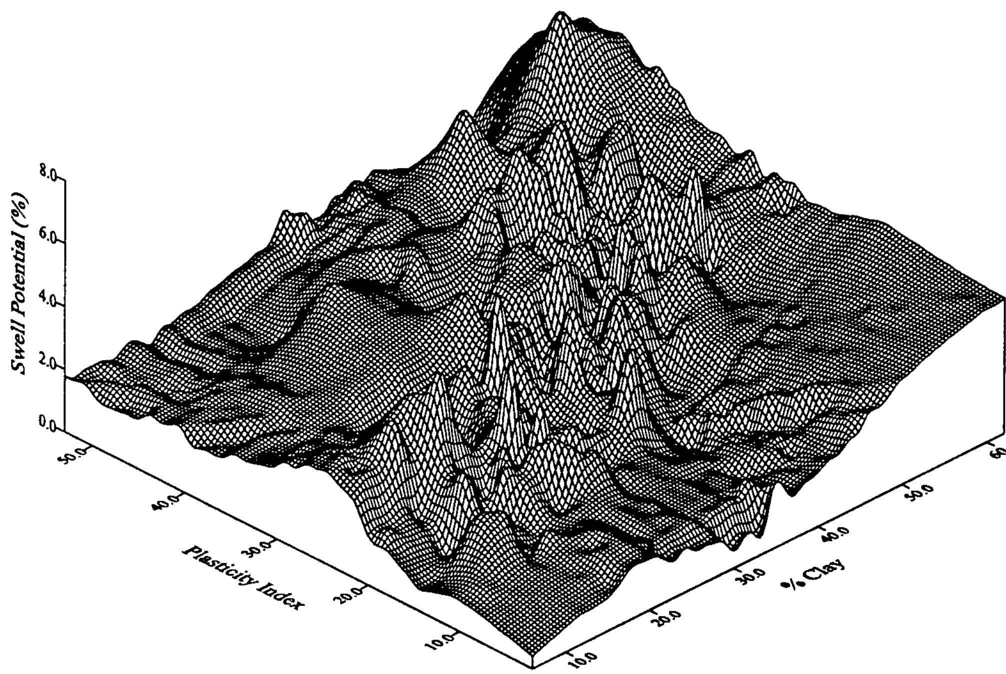


Fig. 2: 3-D plot showing the variability of measured percent swell as function of clay content and plasticity index using 413 swell-test data sets.

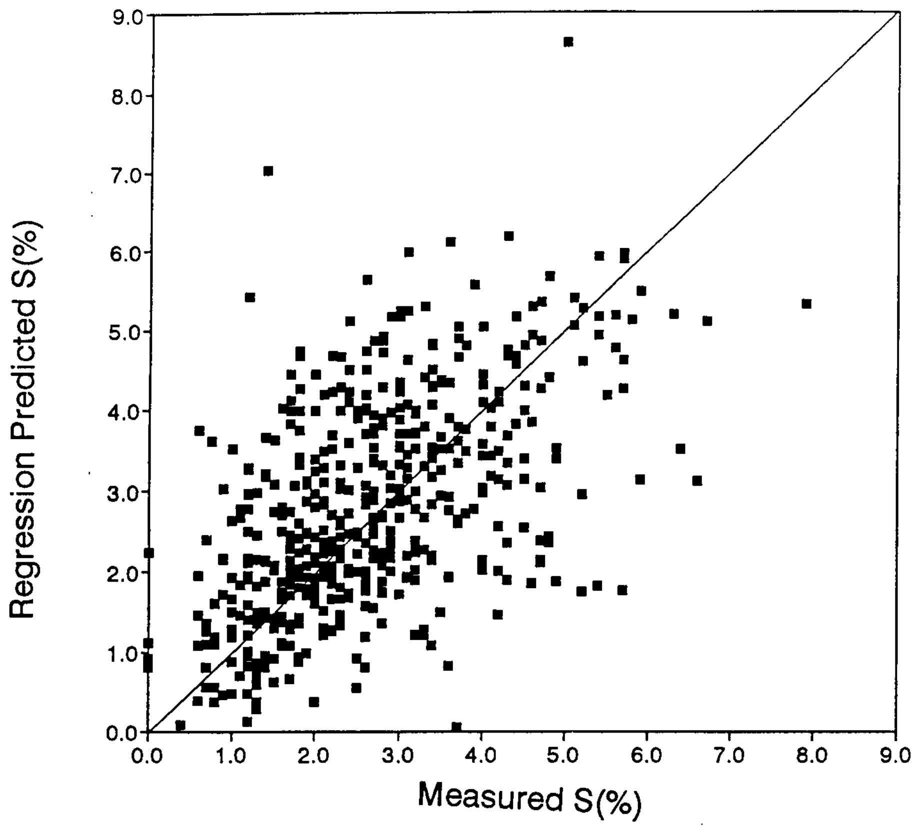


Fig. 3: Plot showing agreement between measured percent swell and predictions using the four-equation regression model developed by Gisi and Bandy (1980).

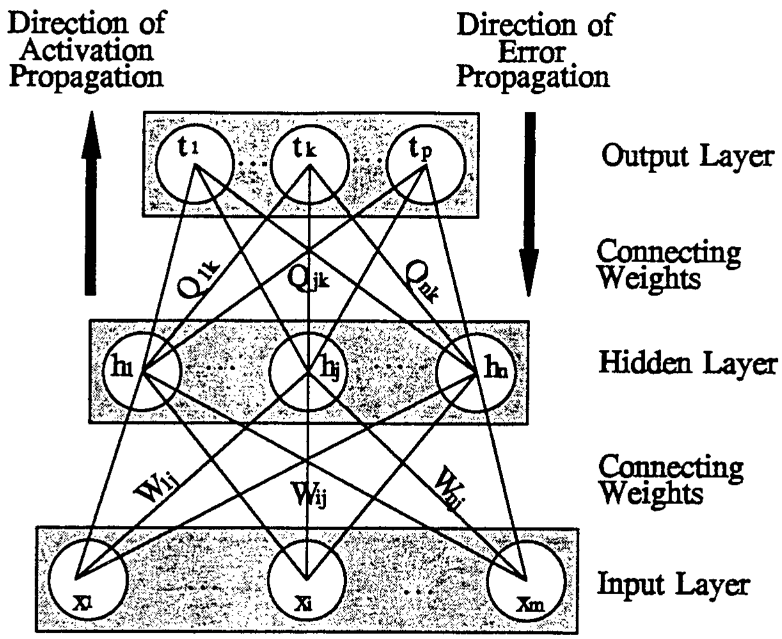


Fig. 4: A schematic of a three-layer backpropagation neural network.

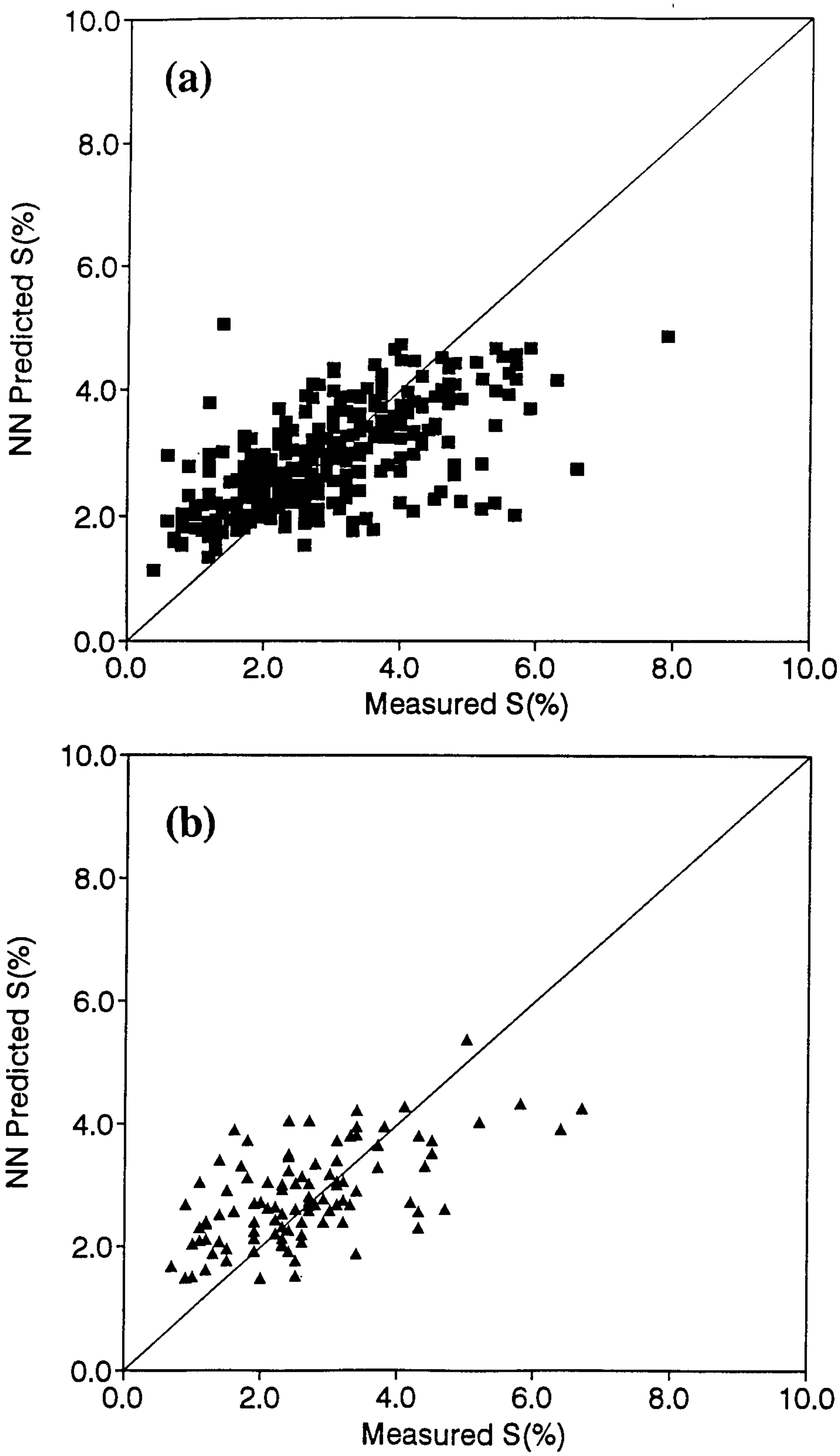
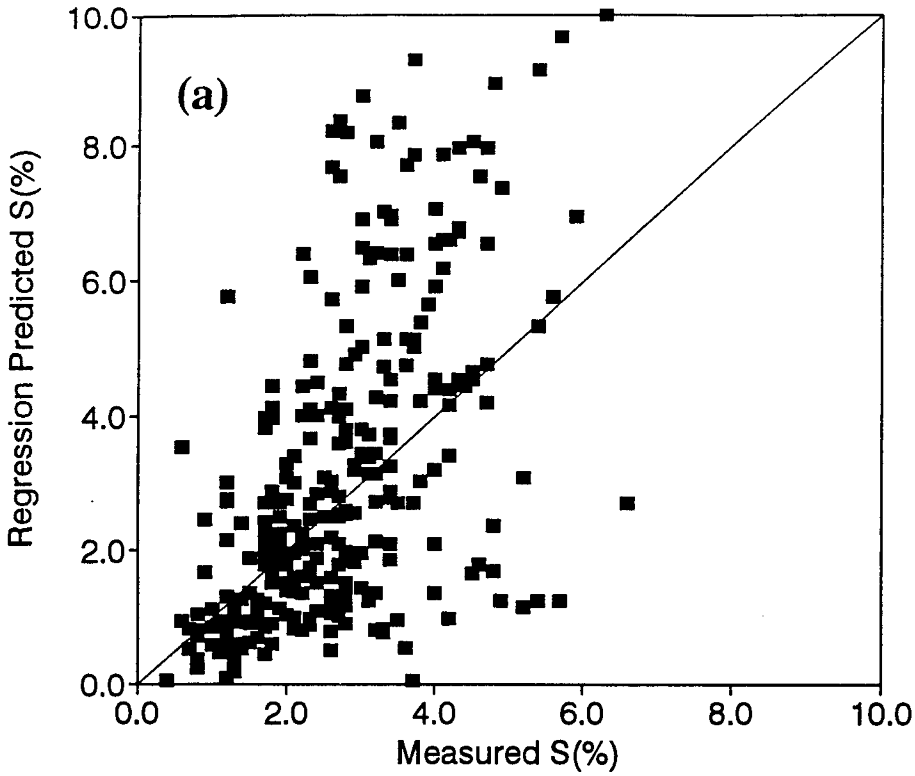


Fig. 5: Prediction of the percent swell by the 3-2-1 neural network: (a) prediction of training sets, and (b) prediction of testing sets.



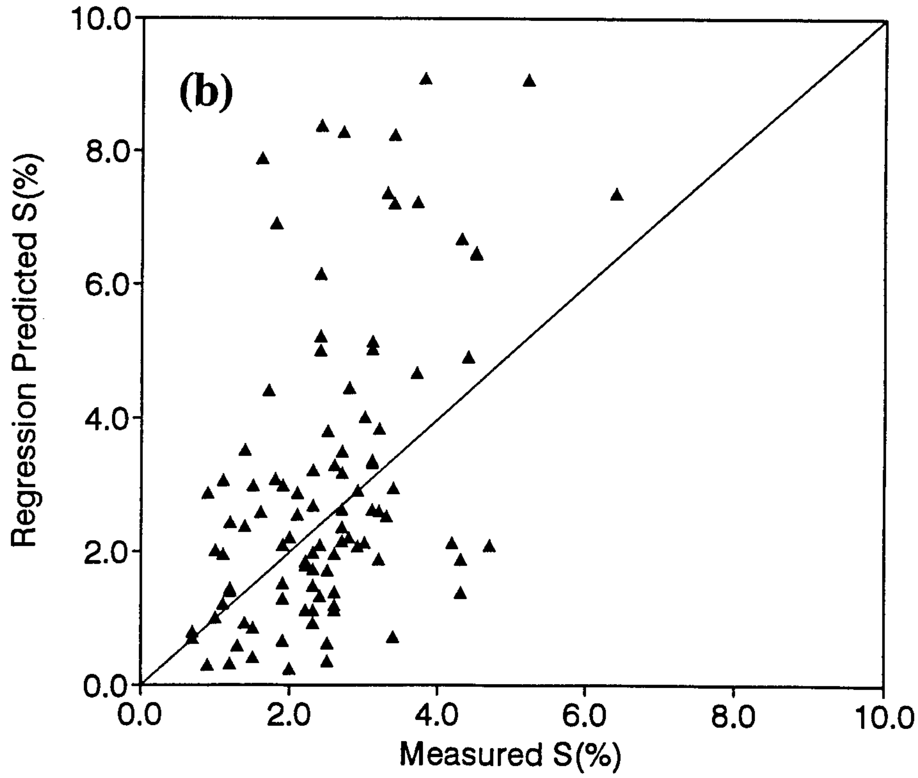


Fig. 6: Prediction of the percent swell by the one-equation model: (a) training sets, and (b) testing sets.

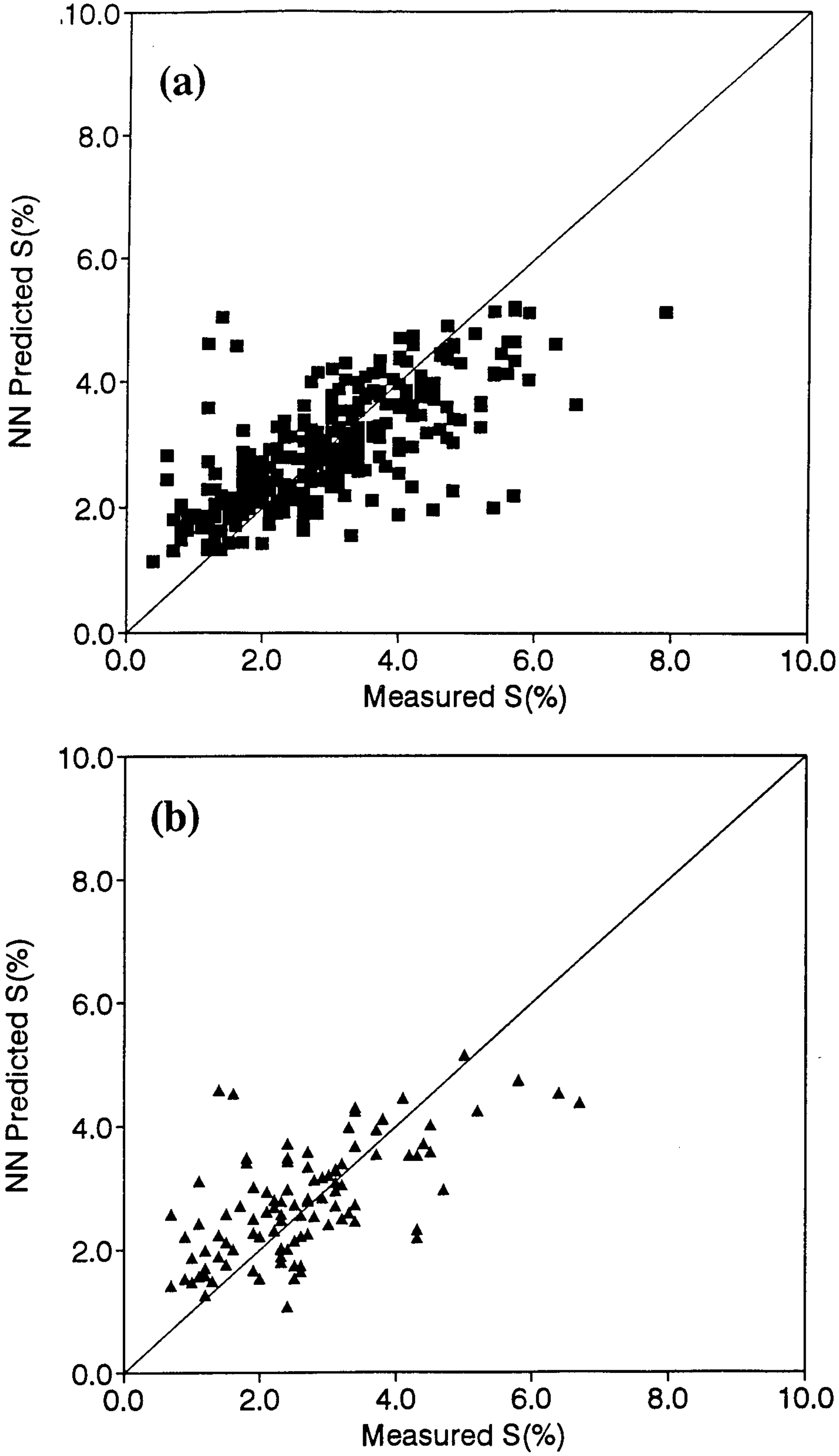


Fig. 7: Prediction of the percent swell by the 5-2-1 neural network: (a) prediction of training sets, and (b) prediction of testing sets.

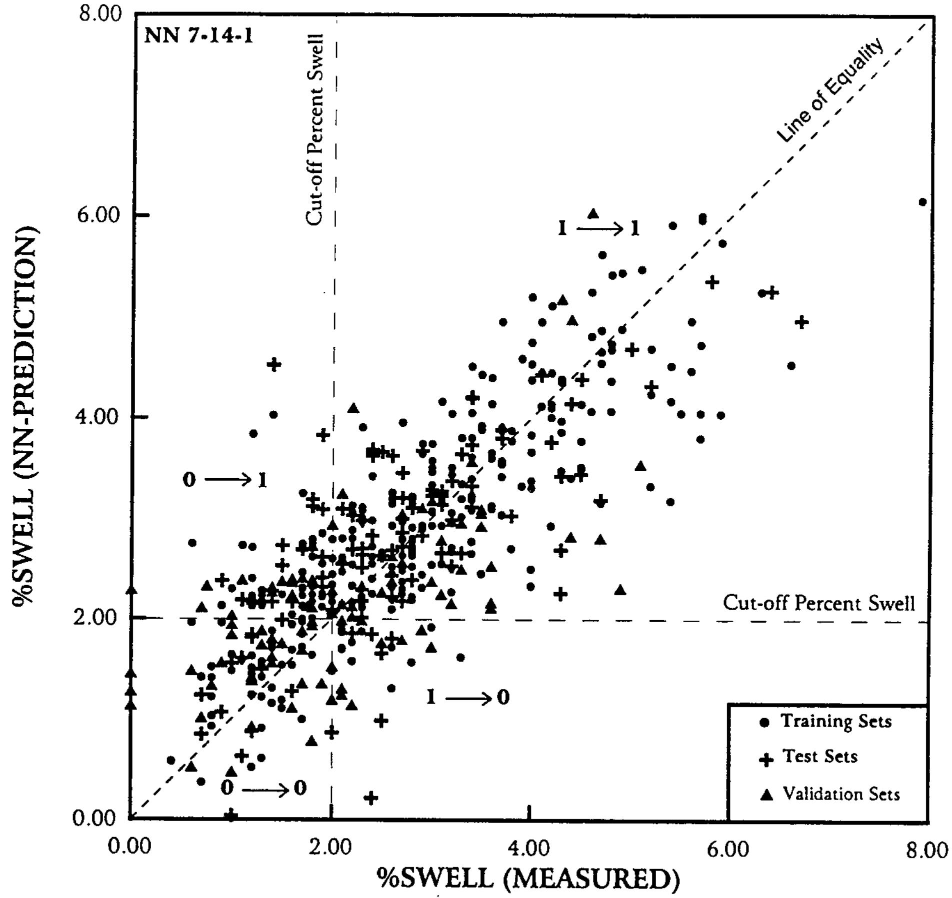


Fig. 8: Plot showing the agreement between measured percent swell and percent swell values predicted by the 7-14-1 network.

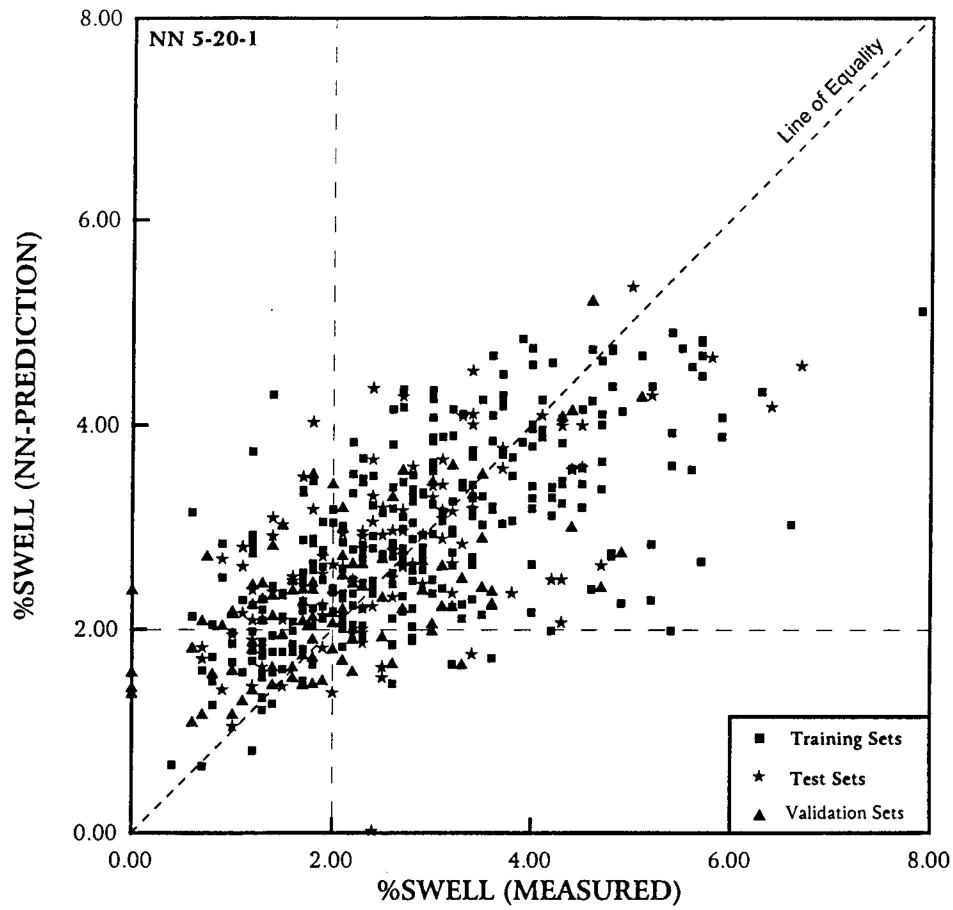


Fig. 9: Plot showing the agreement between measured and predicted percent swell using the 5-20-1 network.