*Geomechanics and Engineering, Vol. 1, No. 4 (2009) 307-321*

DOI: http://dx.doi.org/10.12989/gae.2009.1.4.307

# Modeling sulfuric acid induced swell in carbonate clays using artificial neural networks

P.V. Sivapullaiah†

*Department of Civil Engineering, Indian Institute of Science, Bangalore - 560 012, India*

B. Guru Prasad‡

*Department of Civil Engineering, University of Wollongong, Wollongong-2500, NSW, Australia*

M.M. Allam‡†

*Department of Civil Engineering, Indian Institute of Science, Bangalore - 560 012, India*

*(Received January 21, 2009, Accepted October 30, 2009)*

**Abstract.** The paper employs a feed forward neural network with back-propagation algorithm for modeling time dependent swell in clays containing carbonate in the presence of sulfuric acid. The oedometer swell percent is estimated at a nominal surcharge pressure of 6.25 kPa to develop 612 data sets for modeling. The input parameters used in the network include time, sulfuric acid concentration, carbonate percentage, and liquid limit. Among the total data sets, 280 (46%) were assigned to training, 175 (29%) for testing and the remaining 157 data sets (25%) were relegated to cross validation. The network was programmed to process this information and predict the percent swell at any time, knowing the variable involved. The study demonstrates that it is possible to develop a general BPNN model that can predict time dependent swell with relatively high accuracy with observed data ($R^2$=0.9986). The obtained results are also compared with generated non-linear regression model.

**Keywords:** artificial neural networks; swell percent; calcareous clay; sulfuric acid.

## 1. Introduction

In recent years attention on the behavior of carbonate soils has increased due to the construction of several industrial structures over them. The abundance of carbonate soils in arid and semiarid climate provides interest to the engineers with a valuable insight into their geotechnical properties. Carbonate clays differ from common alumino-silicate clays, in three fundamental and important ways (Angemeer and Mc Neilan 1982). (a) Firstly, carbonates are predominantly produced and deposited by biological process; (b) second, because of the form in which we often find them,

† Professor, Corresponding author, E-mail: siva@civil.iisc.ernet.in
‡ Endeavour Fellow, E-mail:gurubpch@lycos.com
‡† Professor, E-mail: mehter@civil.iisc.ernet.in

carbonates are comparably softer than the constituents comprising most terrigenous clays; (c) third, they are much more susceptible to post-depositional alteration at normal surface temperatures and pressures.

Unforeseen changes can occur in the properties of soils due to contamination which intern leads to severe geo-chemical reactions. It is a known that among the inorganic chemicals sulfuric acid ($H_2SO_4$) is one, widely employed as raw materials in many industrial applications such as lead-acid storage battery, copper smelting industries, production of fertilizers (ex. phosphate), refining of petroleum, removal of impurities from kerosene, pickling of steel (the cleaning of its surface), manufacture of other chemicals (ex. hydro chloric acid) etc. Several cases of foundation failures are reported particularly due to increased volume changes in foundation soil due to chemical contamination (Lukas *et al*. 1972, Stephenson *et al*. 1989, Raid *et al*. 2007). Estimation of such chemically induced swell will be useful to the engineers in general. Mousa and Samer (2000) reported the discrepancy in the values of swelling pressure among free swell, different pressure, and the zero swell methods for natural soils. But, unfortunately the swelling models in carbonate soils are not found in literature. It may be due to several reasons like-volume change behaviour of carbonate soil with sulfuric acid follows complex patterns, which are highly non-linear, time dependant and exhibiting a large amount of scatter and dependent on mineralogy (Sivapullaiah *et al*. 2008a, 2008b, Guru Prasad 2008). ANNs are used to determine soil, mechanical parameters (Yilmaz and Yüksek 2008), swell pressure (Erzin 2009), time dependent swell (Adnan *et al*. 2003). Yilmaz and Yüksek (2009) prepared the models of multiple regression, ANN and ANFIS for strength prediction and elasticity modulus of gypsum. Barakat and Attom (1999) compared multiple regression analysis with ANNs in evaluating pressure of clayey soil. Numerous researchers proposed empirical and regression models for the prediction of swelling in natural soils (O'Neil and Ghazzally 1977, Johnson and Snethen 1978, Yilmaz 2006). However, these models may not fit for more accuracy due to system nonlinearity in carbonate clays. Thus an adaptable computing technique is desired.

Among the computing techniques artificial neural network (ANN) is one in which it mimics the computing models of brain. ANN generally consists of a number of interconnected processing elements (PEs) or neurons. How the inter-neuron connections are arranged and the nature of the connections determines the structure of a network. The strengths of the connections are adjusted or trained to achieve a desired overall behaviour of the network, which is governed by its learning algorithm. The availability of Neural Networks as detectors is based on their capability to incorporate a great quantity of information of several classes, their ability to generalize from noisy or incomplete information, and their robustness to ambiguities. Thus ANN approach is widely used in various geotechnical engineering applications currently. Hence, the present work emphasis on artificial neural network technique in the prediction of volume change behavior of carbonate soils.

## 2. Experimental program

### 2.1 Soil and chemicals

The oven-dried (105±5°C) natural black cotton soil sample (passed through IS 425 μm) was used as a basic soil. The geotechnical and chemical properties of BC soil is presented in Table 1a. Commercial pure carbonate and sulfuric acid were obtained from standard manufacturers. Anhydrite carbonate was mixed to the soil with 0, 5 and 10% by dry weight of soil. To mimic the sulfuric

Table 1a Geotechnical and chemical characteristics of BC soil

| Property | Value |
|---|---|
| Atterberg's limit (ASTM D2487) | |
| Liquid limit, LL (%) | 82 |
| Plastic limit, PL (%) | 35 |
| Plasticity index, PI (%) | 47 |
| Standard Proctor's (ASTM D2937) | |
| Maximum dry unit weight ($kN/m^3$) | 12.9 |
| Optimum water content (%) | 37 |
| Specific gravity, $G_S$ (ASTM D854) | 2.79 |
| Grain size distribution (ASTM D422) | |
| Clay (%) | 40 |
| Silt (%) | 54 |
| Sand (%) | 6 |
| Soil classification (ASTM D2487) | CH |
| Primary mineral (JCPDS 1999) | Montmorillonite |
| Cation exchange capacity, CEC (meq/100 g) (ASTM D9081) | 30 |
| Chemical composition (%) | |
| $SiO_2$ | 41.05 |
| $Al_2O_3$ | 14.31 |
| $Fe_2O_3$ | 21.96 |
| MgO | 1.66 |
| $K_2O$ | 0.04 |
| $Na_2O$ | 0.60 |
| Other | 3.17 |
| Loss on ignition | 17.13 |

acid contamination, the standard 1 and 4N acid solutions are prepared using commercially available sulfuric acid and used for inundation.

### *2.2 Determination of percent swell*

Swell behaviour of samples of black cotton soil with calcium carbonate were evaluated using a modified oedometer test with polypropylene casing to prevent corrosion from hydrogen ions. The schematic view of the setup is presented in Fig. 1. The dried soil samples were mixed with optimum water content and placed in watertight polyethylene bags for about 7 days for moisture equilibration. The soil samples thus conditioned were statically compacted to a thickness of 14 mm and to the maximum dry density in a ring of 60-mm diameter and 20-mm height. The consolidation cell fitted with ring was positioned in the oedometer. The samples were inundated with dilute sulfuric acid solutions (1 and 4N) at a seating pressure of 6.25 kPa. The change in the height of the sample in the ring with time is monitored with dial gauge and the swell percent is calculated using the expression 1.

$$\text{Swell (\%)} = \frac{\Delta H}{H} \times 100 \tag{1}$$

Table 1b Statistical parameters of variables for training, testing and validation

| Parameter | Mode of Operation | T (day) | $A_C$ (N) | $C_C$ (%) | LL (%) | SPp (%) |
|---|---|---|---|---|---|---|
| Minimum | Training | 0 | 1 | 0 | 59 | 0 |
| | Testing | 22.88 | 1 | 0 | 59 | 10.36 |
| | Validation | 9.98 | 1 | 0 | 59 | 3.99 |
| Maximum | Training | 73.75 | 4 | 10 | 87 | 49.94 |
| | Testing | 88.17 | 4 | 10 | 87 | 49.76 |
| | Validation | 88.75 | 4 | 10 | 87 | |
| Mean | Training | 17.59 | 2.39 | 5.11 | 72.92 | 9.94 |
| | Testing | 67.21 | 2.42 | 4.94 | 72.62 | 26.68 |
| | Validation | 42.24 | 2.78 | 4.87 | 70.32 | 23.22 |
| Median | Training | 9.69 | 1 | 5 | 81 | 8.55 |
| | Testing | 70.17 | 1 | 5 | 81 | 26.57 |
| | Validation | 43.90 | 4 | 5 | 65 | 20.59 |
| Mode | Training | 0 | 1 | 10 | 81 | 0 |
| | Testing | 85.01 | 1 | 5 | 81 | 49.76 |
| | Validation | 32 | 4 | 0 | 81 | 26.92 |
| Standard deviation | Training | 19.85 | 1.50 | 4.12 | 11.31 | 10.89 |
| | Testing | 16.14 | 1.50 | 3.94 | 11.04 | 12.07 |
| | Validation | 19.26 | 1.48 | 4.20 | 10.96 | 12.81 |
| Kurtosis | Training | -0.03 | -1.99 | -1.53 | -1.77 | 4.02 |
| | Testing | 0.48 | -2.01 | -1.38 | -1.77 | -0.35 |
| | Validation | -0.46 | -1.88 | -1.58 | -1.63 | 0.03 |
| Skewness | Training | 1.01 | 0.14 | -0.04 | -0.10 | 1.77 |
| | Testing | -1.07 | 0.10 | 0.02 | -0.08 | 0.75 |
| | Validation | 0.49 | -0.38 | 0.05 | 0.36 | 0.95 |
| Count | Training | 280 | 280 | 280 | 280 | 280 |
| | Testing | 175 | 175 | 175 | 175 | 175 |
| | Validation | 157 | 157 | 157 | 157 | 157 |

where $H$ is the initial height of the sample and $\Delta H$ is the change in height.

## 3. System modeling

### 3.1 Parameter and data selection

In this study, the back propagation network (BPN) algorithm was applied to develop the ANN model of swell percent estimation. The input layer in the artificial neural network model included four significant parameters such as time (T), sulfuric acid normality ($A_c$), carbonate percentage ($C_c$) and liquid limit (LL). Since the repetitive data slows down the training as per the ASCE task committee (2000), random selection method was used. A total of 612 data sets were divided into training group with 280 samples (46%) and testing group with 175 samples (29%) and the remaining 157 data sets (25%) were used for cross validation of the network. The statistical

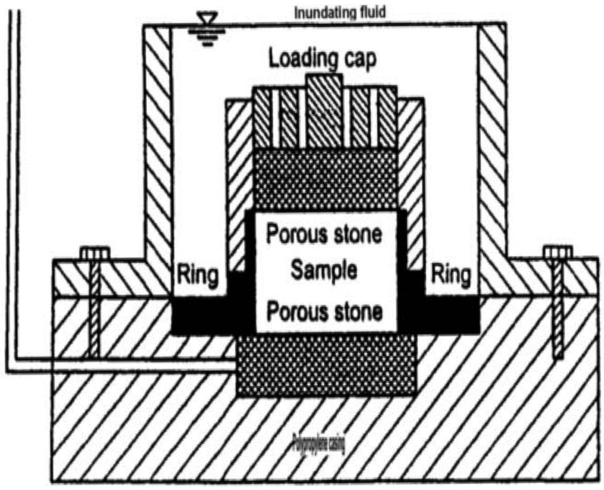


Fig. 1 Schematic view of modified consolidation setup

parameters of variables for training, testing and validation are given in Table 1b.

### *3.2 Model development*

The main steps in design of ANN technique includes,

(a) The network design-variations in performance are analyzed for different numbers of inputs and hidden layer, and different number of nodes in these hidden layers; (b) The network training-using the Back Propagation algorithm; (c) The dependence of the training and the performance on the criterion function to be minimized by the BP algorithm; (d) Analysis of results, and extraction of appropriate conclusions.

In addition multiple regression analysis (MRA) is carried out for multivariate data analysis. MRA can be used to test hypotheses regarding the relationship of one or more predictors to a dependent variable. The concept of regression analysis lies in the idea to predict the scores of one dependent variable $Y$ from the scores of one or several independent variables $X_1, X_2, \ldots, X_m$ in an optimal way. Standard multiple regression can only accurately estimate the relationship between dependent and independent variables if the relationships are linear in nature. If the relationship between independent variables and the dependent variable is not linear, the results of the regression analysis will underestimate the true relationship. In this paper swell prediction with multi regression non- linear model using MATLAB® (platform V.7) was developed with the same selected parameters for the comparison purpose.

### *3.3 Accuracy of model*

The oedometer experimental data was used to check the accuracy of swell percent estimation in this study. The difference of swell percent estimation among four methods was statistically analyzed by comparing coefficient of efficiency (COE), mean sum squared of the error (MSSE), average relative error (ARE) and root mean square error (RMSE) of estimated swell percent in the BPANN model with that of the regression method (MRA). The used statistical methods are defined as,

The coefficient of efficiency ($R^2$),

$$\mathrm{COE}=\frac{\sum_{t=1}^{N}(SP_M-\overline{SP_M})^2-\sum_{t=1}^{N}(SP_P-SP_M)^2}{\sum_{t=1}^{N}(SP_M-\overline{SP_M})^2}, \tag{2}$$

Mean sum square of the error,

$$\mathrm{MSSE}=\frac{1}{N}\sum_{i=1}^{N}(SP_{Mi}-SP_{Pi})^2, \tag{3}$$

Average relative error,

$$ARE=\sum_{i=1}^{N}\frac{Abs\left[\frac{(SP_{Mi}-SP_{Pi})}{SP_{Mi}}\right]}{N}\times 100, \tag{4}$$

and the total error (TOE) or RMSE,

$$TOE=\sqrt{\frac{N_T\times TE^2+N_G\times GE^2+N_C\times CE^2}{(N_T+N_G+N_C)}}. \tag{5}$$

The RMSE takes into the account of training, testing and cross validation errors, and is given as

$$TE=\sqrt{\frac{1}{N_T}\sum_{i=1}^{N_T}(SP_{Mi}-SP_{Pi})^2}, \tag{6}$$

$$GE=\sqrt{\frac{1}{N_G}\sum_{i=1}^{N_G}(SP_{Mi}-SP_{Pi})^2} \tag{7}$$

$$CE=\sqrt{\frac{1}{N_C}\sum_{i=1}^{N_C}(SP_{Mi}-SP_{Pi})^2}, \tag{8}$$

Where, $SP_{Mi}$ is the experimental (actual) value of swell percent, and $SP_{pi}$ the predicted output of the ANN for the ith input. $N_T$, $N_G$ and $N_C$ are the number of data sets used in training, generalization and cross validation respectively.

The training error, generalization error, validation error and total error are measured to study the qualitative performance of the model. Training error (TE) is the root mean squared residuals in the training data, testing/generalization error (GE) is the root mean square error in the testing data and cross validation error (CE) is the root mean squared error in the cross validation data.

## 4. Results and discussion

### 4.1 Supervised learning

The typical processing element used in the model is presented in Fig. 2. Individually, the neurons

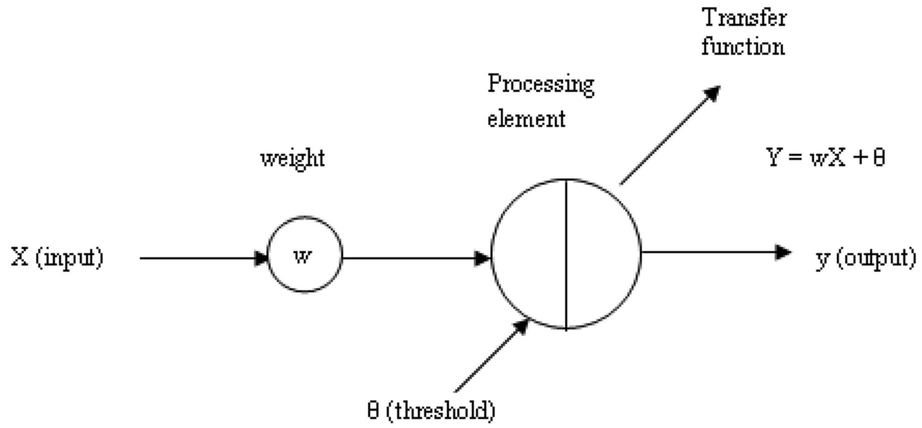


Fig. 2 Typical processing element used in the network

perform trivial functions, but collectively, in the form of a network, they are capable of solving complicated problems. The type of network considered in this example falls into the most popular class that of the layered feed forward network with synchronously operating neurons, and trained using a supervised scheme.

### 4.2 Hidden layer neurons

In order to solve the problem of high estimation error, single and hidden layers were trained with varying the hidden neurons. Generally, there is no direct and precise way of determining the most appropriate number of neurons to include in each hidden layer. Moreover the problem becomes more complicated as the number of neurons in hidden layers in the network increases. Hence to resolve the dilemma, a study is made on the impact of number of hidden layers and its neurons on the performance of network.

It is apparent from Fig. 3, that when one hidden layer is considered the RMS error is optimum with 6 hidden neurons (i.e at 4-6-1) compared to two layers, leading to minimum root mean square error. Thus in the present work 6 hidden neurons, single hidden layered feed forward back propagation network is adopted, and the designed optimal network (4-6-1) is presented in Fig. 4.

### 4.3 Feed forward network applied to swell problem

Fig. 4, illustrates a three-layers neuron network connected in a layered feed forward circuit. A problem is presented to the network as an array of real values, each element of which is entered to a different neuron in the input layer. The input neurons transmit these values across the links to the second (hidden) layer of neurons. On each link is a weight used to multiply transmitted values. The weighted values converging at a neuron in the hidden layer are summed along with a weighted bias associated with that neuron and is given as,

$$x_i=y_i w_{ji}+b_i \tag{9}$$

The result is then put through a simple function (as given in Eq. 10) to generate a level of activity for the neuron.

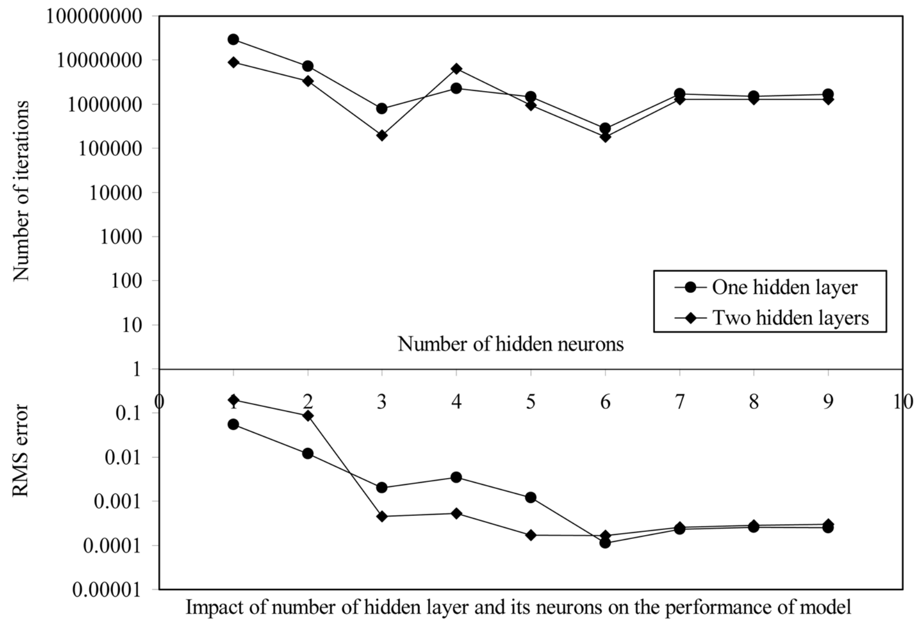


Fig. 3 Impact of hidden layer and its neurons on the RMS error

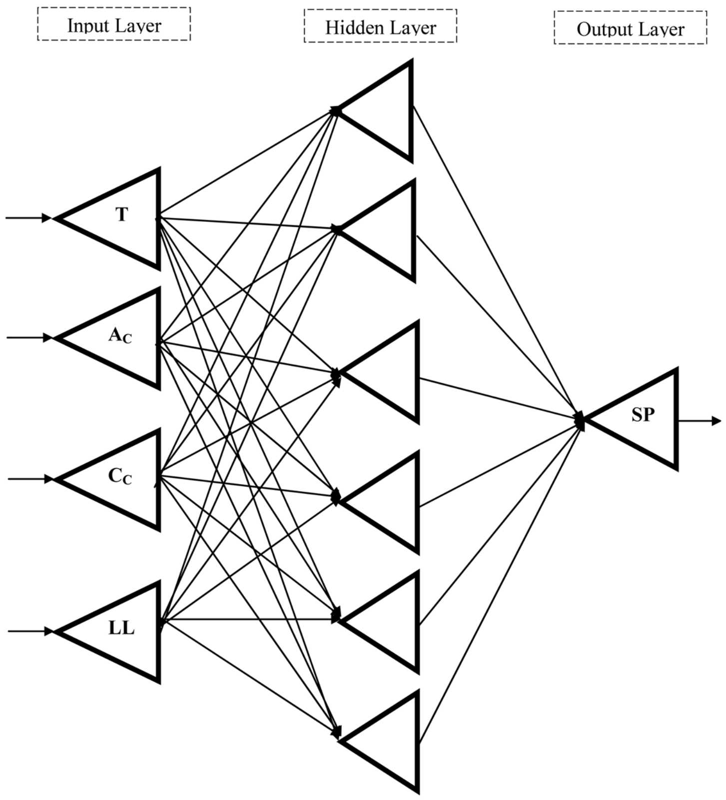


Fig. 4 Proposed ANN architecture to the percent swell prediction

Table 2 Input and output for each neural network layer

| Performed task | Layer | No. of neurons | Input to neuron | Output from neuron |
|---|---|---|---|---|
| Swelling Percent | Input | k=4 | $x_i$ i=1, 2…..k | $y_i=x_i$, i=1, 2,…k |
| | One hidden | 9 | $x_i=\sum^k_{j-1} y_i w_{ji}$, i=1, 2,…..9 | $y_i=1/[1+\exp(-x_i)]$ i=1, 2,…9 |
| | Two hidden | 9 | $x_i=\sum^k_{j-1} y_i w_{ji}$, i=1, 2,…..9 | $y_i=1/[1+\exp(-x_i)]$ i=1, 2,…9 |
| | Output | 1 | $x_i=\sum^k_{j-1} y_i w_{ji}+b_i$ | $y_i^0=x_i^0$ |

$$y_i=\frac{1}{(1+e^{-X_i})} \tag{10}$$

The activation levels of the hidden neurons are then transmitted across their outgoing links to the neurons in the output layer. As before, these values are weighted during transmission across the links, then summed at the output neuron and put through an activation function.

The level of activity generated at the output neuron(s) is the network's solution to the problem presented at the inputs. All neurons within a layer in this type of network operate synchronously in the sense that, at any point in time, they will all be at the same stage in processing. The sigmoid function presents the advantage of relating a wide ranging input to a finite output range. That means it takes the input, which may have any value between plus and minus infinity, and squashes the output into the range 0-1. This transfer function is commonly used in the back propagation networks, in part because it is differentiable. BPNNs were developed on 80486 personal computer using the WinNN software package. The internal network parameters of learning rate ($\eta$=0.5), and momentum ($\mu$=0.2), are considered to train, test and cross validate the network. The input and out put of neuron for each neural network layer is given in Table 2.

### *4.4 Prediction of percent swell*

The stages of training includes, assembling the data, creating the network object, training the network and simulating the ANN response to new inputs. To know the effect of carbonate content on swell behaviour a plot is drawn between time Vs swell percent and is presented in Fig. 5. The predicted and actual swell values for training and testing sets are shown very strong correlation by showing $R^2$ values as 0.9986 and 0.9925 with RMS errors as 0.5318 and 1.2323 respectively. It can be noted from Fig. 6 that almost all training and testing data points lying on zero error line. The close correlation of the experimental and predicted percent swell of soil with different amounts of carbonate inundated with 1N and 4N sulfuric acid indicates that the ANN model is capable of correlating the non-linear time series of swell to the multiple forcing signals of sulfuric acid normality, and carbonate content in the soil (Fig. 7). However, at certain data points little noise has shown, and can be generalized better with more sets of data points.

### *4.5 Validation of network*

Prior to usage of a developed model there is a need to establish the validity of the results it

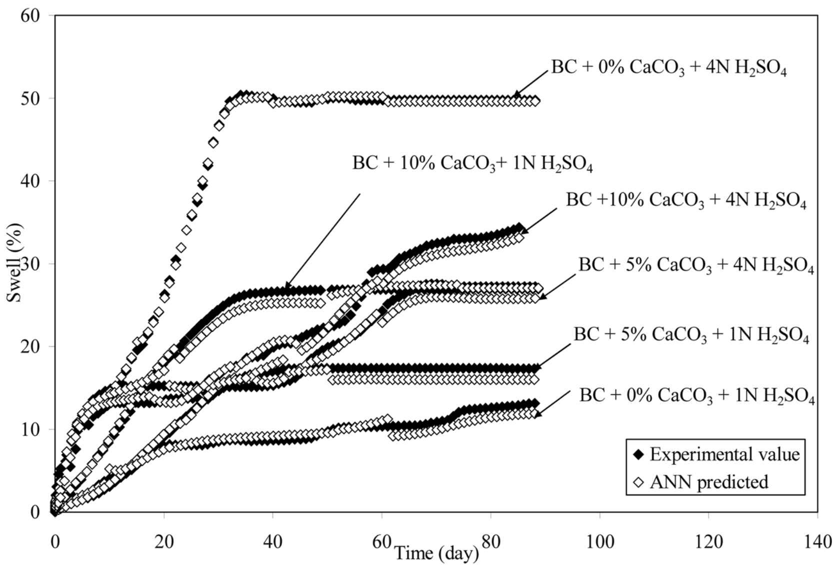


Fig. 5 Effect of carbonate content on percent swell

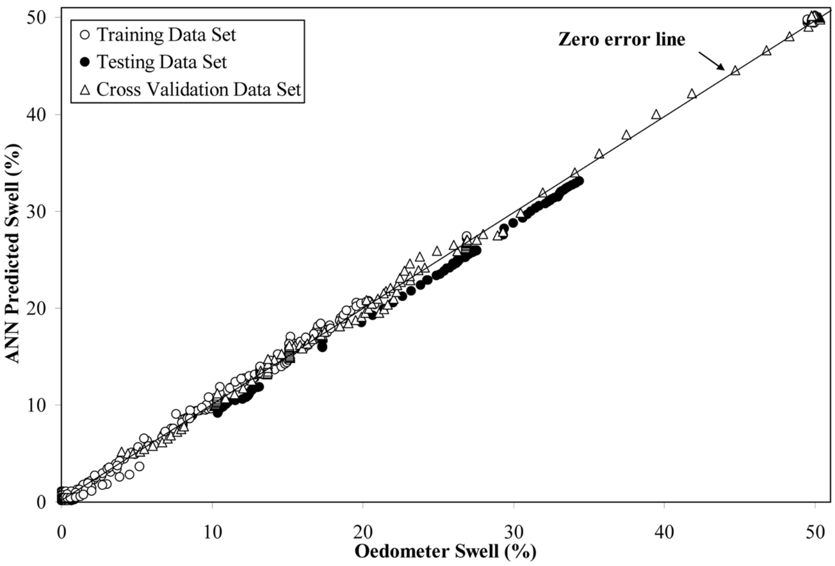


Fig. 6 Correlation between experimental and predicted swell percent

generates hence a separate data sets were assigned to this task. To check the strength of values a plot is drawn between the values of experimental swell and ANN predicted values (Fig. 6). The strong correlation coefficient ($R^2$=0.9986) of the developed model leading to a conclusion that the network could provide almost perfect answers to the set of problems with which it was trained.

### *4.6 Statistical discussions*

The performance measures values of the computed models are shown in Tables 3a and 3b. The

Table 3a Performance measures of regression and ANN intelligence models

| Model | Root mean square error | | | | Mean sum square of the error | | | |
|---|---|---|---|---|---|---|---|---|
| | Training | Testing | Cross validation | Total | Training | Testing | Cross validation | Total |
| Non-linear multiple regression | - | - | - | 6.2235 | - | - | - | 32.9865 |
| Artificial neural network | 0.5318 | 1.2323 | 0.5103 | 0.7940 | 0.2828 | 1.5186 | 0.2604 | 0.6304 |

Table 3b Performance measures of regression and ANN intelligence models

| Model | Average relative error | | | | $R^2$ estimate | | | |
|---|---|---|---|---|---|---|---|---|
| | Training | Testing | Cross validation | Total | Training | Testing | Cross validation | Total |
| Non-linear multiple regression | - | - | - | 85.6543 | - | - | - | 0.7698 |
| Artificial neural network | 33.6359 | 24.6283 | 5.6808 | 17.5861 | 0.9986 | 0.9925 | 0.9986 | 0.9968 |

mean sum square error between the regression and ANN predicted values are found to be 32.9865 and 0.6304 and that for corresponding $R^2$ values are 0.7698 and 0.9968 respectively. The same for the average relative error is 85.6543 and 17.5861, whereas the corresponding values for root mean square error are 6.2235 and 0.7940. The closeness of the points to the equality line and the high $R^2$ along with low MSSE, RMSE values clearly reflect the accuracy of the neural network model.

### *4.7 Proposed ANN model equation for the swell percent ($S_p$) based on trained neural network*

The basic mathematical equation as per the ANN relating the input variables and the output can be written as

$$\text{Swell, } SP_{Pn}=f_{sig}\left\{b_0+\sum_{k=1}^{h}\left[W_K\times f_{sig}\left(b_{hk}+\sum_{i=1}^{m}W_{ik}X_i\right)\right]\right\} \tag{11}$$

where $SP_{Pn}$ is the normalized (in the range of −1 to 1) $S_p$ value; $b_0$ is the bias at the out put layer; $w_k$ is the connection weight between $k^{th}$ neuron of hidden layer and the single output neuron; $b_{hk}$ is the bias at the $k^{th}$ neuron of hidden layer; $h$ is the number of neurons in the hidden layer; $w_{ik}$ is the connection weight between $i^{th}$ input variable and $k^{th}$ neuron of hidden layer; $X_i$ is the normalized input variable $i$ in the range [−1, 1].

Hence, the model equation for the output can be formulated based on the trained weights of the ANN model. In this case, such a model equation for swell percent of carbonate soil was established using the values of the weights and biases as shown in Table 4 as per the following expressions.

$$G_1=-10.300+6.177\,(T)+3.597\,(A_C)-13.717\,(C_C)-5.344\,(LL) \tag{12a}$$

Table 4 Connection weights and bias of the predicted swell percent

| Hidden layer neuron | Weights | | | | | Biases | |
|---|---|---|---|---|---|---|---|
| | Inputs | | | | Output | | |
| | Time (T) | Sulfuric acid concn ($A_C$) | Carbonate percent ($C_C$) | Liquid Limit (LL) | Swell (%) ($S_P$) | $b_{hk}$ | $b_o$ |
| 1 | 6.177 | 3.597 | -13.717 | -5.344 | -6.924 | -10.300 | 4.213 |
| 2 | -1.080 | 5.113 | 0.343 | -19.106 | -1.831 | -3.045 | |
| 3 | -4.515 | -16.646 | -18.756 | -1.689 | 28.111 | -1.618 | |
| 4 | -1.974 | -14.220 | -2.615 | -5.560 | 10.897 | 1.126 | |
| 5 | -7.821 | 9.674 | -7.658 | -21.124 | 11.178 | -1.065 | |
| 6 | 14.765 | 19.388 | -21.620 | -5.125 | 5.788 | -4679 | |

$$G_2=-3.045-1.080\ (T)+5.113\ (A_C)+0.343\ (C_C)-19.106\ (LL) \tag{12b}$$

$$G_3=-1.618-4.515\ (T)-16.646\ (A_C)-18.756\ (C_C)-1.689\ (LL) \tag{12c}$$

$$G_4=1.126-1.974\ (T)-14.220\ (A_C)-2.615\ (C_C)-5.560\ (LL) \tag{12d}$$

$$G_5=-1.065-7.821\ (T)+9.674\ (A_C)-7.658\ (C_C)-21.124\ (LL) \tag{12e}$$

$$G_6=-4.679+14.765\ (T)+19.388\ (A_C)-21.620\ (C_C)-5.125\ (LL) \tag{12f}$$

The $SP_{Pn}$ value as obtained from Eq. (12) is in the range [−1, 1] and this needs to be denormalized as

$$SP_P=S_{Pn\ \mathrm{model}}\ (S_{P\ \max}-S_{P\ \min})+S_{P\ \min} \tag{13}$$

Where, $SP_P$=Predicted model swell percent; $SP_{Pn\ \mathrm{model}}$=The model output;
$S_{P\ \max}$=The maximum swell percent; and $S_{P\ \min}$=The minimum swell percent

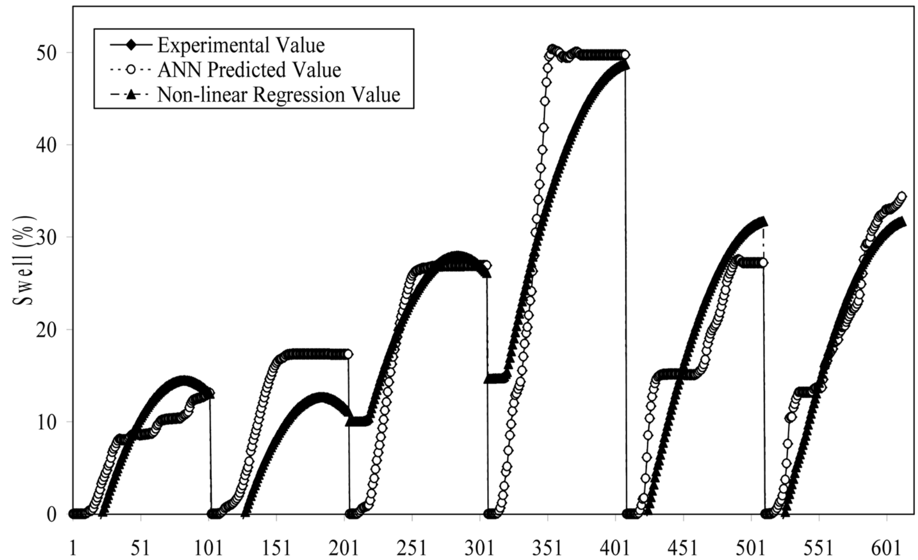


Fig. 7 Comparison between ANN and MRA predicted swell models.

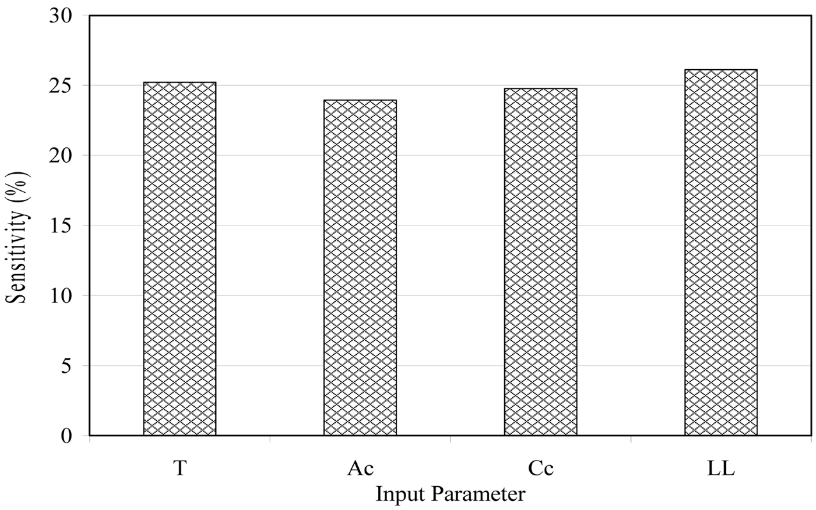


Fig. 8 Variation of selected input parameters on output swell

### *4.8 Sensitivity analysis*

A step-by-step sensitivity method was carried out on the trained percent swell by varying each of the input neurons, one at a time, at a constant rate (Liong *et al.* 2000). Various constant rates (−5, 5, 10, and 20%) were selected in the study. For every input neuron, the percentage change in the output, as a result of the change in the input neuron, was observed. The sensitivity of each input neuron is calculated by the following approach:

$$\text{Sensitivity}=\frac{1}{N}\sum_{j=1}^{N}\left(\frac{\%\ \text{changeinoutput}}{\%\ \text{changeininput}}\right)_j \times 100 \tag{14}$$

where, $N$=number of data sets used in the study.

Fig. 8 shows how sensitive the percent swell was, at each of the selected input parameters and how they would affect the changes. Almost all the selected parameters showed the significant contribution to the percent swell.

### *4.9 Non liner multiple regression model of swell percent*

Non-linear multi regression model swell percent,

$$\begin{aligned} SP=&0.0756-2.4748(T)-0.4239(A_C)+0.1566(C_C)+5.7099(LL)\\ &-0.0052(T)^2-2.4217(A_C)^2+0.5419(C_C)^2-0.0641(LL)^2+0.3014(TA_C)\\ &+0.0176(T\ C_C)+0.0329(T\ LL)-1.0413(A_C\ CC)-0.1779(A_C\ LL)-0.0795(C_C\ LL) \end{aligned} \tag{15}$$

## 5. Conclusions

The paper compares the relative advantages of artificial neural network technique and regression method to model and predict time dependent percent swell in carbonate soils. Based on the results of this investigation the following specific conclusions are drawn:

a) Increase in the number of hidden layer neurons increases the performance of network up to certain level and there after the generalization ability reduces significantly.

b) ANNs are based on the data alone in which the model can be trained on input-output data pairs to determine the parameter of the model. In this case, there is no need to simplify the problem nor to make any assumptions.

c) The swell percent obtained for carbonate soil by ANN technique shows good correlation with experimental swell for training, testing and cross validation, leading to a conclusion that ANN is better applicable for complex problems than regression method.

d) A model equation is offered based on the trained weights of the ANN. The designed model of ANN can always be updated to obtain better results by presenting new training examples as new data become available.

e) The difference of swell percent estimation, analyzed by four statistical methods (the best fit line (COE) for predicted swell percent ($SP_P$) and measured capacity ($SP_M$), the mean sum squared of the error (MSSE), average relative error (ARE) and root mean square error (RMSE)), showed that the developed ANN model is more efficient compared to regression model.

## References


Basma, A.A., Barakat, S.A. and Omar, M. (2003), "Modeling of time dependent swell of clays using sequential artificial neural networks", *Environ. Eng. Geosci.*, **9**(3), 279-288.

Angemeer, J. and Mc Neilan, T.W. (1982), "Subsurface variability –The key to investigation of Coral Atoll, Geotechnical properties, behaviour and performance of calcareous soils", *ASTM Special Technical Publication*, 36-53.

ASCE Task Committee (2000), "Artificial neural network in Hydrology", *J. Hydrologic Eng.*, **5**(2), 124-144.

Barakat, S. and Attom, M.F. (1999), "Comparison between multiple regression analysis and artificial neural networks in evaluating swelling pressure of clayey soil using three methods", *J. Inst. Eng. India*, **80**, 86-93.

Guru Prasad, B. (2008), *Mechanism and control of sulphuric acid induced heave in soils*, Ph.D. Thesis, Indian Institute of Science, Bangalore, India.

Yilmaz, I. (2006), "Indirect estimation of the swelling percent and a new classification of soils depending on liquid limit and cation exchange capacity", *Eng. Geol.*, **85**, 295-301.

Johnson, L.D. and Snethen, D.R. (1978), "Prediction of potential heave of swelling soils", *Geotech. Test. J.*, **1**, 117-124.

Liong, S.Y., Lim, W.H. and Paudyal, G.N. (2000), "River stage forcasting in Bangladesh: Neural Network Approach," *J. Comput. Civil Eng.*, 1-8.

Lukas, R.G. and Ganedinger Jr. R.J. (1972), "Settlement due to chemical attack of soils", *Proccedings of the ASCE Special Conference on the Performance of Earth and Earth Suported Structures*, West Lafayette, June.

MATLAB® Compiler (version 7.0), (2007), The Math Works.

Attom, M.F. and Barakat, S. (2000), "Investigation of three methods for evaluating swelling pressure of soils", *Environ. Eng. Geosci.*, **6**(31), 293-299.

O'Neil, M.W. and Ghazzally, O.I. (1977), "Swell potential related to building performance", *J. Geotech. Eng. Div.*, **103**(GT12), 1363-1379.

Al-Omari, R.R., Mohammed, W.K., Nashaat, I.H. and Kaseer, O.M. (2007), "Effect of sulfuric and Phosphoric acids on the behaviour of a lime stone foundation", *Indian Geotech. J.*, **37**(4), 263-282.

Sivapullaiah, P.V., Guru Prasad, B. and Allam, M.M. (2008a), "Volume change behaviour of Calcitic soil influenced with sulfuric acid", *ASCE, Geotechnical Special Publication 177*, Louisiana, USA, GeoCongress 2008: Geotechnics of Waste Management and Remediation.

Sivapullaiah, P.V., Guru Prasad, B. and Allam, M.M. (2008b), "Volume change behavior in Calcitic soil influenced

with sulphuric acid using artificial neural networks", *Proceedings of the 12th International Conference of International Association for Computer Methods and Advances in Geomechanics,* India.
Stephenson, R.W., Dempsey, B.A. and Heagler, J.B. (1989), "Chemically induced foundation heave", *Proceedings of the Foundation Engineering Conference*, Evanston, June.
Yilmaz, I. and Yüksek, A.G. (2008), "An example of artificial neural network application for indirect estimation of rock parameters", *Rock Mech. Rock Eng.*, **41**(5), 781-795.
Yilmaz, I. and Yüksek, A.G. (2009), "Prediction of the strength and elasticity modulus of gypsum using multiple regression, ANN, ANFIS models and their comparison", *Int. J. Rock Mech. Min.*, **46**(4), 803-810.
Erzin, Y. (2009), "The use of neural networks for the prediction of swell pressure", *Geomech. Eng.*, **1**(1), 75-84.

*JS*

## Nomenclature

| | |
|---|---|
| $SP_M$ | : Measured swell percent |
| $SP_P$ | : Model predicted swell percent |
| SP | : Swell percent |
| N | : Number of data sets |
| T | : Time |
| $A_c$ | : Sulfuric acid normality |
| $C_c$ | : Carbonate percentage |
| LL | : Liquid limit |
| $\Delta H$ | : Change in thickness of oedometer sample |
| H | : Total thickness of oedometer sample |
| $SP_{Mi}$ | : Experimental (actual) value of swell percent, |
| $SP_{Pi}$ | : Predicted output of the ANN for the ith input. |
| $N_T$ | : Number of data sets used in training |
| $N_G$ | : Number of data sets used in generalization |
| $N_C$ | : Number of data sets used in cross validation |
| MSE | : Mean square error |
| RMSE | : Root mean square error |
| $R^2$ | : Coefficient of efficiency |
| $b_0$ | : Bias at the out put layer |
| $w_k$ | : Connection weight between kth neuron of hidden layer and the single output neuron |
| $b_{hk}$ | : Bias at the kth neuron of hidden layer |
| h | : Number of neurons in the hidden layer |
| $w_{ik}$ | : Connection weight between ith input variable and kth neuron of hidden layer |
| $X_i$ | : Normalized input variable i in the range [−1, 1] |
| fsig | : Sigmoid transfer function |