

## Integrated approach of ANN and Taguchi algorithms for soils swelling estimation

Nawal Dounane<sup>1\*</sup> and Habib Trouzine<sup>2</sup>

<sup>1</sup>PhD Student, Civil Engineering and Environmental Laboratory (LGCE), Sidi Bel Abbes University, BP 89, DZ 22000 Sidi Bel Abbes, Algeria

<sup>2</sup>Full Professor, Civil Engineering and Environmental Laboratory (LGCE), Sidi Bel Abbes University, BP 89, DZ 22000 Sidi Bel Abbes, Algeria

\*Corresponding author: [nawel.dounane@gmail.com](mailto:nawel.dounane@gmail.com)

### ABSTRACT

**Received:** 15 December 2019 **Accepted:** 11 December 2020

Soils swelling behavior is one of the most damaging geohazard in the world. It can cause engineering problems such as damage to foundations, buildings and infrastructure. The prediction of this type of soil is a very complex issue that depends on geological, environmental and structural factors alongside many others. Classical statistical methods adopted to predict vertical movements of soils require numerous long and expensive experiments. This paper explores the effects and interactions of clay content and plasticity index factors on the swelling potential and pressure estimates. The analysis was conducted using Taguchi's  $L_9(3^2)$  orthogonal array, and back-propagation ANN was used to complete the design. Results indicate that integrating the Taguchi method and the network (ANN) approach is very efficient and accurate in predicting soil swelling as well as determining the effects and optimal conditions of different parameters. Analysis of variance (ANOVA) of the proposed integrated approach indicated that the plasticity index significance is about 91.66% and 95.77% respectively, for the estimation of swelling potential and swelling pressure.

**Keywords:** Taguchi design; ANN; foundation; swelling potential; swelling pressure; S/N ratio; ANOVA

## Introduction

Expansive soils are one of the most costly and globally widespread geological hazards. In Algeria, as in many parts in the world, engineering problems due to soil swelling have been reported. Soil swelling depends on the type and quantity of clay minerals, generally of the Montmorillonite group, the water content, and surcharges weight [1-3]. Soil swelling is especially noted in regions with arid and semi-arid climates; the soil undergoes high volumetric deformations due to the variation of the moisture content, which poses problems in the geotechnical and civil engineering fields [4-7]. Bases constructed on these types of soil are exposed to the high pressures caused by the swelling of these soils. These pressures cause damage in the form of fractures and fissures in the building foundations or floor components [8, 9]. The most obvious identifications on damage to buildings are doors and windows that get jammed, uneven floors, and cracked foundations, floor, masonry walls and ceilings. Moreover different crack patterns mean different causes for different foundation materials. In most cases, cracks due to



expansive clay usually run from corner to wards adjacent opening and are uniform in width or v-shaped, wider at the top the foundation wall [10]. Therefore, these soils present significant geotechnical and structural challenges to anyone wishing to build on or in them. In this context, it is important to predict soils prone to swelling prior to construction to reduce costly damages and ensure the durability of different constructions.

According to several researchers [4, 11, 12], the estimation of soil swelling is determined by two main parameters: the swelling potential and the swelling pressure. These parameters are identified either by direct measurements in the laboratory using the Oedometer, where such tests are costly in time and money, or by indirect measures which involve the use of soil properties and classification [2, 3, 7, 13]. Indirect methods are simple, rapid, and inexpensive compared to the experimental tests, but the prediction models established up to now by these types of methods, are often not universal. They are valid only for the soil of the region where it has been studied [7, 13]. In addition, they involve several parameters and often complicated approaches that achieve a plethora of results that are not always easily interpretable.

Generally, the typical expansive soils can be easily identified from their high plasticity, excessive heave, and high swell-shrink potential which are made up of clay, shale or marl [14].

Many researchers have indicated that clay content ( $C_c$ ) and plasticity index ( $I_p$ ) have an influence on soil swelling. They also related these parameters with simple empirical correlations [4, 11, 12, 15-17], also these two parameters are simple and easy to determine. Consequently, these parameters were selected as input parameters in this study.

The Taguchi method is an easy and economic statistical tool which can be used in a robust design, as it requires the use of a minimal number of experimental tests to study many variables [18-20]. Taguchi's robust design differs from a classical experimental design, through the idea of designing special standard tables (orthogonal arrays) that estimate a maximum number of main effects in an unbiased manner of a set of controllable (dynamic) and uncontrollable (noise) factors, on definite levels, and this with the least number of experiments [18, 21-23]. These types of arrays are balanced such that all factor levels are weighted. Therefore, it identifies the influence of the factors independently of all the others, and also the impact of one factor does not influence the estimation of the others, thus considerably reducing the time and cost demanded in experimental studies [24, 25]. Moreover, Taguchi's method has other advantages, including the optimization of the design parameters, model prediction, determining optimal factor levels and reducing noise sensitivity using robust parameter design, evaluating the effect of factors independently on the result [19, 20, 22-24]. To date, the Taguchi method has been successfully applied in civil engineering, notably in the studies of slope stability [24], soil erosion [20, 26] and liquefaction of soil [27], but never for completing and estimating geotechnical parameters.

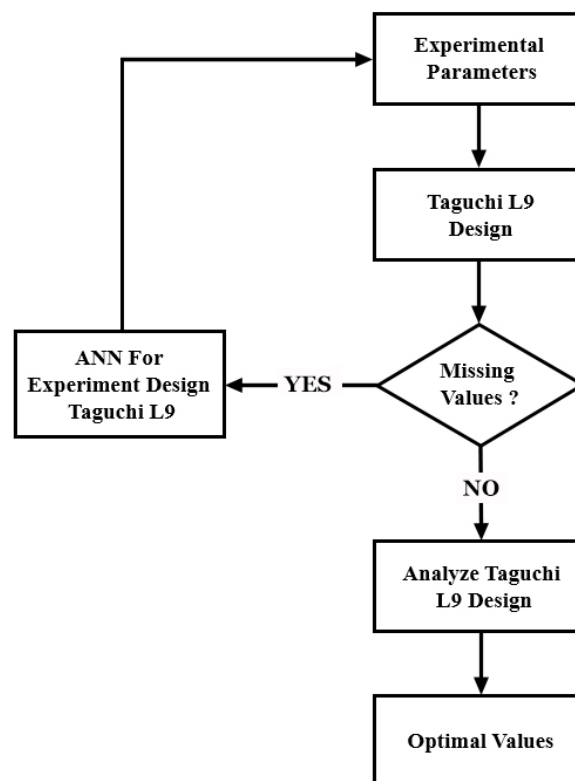
For this, a new approach, reliable, inexpensive, short time and with universal application is applied in this article to study this type of soil. This approach involves using a type of experiment design 'the Taguchi method' to examine the effects and interactions with determining the optimal levels of selected factors on swelling potential and swelling pressure.

This study borrows the use of the experimental design of Taguchi established by a database that was collected from the area of Western Algeria, which gives an evaluation of the investigated parameters (clay content, plasticity index, swelling potential and swelling pressure).

Each factor has three levels chosen according to the BRE classification [28], (see Table 1). The available data did not correspond to those required for the orthogonal array design Taguchi  $L_9$  selected for this study, because of the non-orthogonality of the table. Therefore, an artificial neural network was created with the available experimental database to calculate the swelling pressure and swelling potential for clay content and plasticity index to complete the orthogonal array design Taguchi  $L_9$ . For the table to be orthogonal, it is necessary that between each pair of columns, the combination of variables appears an equal number of times [18]. However, it was impossible to set the values of the first parameter (clay content) in one level and fix the second parameter (the plasticity index) in one of the other levels or the opposite level in this case.

**Table 1.** Swelling potential after the Building Research Establishment

| $I_p$ (%) | $C_c < 2 \text{ um}$ (%) | $S_p$ (%) |
|-----------|--------------------------|-----------|
| > 35      | > 95                     | Very high |
| 22 – 30   | 60 – 95                  | High      |
| 18 – 22   | 30 – 60                  | Moderate  |
| < 18      | < 30                     | Low       |



**Figure 1.** General structure for the proposed methodology.

Recently, ANN has been widely applied successfully in the engineering in general, according to the authors [29, 30, 31]. This method has been used in many studies, including the liquefaction of soil [27, 32], slope stability and earth retaining structures [33, 34], prediction of soil swelling pressure [35], design of tunnels [36] and settlement of structures [37, 38].

Finally, the orthogonal array design Taguchi  $L_9$  is completed and used to analyze and determine the different effects and interactions as well as the optimal conditions for the studied parameters. The structure of the suggested methodology is shown in Figure 1.

## Methodology

First, an experimental database on soil swelling in the area of Western Algeria was collected [39-46]. In each experiment, four parameters were determinate, in accordance with international ISO standards: the clay content  $C_c$  (NF P94-056, NF P94-057), the plasticity index  $I_p$  (NF P94-051), the swelling potential  $S_p$  (ASTM D 4546-90) and the swelling pressure  $P_s$  (XP P94 - 091).

### The design of Taguchi's plan

In this work, two three-level factors was selected, the clay content and the plasticity index as shown in Table 2: symbol 1, 2 and 3 indicate respectively low, moderate and high to a very high degree of swelling potential. The same levels of parameters were used for the estimation of the swelling pressure.

Estimating the swelling potential/pressure as a function of two factors and three levels using a complete classical experimental design would require 27 experiments (each  $(levels)^{factors}=3^2$  experiments with three repetitions for all

**Table 2.** Factors and levels selected

| Factors                      | Levels |      |      |
|------------------------------|--------|------|------|
|                              | 1      | 2    | 3    |
| $C_c$ : clay content (%)     | 29     | 32   | 60   |
| $I_p$ : plasticity index (%) | 17.1   | 27.3 | 93.5 |

**Table 3.** Experiment design using a Taguchi  $L_9$  orthogonal array

| $C_c$ | $I_p$ |
|-------|-------|
| 1     | 1     |
| 1     | 2     |
| 1     | 3     |
| 2     | 1     |
| 2     | 2     |
| 2     | 3     |
| 3     | 1     |
| 3     | 2     |
| 3     | 3     |

combinations of parameters), whereas similar results can be obtained by the use of orthogonal plane Taguchi  $L_9$ .

The use of orthogonal arrays in the Taguchi design ensures the equilibration of the experiments, where each factor is evaluated independently of the others. Table 3 shows the design of the Taguchi  $L_9$  plan, including the combinations of known variables, where the values of the swelling potential and the swelling pressure for two variables, the clay content and the plasticity index, are available at the database and that for the combinations (1,1); (2,2) and (3,3). A neural network was also created to calculate the responses to combinations of unknown variables, where the values of the swelling potential and the swelling pressure for two variables, the clay content and the plasticity index, were not available at the time in a database.

The Taguchi method requires the use of the Signal/Noise ratios (S/N) to estimate the influence of the factors on a response, such that the S/N ratio represents the measure of the mean square deviation to the ideal function. S/N ratios are calculated for three categories based on the objective of the problem: the higher-the-better (HTB), the nominal-the-better (NTB) and the lower-the-better (LTB) [20]. The most important in a study of soil swelling is to identify the optimal conditions in which soil swelling is maximal. Consequently, the higher-the-better analysis was used for this study. According to [47], the equation used to calculate the ratio (S/N) for the higher-the-better (HTB) is as below:

$$\frac{S}{N} = -10 \log_{10} \left( \frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2} \right) \quad (1)$$

Where:  $y$  is the average of the observed data,  $n$  is the number of repetitions of trial  $i$ .

Moreover, the main effect plots are also used to determine which factors affect the response the most by examining the changes in the mean of each level, such that it defines the means of the responses of each factor level related by a line. There will be no main effect if this line is parallel to the X-axis; as each level of the factor affects the response in the same way. On the other hand, if the line is not horizontal, this shows the existence of the main effect and different levels of the factor affecting the response independently. In addition, the steeper the slope of the line the higher the value of the main effect [27].

### Artificial neural networks completion

ANN has been developed for the modeling of complex problems for which the relationship between the model variables is unknown [30, 48]. Moreover, generalization, the universal approximation of functions, adaptation, parallel processing of data and robustness, are many other advantageous features of this technique that saves a lot of money and time [23, 49].

The ANN structure generally includes the number of hidden layers, the number of hidden nodes or neurons, the activation function (sigmoid, linear and tangent) and the number of output nodes. The neuron of the previous layer and the next layer are connected with adjustable weights ( $w_i$ ) so that each has a threshold value ( $bais_i$ ) that functions according to the input signal. This value is added to the sum of the weights multiplied by the input of each

processing element in the previous input layer, and the transfer function also processes this input to gives the output of the neuron [25, 35]. The Eq.(2) describes the weighted sum of the input components of each neuron where (j) indicates the number of neurons in the previous layer [25, 49].

$$(input)_i = \sum_{k=0}^n w_{ij} + bias_j \quad (2)$$

For this study, 21 experiments were available for training the network, to predict the  $S_p$  and  $P_s$  values for the combinations levels unknown of the  $C_c$  and  $I_p$  in the Taguchi table. The complete set of data is divided into three subsets, 70% of the data set for training, 15% for validation, and 15% for testing. The training data set for the swelling potential values are presented in Table 4, and the training data set for the swelling pressure values are presented in Table 5. Furthermore, the inputs are processed from the beginning to the end of the network by a sigmoid transfer function in the hidden layer, and a linear transfer function in the output layer.

The “back-propagation” learning algorithm was used for this study. This method essentially consists in adjusting the weights and the biases until the network stabilizes. In order to make the outputs very close to the target outputs of the network, iterative computations are completed which are updated to the mean squared error (MSE) between the calculated output and the desired targets with the transfer of the correction signal from the end of the network to its beginning [23].

**Table 4.** Training data set for the swelling potential

| <i>Input</i> |       | <i>Output</i> |
|--------------|-------|---------------|
| $C_c$        | $I_p$ | $S_p$         |
| 55.3         | 22    | 4.75          |
| 61.2         | 83    | 11.89         |
| 48           | 14    | 0.87          |
| 26           | 27.5  | 9.5           |
| 32           | 27.3  | 22            |
| 35           | 46.8  | 19.5          |
| 42           | 62    | 38.7          |
| 60           | 71    | .20.4         |
| 34           | 62.5  | 31.9          |
| 46           | 48.5  | 19            |
| 55           | 44.2  | 25.2          |
| 52           | 50.3  | 28.9          |
| 29           | 17.1  | 9.7           |
| 42           | 22.3  | 13.5          |
| 69           | 35    | 5.72          |
| 40           | 83.43 | 27.08         |
| 60           | 93.5  | 47.5          |
| 44           | 37.42 | 4             |
| 48           | 36.2  | 6.5           |
| 44.8         | 42.04 | 2.17          |
| 50           | 87.94 | 23.44         |

**Table 5.** Training data set for the swelling pressure

| <i>Input</i> |       | <i>Output</i> |
|--------------|-------|---------------|
| $C_c$        | $I_p$ | $S_p$         |
| 55.3         | 22    | 65            |
| 61.2         | 83    | 148           |
| 48           | 14    | 23            |
| 26           | 27.5  | 175           |
| 32           | 27.3  | 310           |
| 35           | 46.8  | 100           |
| 42           | 62    | 252           |
| 60           | 71    | 200           |
| 34           | 62.5  | 150           |
| 46           | 48.5  | 46            |
| 55           | 44.2  | 80            |
| 52           | 50.3  | 84            |
| 29           | 17.1  | 100           |
| 42           | 22.3  | 100           |
| 69           | 35    | 201.3         |
| 40           | 83.43 | 447           |
| 60           | 93.5  | 852           |
| 44           | 37.42 | 120           |
| 48           | 36.2  | 33            |
| 44.8         | 42.04 | 43            |
| 50           | 87.94 | 158           |

Also, to evaluate the performance of the model ANN in this study, two statistical analyses involving the mean squared error (MSE) and the correlation coefficient  $R^2$  are used. The model estimate is more accurate when the mean squared error is very small, and the value of  $R^2$  is close to 1.

## Result and Discussions

The ANN architecture selected for the prediction of the swelling potential is indicated in Figure 2. This final architecture was chosen after a few attempts. The network has only one hidden layer, and each hidden layer contains 12 neurons (2-12-1-1). The statistical values of the swelling potential obtained from the training, validation, and tests of the ANN model show the mean squared error (MSE) to be at a value of  $6.67 \cdot 10^{-09}$ , and the correlation coefficient  $R^2$  is almost 1, between the calculated output and the desired targets of the learning set. These results indicate that a very good agreement between the production and the target has been achieved. Therefore, the model analysis gives good results in the validation and test set for the prediction of the swelling potential.

After a few attempts, the ANN analysis results for the prediction of the swelling pressure is shown that the selected architecture was (2-12-1-1), therefore, it is the same neural network architecture shown in Figure 2. The results of this task obtained from the training, validation and testing of this type of model indicate that a value of

$1.82 \cdot 10^{-10}$  of the mean squared error (MSE) and a correlation coefficient  $R^2$  is almost 1, between the calculated output and the desired targets of the training set, which means a good model for the prediction of swelling pressure. Table 6 shows the set of statistical values obtained by the proposed ANN model.

Finally, the unavailable data was calculated with this ANN modeling, and the Taguchi  $L_9$  plans were completed as shown in Table 7 and 8 respectively. These orthogonal arrays have been designated by the code  $L_9$ , which are composed of 9 lines and 3 columns, such as presented above. Following this, an analysis of the Taguchi plans was executed to calculate the average ratios and S/N reports of each parameter ( $S_p$  and  $P_s$ ). The results analysis is as follows:

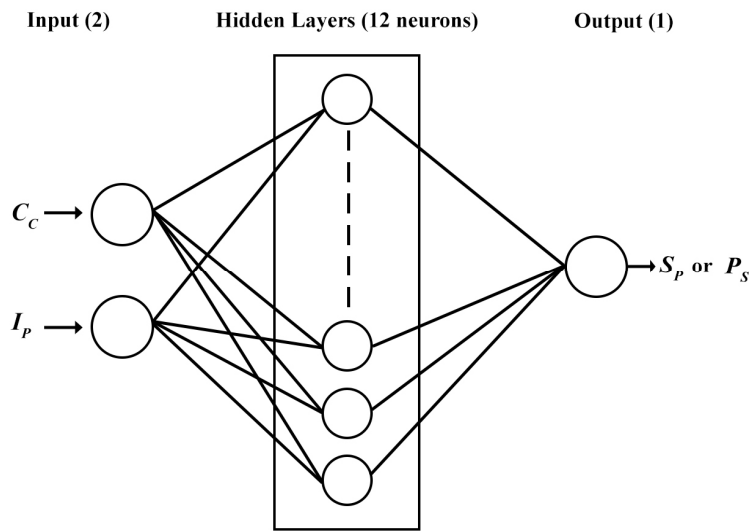


Figure 2. ANN structure proposed.

Table 6. Results of Statistical values of ANN model

| ANN model for      | Statistical parameters |                 |                   |              |                       |
|--------------------|------------------------|-----------------|-------------------|--------------|-----------------------|
|                    | Training data          | Validation data | swelling pressure | All training | MSE                   |
|                    | $R^2$                  | $R^2$           | $R^2$             | $R^2$        |                       |
| Swelling potential | 0.986                  | 1               | 0.999             | 0.991        | $6.67 \cdot 10^{-9}$  |
| Swelling pressure  | 0.984                  | 0.996           | 0.951             | 0.985        | $1.82 \cdot 10^{-10}$ |

Table 7. Orthogonal array design Taguchi  $L_9$  for the swelling potential

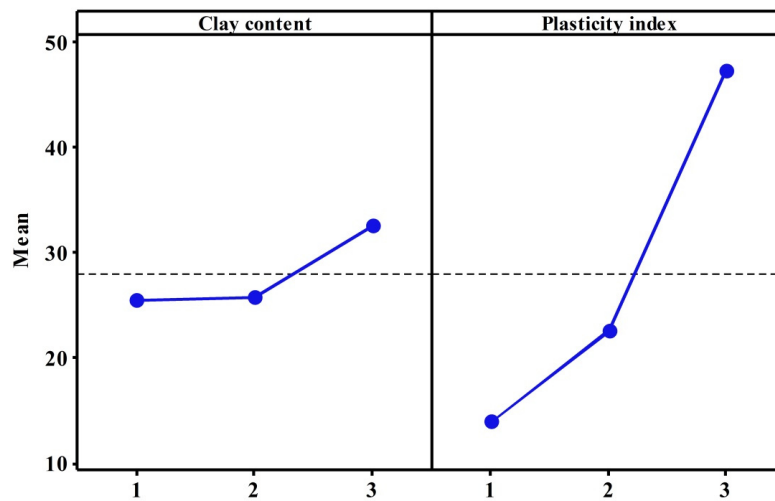
| $C_c$ | $I_p$ | $S_p$  |
|-------|-------|--------|
| 29    | 17.1  | 9.700  |
| 29    | 27.3  | 17.510 |
| 29    | 93.5  | 49.118 |
| 32    | 17.1  | 10.075 |
| 32    | 27.3  | 22.000 |
| 32    | 93.5  | 45.069 |
| 60    | 17.1  | 22.015 |
| 60    | 27.3  | 28.113 |
| 60    | 93.5  | 47.500 |



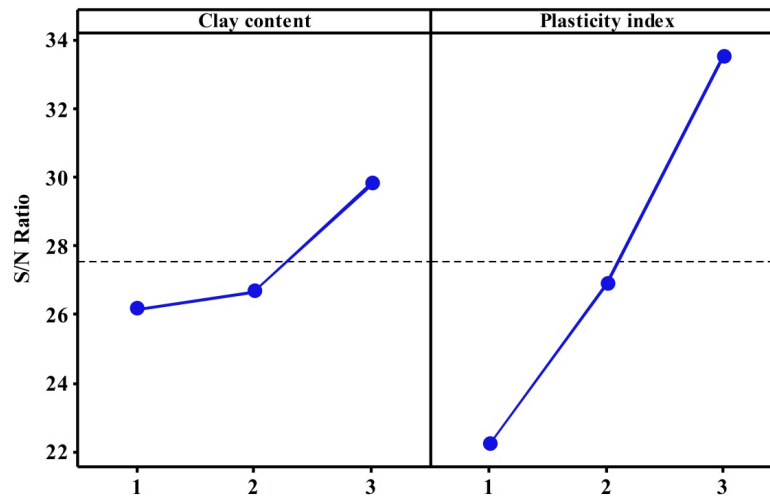
**Table 8.** Orthogonal array design Taguchi  $L_9$  for the swelling pressure

| $C_c$ | $I_p$ | $P_s$   |
|-------|-------|---------|
| 29    | 17.1  | 100.000 |
| 29    | 27.3  | 255.080 |
| 29    | 93.5  | 674.991 |
| 32    | 17.1  | 202.483 |
| 32    | 27.3  | 310.000 |
| 32    | 93.5  | 751.389 |
| 60    | 17.1  | 219.276 |
| 60    | 27.3  | 289.914 |
| 60    | 93.5  | 852.000 |

According to Figures 3 and 4, all parameters selected ( $C_c$  and  $I_p$ ) affect the swelling potential. These results also showed that the swelling potential increases as the plasticity index and clay content increase, and that the plasticity index has the highest effect on the swelling potential followed by clay content. The highest levels (3,3) special to an effect on means and S/N ratios gave the excellent combination of levels, consequently, optimal swelling potential



**Figure 3.** Effects of clay content and plasticity index on swelling potential.



**Figure 4.** S/N ratio for swelling potential.

combination predicted for parameters examined is the plasticity index  $I_p = 93.5\%$ , and the clay content  $C_c = 60\%$ . The greatest factor effect is noted for the plasticity index. These results can be confirmed in Table 7, where the greatest swelling potential value was at the highest level (3,3), as well as the output of the neural network for the input (60,93.5) was  $S_p = 47.074\%$ .

Figures 5 and 6 present the plot for mean and S/N ratio for the selected factors ( $C_c$  and  $I_p$ ) on the swelling pressure. These results show that the swelling pressure increases as the plasticity index and clay content increase and that the plasticity index has the highest effect on the swelling pressure allowed by clay content. They further indicate that the highest levels (3, 3) special to an effect on means and S/N ratios gave the excellent combination of levels, therefore, optimal swelling pressure combination predicted for parameters examined is the plasticity index  $I_p = 93.5\%$ , and the clay content  $C_c = 60\%$ . These results can be confirmed in Table 8, where the greatest swelling pressure value was at the highest level (3,3), and where the output of the neural network for the input (60,93.5) was  $P_s = 873.969 \text{ kPa}$ . In this case, the factors having the greatest effect are the clay content followed by the plasticity index.

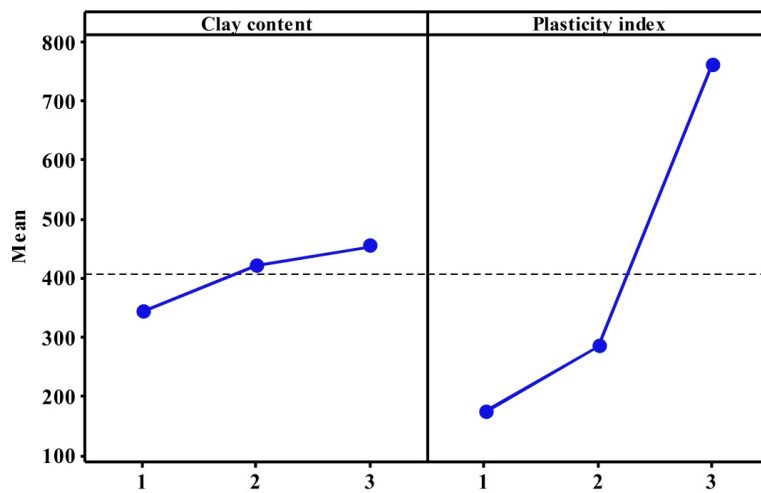


Figure 5. Effects of clay content and plasticity index on swelling pressure.

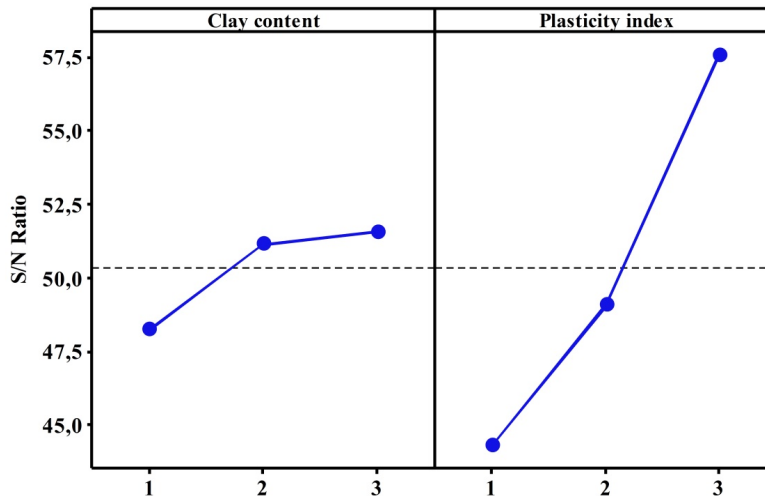


Figure 6. S/N ratio for swelling pressure.

The results of the method used for this study (Taguchi  $L_9$ ) showed the strength of the effect of the two parameters, the clay content and the plasticity index, on soil swelling (swelling potential and the swelling pressure), so that the higher the percentage of clay content and the plasticity index, the greater the degree of swelling. In this study, soil swelling is observed from value  $C_c = 29\%$  and  $I_p = 17.1\%$ , and reaches a maximum value at  $C_c = 60\%$  and  $I_p = 93.5\%$ . These results are in agreement with those obtained by several researchers who studied and classified soil swelling from these two parameters ( $S_p$  and  $P_s$ ). Moreover, the importance of the applicability of the Taguchi method in geotechnical engineering studies in general, and particularly in the prediction of soil swelling, is demonstrated as it ensures very high accuracy and comprehensibility of the effect and robustness of each parameter separately on the soil swelling, compared to the use of other conventional statistical methods.

### Analysis of variance (ANOVA)

Analysis of variance (ANOVA) is a standard statistical technique that was used to determine the reliability of the results of the Taguchi experiment and provide information about the degree of effect of each factor of the orthogonal array on the result. This analysis was carried out at 95% confidence level and a significance level of  $\alpha = 0.05$ . The percentage contribution for each factor is represented by the ratio of pure sum to the total sum of the squares [22]. The P-value in the ANOVA is a probability for determining the differences between the factors means are statistically significant.

Table 9 shows the ANOVA analysis results for the swelling potential with the percentage contribution of each factor to column 4. It is observed that the plasticity index has the highest significance (91.66%) followed by clay content (4.97%). Moreover, the “P” value for the plasticity index is less than 0.05 indicates that this factor had a significant effect on the swelling potential.

The results of ANOVA for swelling pressure in Table 10, indicate the percentage contribution of each factor. It was found that the most influential factor was the plasticity index representing about 95.77%, followed by the clay content with a percentage of 3.19%. Similarly, the “P” value for the plasticity index is less than 0.05, which means that this factor had a significant effect on the swelling pressure.

**Table 9.** Analysis of Variance (ANOVA) for swelling potential

| Source           | DF | Seq SS  | Contribution (%) | Adj SS  | Adj MS | F     | P     |
|------------------|----|---------|------------------|---------|--------|-------|-------|
| Clay content     | 2  | 97.10   | 4.97             | 97.10   | 48.55  | 2.94  | 0.164 |
| Plasticity index | 2  | 1792.50 | 91.66            | 1792.50 | 896.25 | 54.33 | 0.001 |
| Error            | 4  | 65.98   | 3.37             | 65.98   | 16.50  |       |       |
| Total            | 8  | 1955.58 | 100              |         |        |       |       |

**Table 10.** Analysis of Variance (ANOVA) for swelling pressure

| Source           | DF | Seq SS | Contribution (%) | Adj SS | Adj MS | F      | P     |
|------------------|----|--------|------------------|--------|--------|--------|-------|
| Clay content     | 2  | 19308  | 3.19             | 19308  | 9654   | 6.09   | 0.061 |
| Plasticity index | 2  | 580310 | 95.77            | 580310 | 290155 | 183.15 | 0.000 |
| Error            | 4  | 6337   | 1.05             | 6337   | 1584   |        |       |
| Total            | 8  | 605955 | 100              |        |        |        |       |

The ANOVA analysis results show that the interactions between the selected factors have no statistical significance or contribution to the swelling potential or swelling pressure. In addition, the ANOVA analysis confirms the results predicted by the Taguchi analysis, which gave a very good result in determining the optimal conditions for estimating the swelling potential and pressure.

## Conclusions

In this paper, a new integrated approach of ANN and Taguchi algorithms is presented to solve the soil swelling estimation problems. The quite well promising outcomes of this research provide that Taguchi  $L_9$  and ANN method can be widely efficient to predict two essential parameters for the engineer and difficult to determine (swelling potential and pressure) from two simply measurable parameters (clay content and plasticity index). Analysis of variance (ANOVA) has also demonstrated that the reliability of the results of the proposed algorithms is very acceptable. Finally, this approach has the capacity to predict and determine optimal conditions of swelling potential and swelling pressure in a very short time with inexpensive cost, in comparison to other methods, and this in response to different combinations of factors/levels by conducting a very small number of experiments with good accuracy. Further research can be carried out to advance this design methodology.

## Notation

|              |  |
|--------------|--|
| <i>ANN</i>   | <i>Artificial neural network</i>       |
| <i>ANOVA</i> | <i>Analysis of variance</i>            |
| $C_c$        | <i>Clay content (%)</i>                |
| $I_p$        | <i>Plasticity index (%)</i>            |
| $L_9$        | <i>Orthogonal array design Taguchi</i> |
| <i>MSE</i>   | <i>Mean squared error</i>              |
| $P_s$        | <i>Swelling pressure (kPa)</i>         |
| $R^2$        | <i>Correlation coefficient (%)</i>     |
| <i>S/N</i>   | <i>Signal-to-Noise ratios</i>          |
| $S_p$        | <i>Swelling potential (%)</i>          |

## References

- [1] V.P. Rao, *Swelling pressure of soil predictive tool*. International Journal of Computer Application. 63 (2013), pp. 27-32.
- [2] M. Zumrawi, *Prediction of swelling pressure for compacted expansive soils*. UofKEJ 3 (2013b), pp. 35-39.
- [3] N.R. Galaviz-González, J. Horta, E. Rojas, M. de la Luz Pérez-Rea, and J. Robles Sotelo, *Predicting the volumetric variation due to changes in, applied stress and swelling pressure*. E3S Web of Conferences. 9 (2016), pp. 1-6.
- [4] F. Chen, *Foundations on Expansive Soil*. 1988, Elsevier Scientific Publishing Co., Amsterdam.
- [5] M. Zumrawi, *Geotechnical aspects for roads on expansive soils*. International Journal of Science and Research. 3 (2013a), pp. 1-6.
- [6] M. Hajjalilue-Bonab and F. Behrooz-Sarand, *Physical and numerical modeling of canal lining on expansive soil*. Japanese Geotechnical Society Special Publication. 2 (2016), pp. 484-489.

- [7] E. Wójcik and I. Gawriuczenkow, *Determination of swell index and swelling pressure from suction tests-a case study of neogene clays from warsaw (Poland)*. Geological Quarterly. 61 (2017), pp. 738-750.
- [8] M. Turkoz and H. Tosun, *The use of methylene blue test for predicting swell parameters of natural clay soils*. Scientific Research and Essays. 6 (2011), pp. 1780-1792.
- [9] D.K. Srivastava, A. Srivastava, A.K. Misra, and V. Sahu, *Forensic assessment of a fail head wall of Hume Pipe Culvert: Focus on Geotechnical prospective*. International Journal of Sustainable Building Technology and Urban Development. (2018), pp. 96-109.
- [10] M. Mokhtari and M. Dehghani, *Swell-shrink behavior of expansive soils, damage and control*. Elect. J. Geot. Eng. 17 (2012), pp. 2673-2682.
- [11] W. Holtz and H. Gibbs, *Engineering properties of expansive clays*. Transactions of the American Society of Civil Engineers. 121 (1956), pp. 641-677.
- [12] H. Seed, R. Woodward, and R. Lundgren, *Prediction of swelling potential for compacted clays*. Journal of the Soil Mechanics and Foundations Division. 88 (1962), pp. 53-87.
- [13] Y. Berrah, A. Boumezbear, N. Kherici, and N. Charef, *Application of dimensional analysis and regression tools to estimate swell pressure of expansive soil in Tebessa (Algeria)*. Bulletin of Engineering Geology and the Environment. 77 (2016), pp. 1155-1160.
- [14] M. Steinberg, *Expansive soils and the geomembrane remedy*. in: Advances in Unsaturated Geotechnics, 2000, pp. 456-466.
- [15] T. Lambe, *The character and identification of expansive soils*. 1960, Fed. Housing Admin.Rep. 701. U.S. Gov. Print. Office, Washington, DC.
- [16] D. McCormack and L. Wilding, *Soil properties influencing swelling in Canfield and Geeburg soils*. Soil Science Society of America Journal. 39 (1975), pp. 496-502.
- [17] A. Sudjianto, K. Suryolelono, A. Rifa, and I. Mochtar, *The effect of variation index plasticity and activity in swelling vertical of expansive soil*. International Journal of Engineering & Technology IJET-IJENS. 11 (2011), pp. 117-123.
- [18] R. Rao, C. Kumar, R. Prakasham, and P. Hobbs, *The Taguchi methodology as a statistical tool for biotechnological applications: A critical appraisal*. Biotechnology Journal. 3 (2008), pp. 510-523.
- [19] A. Yıldız, N. Öztürk, N. Kaya, and F. Öztürk, *Hybrid multi-objective shape design optimization using Taguchi's method and genetic algorithm*. Structural and Multidisciplinary Optimization. 34 (2007), pp. 317-332.
- [20] F. Zhang, Z. Wang, and M. Yang, *Assessing the applicability of the Taguchi design method to an interrill erosion study*. Journal of Hydrology. 521 (2015), pp. 65-73.
- [21] G. Taguchi, *System of Experimental Design*. 1987, International Publications, New York.
- [22] S.V. Mohan, K. Sirisha, R.S. Rao, and P. Sarma, *Bioslurry phase remediation of chlorpyrifos contaminated soil: Process evaluation and optimization by Taguchi design of experimental (doe) methodology*. Ecotoxicology and Environmental Safety. 68 (2007), pp. 252-262.
- [23] M. Madić and M. Radovanović, *Optimal selection of ANN training and architectural parameters using Taguchi method: A case study*. FME Transactions. 39 (2011), pp. 379-86.
- [24] O. Tan, *Investigation of soil parameters affecting the stability of homogeneous slopes using the Taguchi method*. Eurasian Soil Science. 39 (2006), pp. 1248-1254.
- [25] A. Olabi, G. Casalino, K. Benyounis, and M. Hashmi, *An ANN and Taguchi algorithms integrated approach to the optimization of CO<sub>2</sub> laser welding*. Advances in Engineering Software. 63 (2006) pp. 643-648.
- [26] S. Sadeghi, V. Moosavi, A. Karami, and N. Behnia, *Soil erosion assessment and prioritization of affecting factors at plot scale using the Taguchi method*. Journal of Hydrology. 448-449 (2012), pp. 174-180.
- [27] A. Baykasoglu, A. Cevik, L. Ozbakir, and S. Kulluk, *Generating prediction rules for liquefaction through data mining*. Expert Systems with Applications. 36 (2009), pp. 12491-12499.
- [28] BRE, *Building research establishment united kingdom*, 1980.

- [29] Y. Erzin, *Artificial neural networks approach for swell pressure versus soil suction behavior*. Canadian Geotechnical Journal. 44 (2007), pp. 1215-1223.
- [30] M. Shahin, M. Jaksa, and H. Maier, *Artificial neural network applications in geotechnical engineering*. Australian geomechanics. 36 (2001), pp. 49-62.
- [31] S.H. Lee, H.Y. Kim, H.K. Shin, Y. Jang, and Y.H. Ahn, *Introducing a model for evaluating concrete structure performance using deep convolutional neural network*. International Journal of Sustainable Building Technology and Urban Development. (2017), pp. 285-295.
- [32] A.M. Hanna, D. Ural, and G. Saygili, *Neural network model for liquefaction potential in soil deposits using Turkey and Taiwan earthquake data*. Soil Dynamics and Earthquake Engineering. 27 (2007), pp. 521-540.
- [33] A. Goh, K. Wong, and B. Broms, *Estimation of lateral wall movements in braced excavation using neural networks*. Canadian Geotechnical Journal. 32 (1995), pp. 1059-1064.
- [34] M. Sakellariou and M. Ferentinou, *A study of slope stability prediction using neural networks*. Canadian Geotechnical and Geological Engineering. 23 (2005), pp. 419-445.
- [35] S. Das, P. Samui, A. Sabat, and T. Sitharam, *Prediction of swelling pressure of soil using artificial intelligence techniques*. Environmental Earth Sciences. 61 (2010), pp. 393-403.
- [36] J. Shi, J. Ortigao, and J. Bai, *Modular neural networks for predictive settlement during tunneling*. Journal of Geotechnical and Geoenvironmental Engineering. 124 (1998), pp. 389-395.
- [37] M. Shahin, M. Jaksa, and H. Maier, *Predicting the settlement of shallow foundations on cohesion less soils using back-propagation neural networks*. Research Report No. R167, the University of Adelaide, Adelaide, Australia (2000), p. 19.
- [38] M. Shahin, H. Maier, and M. Jaksa, *Predicting settlement of shallow foundations using neural networks*. Journal of Geotechnical and Geoenvironmental Engineering. 128 (2002), pp. 785-793.
- [39] A. Hachichi and J. Fleureau, *Characterization of a few expansive soils from Algeria*. Revue française de géotechnique. 86 (1999), pp. 37-51.
- [40] H. Trouzine, *Pneusol sous fondations en sols gonflants*. Doctorate thesis, Sidi Bel Abbes University, 2008.
- [41] A. Hachichi, S. Bourokba Mrabent, and L. Bengraa, *Influence de l'ajout de chaux sur le potentiel de gonflement et de la microstructure d'une argile naturelle d'Algérie*. Séminaire International, Innovation & Valorisation En Génie Civil & Matériaux de Construction 1P-259 (2011), pp. 1-7.
- [42] Z. Belabbaci, S. Mamoune, and A. Bekkouche, *Stabilization of expansive soils with milk of lime: the case of clays of Tlemcen, Algeria*. Electronic Journal of Geotechnical Engineering. 17 (2012), pp. 1293-1304.
- [43] H. Trouzine, M. Bekhiti, and A. Asroun, *Effects of scrap tyre rubber fibre on swelling behaviour of two clayey soils in Algeria*. Geosynthetics International. 19 (2012), pp. 124-132.
- [44] M. Gueddouda, M. Lamara, N. Aboubaker, and S. Taibi, *Hydraulic conductivity and shear strength of dune sand-bentonite mixtures*. Electronic Journal of Geotechnical Engineering. 13 (2008), pp. 1-15.
- [45] M. Gueddouda, G. Idriss, and B. Bencha, *Effet de chaux, ciment et sel sur le potentiel de gonflement des argiles gonflantes des régions arides en Algérie*. European Journal of Environmental and Civil Engineering. 15 (2013), pp. 315-328.
- [46] F. Azzouz, *Stabilisation des sols argileux de la région de Tlemcen par les sels*. El-Wahat pour les Recherches et les Etudes. 8 (2015), pp. 108-117.
- [47] G. Taguchi, *Introduction to quality engineering*. 1990, McGraw-Hill, New York, USA, p. 191.
- [48] K. Hubick, *Artificial neural networks in Australia*. Department of Industry, Technology and Commerce, Commonwealth of Australia, Canberra, 1992.
- [49] B. Rahali, S.M. Aissa Mamoune, and H. Trouzine, *Using artificial neural networks approach to estimate compressive strength for rubberized concrete*. Periodica Polytechnica Civil Engineering. 62 (2018), pp. 858-865.