Predicting the Stress-Strain Behaviour of Zeolite-Cemented Sand based on the Unconfined Compression Test using GMDH type Neural Network

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Abstract:

Stabilizing sand with cement is considered to be one of the most cost-effective and useful methods of in-situ soil improvement, and the effectiveness is often assessed using unconfined compressive tests. In certain cases, zeolite and cement blends have been used; however, even though this is a fundamental issue that affects the settlement response of a soil, very few attempts have been made to assess the stress-strain behaviour of the improved soil. Also, the majority of previous studies that predicted the unconfined compressive strength (*UCS*) of zeolite cemented sand did not examine the effect of the soil improvement variables and strain concurrently. Therefore, in this paper, an initiative is taken to predict the relationships for the stress-strain behaviour of cemented and zeolite-cemented sand. The analysis is based on using the unconfined compression test results and Group Method of Data Handling (*GMDH*) type Neural Network (*NN*). To achieve this end, 216 stress-strain diagrams resulting from unconfined compression tests for different cement and zeolite contents, relative densities, and curing times are collected and modelled via *GMDH* type *NN*. In order to increase the accuracy of the predictions, the parameters associated with successive stress and strain increments are considered. The results show that the suggested two and three hidden layer models appropriately characterise the stress-strain variations to produce accurate results. Moreover, the *UCS* values derived from this method are much more accurate than those provided in previous approaches. Moreover, the *UCS* values derived from this method are much more accurate than those provided in previous approaches which simply proposed the *UCS* values based on the content of the chemical binders, compaction, and/or curing time, not considering the relationship between stress and strain. Finally, *GMDH* models can be considered to be a powerful method to determine the mechanical properties of a soil including the stress-strain relationships. The other novelty of the work is that the accuracy of the prediction of the strain-stress behaviour of zeolite-cement-sand samples using the *GMDH* models is much higher than that of the other models.

Keywords: Stabilisation, Zeolite, Cement, Unconfined Compression Test, Stress-Strain Behaviour, *GMDH*.

Notation			
R^2	Absolute Fraction of Error	UCS	Unconfined Compressive Strength
$MAPE$	Mean Absolute Error	C	Cement Content
$RMSE$	Root Mean Square Error	Z	Zeolite Replacement Percent
MAD	Mean Absolute Deviation	Dr	Relative Density
M	Total Number of Data	ε	Strain
a_i	Constant Coefficient	q_{n-1}	Stress in the Lower Level
X	Input Vector	day	Curing Time
x_i	Input Variable	$\Delta\varepsilon$	Strain Increment
Y	Output Vector	q_{mi}	Measured Stress
y_i	Output Variable	q_{pi}	Predicted Stress

1- Introduction

With the increasing population of large cities, there is diminishing land space for new construction. Thus, there is an increasing need to build on any existing weak ground by first treating the site soil; for example, saturated loose sand and cement are widely used for this. In some cases, mixing cemented sand with other additives including fibres, glass, or nanoparticles, can make the stabilisation more efficient, especially in pavement construction projects as a support layer for shallow foundations to stabilise and strengthen slopes as well as to prevent sand liquefaction [1].

The mechanical and physical properties of cemented sand in different subsections, such as constitutive models, cement blends together with other additives, and the usage of soft computing techniques in predicting the strength properties (e.g., tensile strength (*qt*) and unconfined compressive strength (*UCS*)) and stress-strain behaviour have been investigated by several researchers. In this paper, the mechanical behaviour of zeolite-cemented sand is examined (particularly in terms of predicting the stress-strain behaviour obtained from the unconfined compression test) using the Group Method of Data Handling (*GMDH*) type Neural Network (*NN*). This research aims to propose mathematical models for the stress-strain behaviour of zeolite-cemented sand resulting from unconfined compression tests. Careful consideration is made to accommodate a range of input parameters, such as cement content, zeolite replacement percent, relative density, and curing time.

The *GMDH* type *NN* is a combinational multi-layer algorithm that enables progressively improved models to be generated, through the continuous evaluation of performance against a series of multi-input single-output data pairs (X_i , y_i) ($i=1, 2,..., M$). *GMDH* was first proposed by Ivakhnenko to determine the functional structure of a model within the empirical data [2]. *GMDH* would be applied to model complex systems despite the possibility that there would not be any kind of specific knowledge about them. A model would typically comprise a series (set) of neurons when employing the *GMDH* algorithm so that the different pairs distributed in each layer would be connected by a quadratic polynomial that results in producing new neurons for the next layer. The model would be applied to map inputs to outputs.

The majority of previous studies that predicted the *UCS* of zeolite cemented sand did not examine the effect of the soil improvement variables and strain concurrently. Therefore, in the current study, *GMDH*-type *NN* optimised by genetic algorithms are developed to predict the axial stress (q) on the basis of the laboratory test results, which are the characteristics of the zeolite cemented sand properties. Furthermore, in spite of the acceptable performance of computational Intelligence Methods, such as *SVM, FIS, ANN, ANDIS*, and *GEP*, etc., the black-box methods are not completely able to provide practical equations due to their weaknesses as well as their limited applicability and workability [10]. This problem is solved for *GMDH*-type *NN* in this study.

In this paper, an initiative is taken to predict relationships for the stress-strain behaviour of cemented and zeolite-cemented sand. Therefore, the *GMDH*-type *NN*, optimised by genetic algorithms, is developed in the current study to estimate and predict the stress-strain of a zeolite cement sand mixture. Finally, the *UCS* values forming the predicted stress-strain diagrams have been compared to previously published empirical correlations.

2- Materials and Methods

Cemented sand has been studied by several investigators, mostly in terms of three aspects – proposition of constitutive models based on critical state, cement replacement by additives, and using soft computing techniques to predict the mechanical properties of cemented sand. These aspects are briefly explained in the following sections.

2-1- Constitutive Models

In these studies, a constitutive model was proposed to provide the mechanical behaviour of cemented sand. The constitutive model was based on the separation and analysis of the behavioural mechanisms of cemented soils in terms of the distinct responses of the loose soil matrix and the interparticles as two entities. For the uncemented sand, a model was used based on the critical state theory. The model was able to simulate the behaviour of sandy soil in a wide range of confining pressures. An elastic-plastic shear bond model was also employed for the cemented bonds. This combination provided satisfactory results to model the characteristics of the cemented soil in both drained and undrained states. The constitutive model was then validated based on the use of the triaxial test results. The modelling output was a group of deviator axial stress-axial strain, volumetric strain-axial strain, and deviator axial stress-mean effective stress curves [11] and [12].

2-2- Mixture of Cement with Other Additives

Some researchers introduced other additives, such as glass, nanoparticles and fibres, into the soils to enhance the strength and reduce the brittleness of the cemented soils [15-18]. Other researchers [17] considered the possibility of the partial replacement of cement by zeolite in the stabilised soils. Zeolite is a natural pozzolan that consists of high amounts of reactive SiO_2 and Al_2O_3. The oxide components are important in the pozzolanic reactions involved in soil treatment. Table 1 provides some of the previous findings about the addition of zeolite to the cemented sand.

Table 1. Previous studies on the zeolite-cement-sand blends.

2-3- Soft Computing Techniques

Based on the utilisation of the actual soil test results measured in the laboratory, the strength parameters of cemented soils can be expressed by formulating appropriate empirical relationships. To this effect, several empirical correlations based on regression and neural networks have been suggested. Neural networks, being data-driven and of high mathematical/ statistical rigour, promise to be superior to regression based empirical correlation, even though the latter are more general in form. In the studies related to regression, Consoli et al. conducted considerable research between 2007 and 2017. In their research, the colouration between the different parameters, such as q_t, and the *UCS* and triaxial strength to other parameters, including porosity(η) and volumetric cement content (C_v), with the use of an exponential function $a\eta^b c_v^c$ (a, b, and c are constant) were analysed [24] and [25]. Similarly, in 2016, MolaAbasi et al. [21] showed that $\frac{\eta}{C_v}$ is one of the key parameters in the assessment of *UCS* zeolite cemented sand.

There are two approaches to using neural networks in geotechnical applications. In the first approach, the objective is to predict the soil strength properties more accurately than that presently possible with standard regression methods. In the second approach, the aim is to develop stress-strain relationships and behavioural equations, which is the main aim of the current work.

Kohestani and Hassanlourad [26] used the artificial neural networks and support vector machine in parallel to study the mechanical behaviour of different types of carbonate sand. The researchers formulated analytical models from an extensive database of triaxial tests performed on three carbonate sand samples. Elsewhere, MolaAbasi and Shooshpasha 2016 suggested a polynomial model for predicting the *UCS* based on the *GMDH* that used several input variables, such as cement content, relative density, curing time, and percentage of cement replacement by zeolite. It was observed that cement and zeolite contents strongly influence the *UCS* [22].

Other researchers; namely, Ellis et al. [27], Penumadu and Zhao [28], Zhao et al. [29], and Banimahd et al. [30] used soft computing techniques to model the mechanical behaviour of stabilised soils, but without producing new predictive equations. This kind of limitation is what the present work seeks to overcome for the benefit of engineers designing stabilised soil materials.

2-4- Modelling Using the *GMDH* Type Neural Network

The steps of the creation and training processes of the *GMDH* polynomial neural network are summarised as follows [3]:

Figure 1. A graphical example of the *GMDH* training process.

Step 1: In the first step, the network's first layer is created. Every single neuron is a partial description. The number of neurons is measured by $\frac{n(n-1)}{2}$, where n is the total number of input parameters. Figure 1.1 depicts a layer created for a network with four inputs.

Step 2: In this step, the performance evaluation should be done and the neurons providing the poorest results should be removed. Figure 1.2 shows the removed neurons in white (lighter colour).

Step 3: Here, one more layer would be created as inputs of the previous layer outputs. The number of neurons for this layer can be also determined by $\frac{n(n-1)}{2}$ (Figure 1.2).

Step 4: This stage entails the training and selecting of the neurons on the recently created layer. After the selection, another layer needs to be added (Figure 1.3).

Step 5: In this step, training should stop – after the selection process – if any layer includes only one neuron (Figure 1.4).

Step 6: The training should be stopped if the best performance value of any layer, except for the first layer, would be poorer than that of the previous layer. In this case, the algorithm adopts the best neuron in the remaining last layer, and deletes the other nodes (Figure 1.5).

Step 7: Finally, all the neurons of the previous layers that would not affect the output of the network are removed (Figure 1.6).

Recently, genetic algorithms have been considered in a feed forward *GMDH*-type *NN* for each neuron to determine its optimal set of connections with the preceding layer. Recently, *GMDH*-type *NN*, optimised by genetic algorithms, has been considered for different geotechnical applications, such as pile bearing capacity [4], undrained shear strength of clays [5], soil compaction parameters [6], liquefaction potential [7], recompression index [8], compressibility indices of clayey soils [3], and shear strength parameters of marine soils [9].

3- Stress-Strain Curve Modelling

In order to model the stress-strain response realistically, a series of unconfined compression test datasets are used. As an illustration, a stress-strain diagram is depicted in Fig. 2 and the variables of the dataset are presented in Table 2. To reserve some of the data for neural network training, considerable effort is made to link the indexes (input parameters) in the model to sample properties. To model GMDH generally, two groups of indexes for each case are selected in the database to include:

- The features related to the physical properties of the samples; namely, cement content (C), zeolite replacement percent (Z), relative density (Dr), and curing time (t).
- The features of the soil related to the unconfined compression test; namely, corresponding strain (ε), strain increment ($\Delta\varepsilon$), and stress in previous strain (qn-1).

Additional to the above provisions, the appropriate selection of the stress and strain increments to pair with a previous strain is determined on the basis of neural network training and testing for that particular time series data.

Figure 2. The stress-strain diagram resulting from unconfined compression tests.

Table 2. Description of the soil, cement, zeolite, and sample preparations.

To obtain the stress-strain relationship, an unconfined compression test of two different groups with different input variables are performed.

- Input parameters of group 1 (*GMDH I*): including cement content (*C*), zeolite replacement percent (*Z*), relative density (D_r), corresponding strain (ε), strain increment ($\Delta\varepsilon$), and stress in previous strain (*qn-1*).

- Input parameters of group 2 (*GMDH II*): including cement content (C), zeolite replacement percent (Z), relative density (D_r), corresponding strain (ε), strain increment ($\Delta\varepsilon$), stress in previous strain (q_{n-1}), and curing time (t).

In order to model stress-strain curves, around 80% of the total database is employed for training and the other 20% is used for testing. The number of datasets in GMDH modelling of groups 1 and 2 are given in Table 3.

Table 3. The number of datasets in GMDH modelling for the training and testing sets.

Table 4. Statistical parameters of the samples' parameters considered for the *GMDH*.

One of the fundamental factors to consider in modelling is the optimum percentage of data and the individual sets of values to use for the network training and testing series. For example, if the datasets are randomly dispersed, the model results will be more accurate [8] and [31]. As shown in Table 4, to ensure appropriate selection of the training and testing datasets, the statistical average and variance, as well as the training and testing series, are computed for the whole. As can be seen in Table 4, the statistical variants (the average and variance), training series, testing, and the total data are consistent, showing that the data range is suitable for training and testing.

4- Results

Different parameters could be accounted for the *GMDH* prediction process, such as the number of hidden layers, population size, the number of generations, and mutation and crossover probabilities. In optimizing the generalisation performance of the *GMDH* model, the parameter values had to be controlled. In the current study, a population consisting of 100 individuals with mutation and crossover probabilities of 0.01 and 0.95, respectively, was considered in 300 generations. As for the hidden layers, the best results were achieved with two and three hidden layers for groups 1 and 2, respectively.

4-1- Results of modelling group 1 (GMDH I)

For the first group, a two hidden layer *GMDH* was adopted to estimate and predict the unconfined compressive stresses of the samples cured for 7, 28, and 90 days. The combination of input variables C, Z, D_r, ε, $\Delta\varepsilon$, and q^{n-1} was found to yield the best correlation. Figure 3 provides a view of the structure of the evolved *GMDH*-type *NN*. Eq. (1) shows the polynomials corresponding to this model.

$$Y_1 = a_1 + a_2 Dr + a_3 \varepsilon + a_4 Dr^2 + a_5 \varepsilon^2 + a_6 Dr\varepsilon \tag{1}$$

$$Y_2 = a_1 + a_2 C + a_3 Z + a_4 C^2 + a_5 Z^2 + a_6 CZ$$

$$Y_3 = a_1 + a_2 C + a_3 \varepsilon + a_4 C^2 + a_5 \varepsilon^2 + a_6 C\varepsilon$$

$$Y_4 = a_1 + a_2 q_{n-1} + a_3 \Delta\varepsilon + a_4 q_{n-1}^2 + a_5 \Delta\varepsilon^2 + a_6 \varepsilon q_{n-1}$$

$$Y_5 = a_1 + a_2 Y_1 + a_3 Y_2 + a_4 Y_1^2 + a_5 Y_2^2 + a_6 Y_1 Y_2$$

$$Y_6 = a_1 + a_2 Y_3 + a_3 Y_4 + a_4 Y_3^2 + a_5 Y_4^2 + a_6 Y_3 Y_4$$

$$q = a_1 + a_2 Y_5 + a_3 Y_6 + a_4 Y_5^2 + a_5 Y_6^2 + a_6 Y_5 Y_6$$

Where a_i are constant coefficients of Y_1, Y_2, Y_3, Y_4, Y_5, and Y_6; as presented in Table 5. Fig 4 shows the relationship and comparison between the predicted results (from the training) and measured results (from the experimental tests). Based on the figure it can be concluded that the *GMDH* model can be certainly considered for predicting the strength properties.

Figure 3. A view of the structure of the evolved single hidden layer *GMDH*-type *NN*.

Table 5. Constant coefficients of Eq. (1).

Figure 4. Results obtained from the trained GMDH I with two hidden layers (curing time = 7, 28, and 90).

4-2- Results of modelling Group 2 (GMDH II)

For this group, the use of *GMDH* with a three hidden layer neuron connection is illustrated; as presented in Figure 5. The combination of *C*, *Z*, *Dr*, ε, $\Delta\varepsilon$, q^{n-1}, and *t* as input parameters provides the best correlation, corresponding to the following equation:

$$Y_1 = a_1 + a_2\varepsilon + a_3\Delta\varepsilon + a_4\varepsilon^2 + a_5\Delta\varepsilon^2 + a_6\varepsilon\Delta\varepsilon \tag{2}$$

$$Y_2 = a_1 + a_2\varepsilon + a_3 q_{n-1} + a_4\varepsilon^2 + a_5 q_{n-1}^2 + a_6\varepsilon q_{n-1}$$

$$Y_3 = a_1 + a_2 Dr + a_3\Delta\varepsilon + a_4 Dr^2 + a_5\Delta\varepsilon^2 + a_6 Dr\Delta\varepsilon$$

$$Y_4 = a_1 + a_2 Z + a_3 q_{n-1} + a_4 Z^2 + a_5 q_{n-1}^2 + a_6 Z q_{n-1}$$

$$Y_5 = a_1 + a_2 C + a_3 day + a_4 C^2 + a_5 ady^2 + a_6 Cday$$

$$Y_6 = a_1 + a_2 Z + a_3 Dr + a_4 Z^2 + a_5 Dr^2 + a_6 ZDr$$

$$Y_7 = a_1 + a_2 Y_1 + a_3\Delta\varepsilon + a_4 Y_1^2 + a_5\Delta\varepsilon^2 + a_6 Y_1\Delta\varepsilon$$

$$Y_8 = a_1 + a_2\Delta\varepsilon + a_3 Y_2 + a_4\Delta\varepsilon^2 + a_5 Y_2^2 + a_6 Y_2\Delta\varepsilon$$

$$Y_9 = a_1 + a_2 Y_3 + a_3 Y_4 + a_4 Y_3^2 + a_5 Y_4^2 + a_6 Y_3 Y_4$$

$$Y_{10} = a_1 + a_2 Y_5 + a_3 Y_6 + a_4 Y_5^2 + a_5 Y_6^2 + a_6 Y_5 Y_6$$

$$Y_{11} = a_1 + a_2 Y_7 + a_3 Y_8 + a_4 Y_7^2 + a_5 Y_8^2 + a_6 Y_7 Y_8$$

$$Y_{12} = a_1 + a_2 Y_9 + a_3 Y_{10} + a_4 Y_9^2 + a_5 Y_{10}^2 + a_6 Y_9 Y_{10}$$

$$q = a_1 + a_2 Y_{11} + a_3 Y_{12} + a_4 Y_{11}^2 + a_5 Y_{12}^2 + a_6 Y_{11} Y_{12}$$

Here, a_i are constant coefficients, values of which are presented in Table 6. Fig. 6 shows the relationship between the predicted values (using Eq. (2)) and the output target values. Based on the figure it can be concluded that the experimental results can be successfully modelled and predicted using the proposed *GMDH* model.

Figure 5. *GMDH II* topology considering curing time.

Table 6. Constant coefficients of Eq. (2).

Figure 6. Results obtained from trained GMDH II with three hidden layers.

4-3- Evaluating *GMDH* type *NN* Performance

The predictability of the *GMDH* models is shown statistically. The mean absolute percent error (*MAPE*), mean absolute deviation (*MAD*), root mean squared error (*RMSE*), and absolute fraction of variance (R^2) have been applied to determine and evaluate the performance of the *GMDH* models [8].

$$R^2 = 1 - \left[\frac{\sum_1^M (q_{mi} - q_{pi})^2}{\sum_1^M (q_{mi})^2}\right] \tag{3}$$

$$MAPE = \sum_1^M \left|\frac{q_{mi} - q_{pi}}{q_{mi}}\right| \times 100 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{M}\sum_1^M (q_{mi} - q_{pi})^2} \tag{5}$$

$$MAD = \frac{\sum_1^M |q_{mi} - q_{pi}|}{M} \quad (6)$$

Where q_{mi} and q_{pi} are the measured and predicted values, respectively. The lower the *RMSE*, *MAD*, and *MAPE* values, the better the performance of the *GMDH* models. Based on the results of Table 7, it can be seen that the R^2 values are very close to 1. Therefore, it can be concluded that the performance of the *GMDH* models is acceptable and promising, and that the experimental results can be modelled and predicted using the proposed *GMDH* models. Although the three hidden layer model provides the best results, the double hidden layer model is the most generalised and simplest model.

Table 7. The performance of the *GMDH* models based on different statistical evaluations.

The application of equations 1 and 2 and resulting plots of the stress-strain curves are explained as follows (see Figure 7):

First, stress (q_0) is considered to be zero when the strain is zero ($\mathcal{E}_0 = 0$). Next, having the strain increment ($\Delta\mathcal{E}$) and other input variables, such as stress at previous level (q_0), the stress at the current point can be calculated. On completing this process, the stress-strain curve can be drawn.

Figure 7. The way of plotting the stress-strain diagram or using equations 1 and 2.

One of the uses of equations 1 and 2 is to determine an appropriate relationship for the strain-stress behaviour of both the cement-only and the zeolite-cement samples, without the need for unconfined compression tests. Hence, based on *GMDH* types 1 and 2, the stress-strain diagrams can be drawn. For instance, the stress-strain behaviour of the 90-day cured sample (C=8% and Dr=85%) has been presented in Figure 8. As clearly evident in Figure 8, *GMDH* types 1 and 2 can predict the stress-strain behaviour accurately.

Figure 8. Stress-strain relation for the 90-day sample with 8% cement content and 85% relative density (with the prediction of GMDH I, II).

5- Discussion

The geotechnical properties of stabilised soils can be estimated using analytical models. Several analytical models have been proposed for cemented sand based on the regression and neural networks. The neural networks approach is more accurate than the regression approach although the regression method is widely adopted since it is less complicated. The neural networks are considered to be powerful tools that come from our current knowledge about the neural networks of animals. Neural networks aim at finding the performance of an issue by using many simple computational elements that relate together with a huge number of connections. *GMDH*-type *NN* is one of the types of neural networks. Compared to the other neural network methods, the *GMDH* method has some advantages in that it (1) provides specific relations for the data, and (2) uses a genetic algorithm for optimisation for finding the neurons and constant coefficients of the model.

In order to model the strain-stress behaviour of the UCS test results, several input variables, such as strain increment and stress in previous strain, obtained from the *NN* model have been adopted. Based on the quantitative evaluation of the performance of the *GMDH*-type 1 (i.e., curing time of 7, 28, and 90 days) and *GMDH*-type 2 (with considering the curing period parameter) according to the *MAPE*, *MAD*, and *RMSE* results, it can be stated that the *GMDH*-type *NN* is a powerful tool for modelling and evaluation of the relationship between the stress and strain. One of the main practical benefits of the proposed models for obtaining the relationships between the stress and strain of the zeolite-cemented sand based on the *GMDH*-types 1 and 2 is obtaining the stress-strain curves of the samples without conducting the experimental tests.

Equations 1 and 2 are also useful for considering the stress-strain relations from the unconfined compression test and the fact that failure occurs when the stress-strain curve reaches a plateau. Thus, the maximum stress (*UCS*) and its corresponding strain can be estimated. From this analysis, the UCS graph is drawn in Figure 9 based on the maximum stress of the stress-strain diagrams obtained. Hence, it can be concluded that this approach is completely suitable to estimate the *UCS*.

Figure 9. Unconfined compressive strength with the prediction of GMDH I, II.

Although MolaAbasi et al. have already assessed the *UCS* of the cemented and zeolite-cemented specimens using empirical correlations and GMDH [22], in this paper, the capability of the current approach is analysed. In Table 8, the employed method is compared with the predicted unconfined compressive strength, other neural networks, and polynomial models. It can be concluded that this method is considerably more accurate and reliable.

Table 8. Quantitative comparison of previous proposed relations fitting.

6- Conclusions

There is limited information about assessing and predicting the stress-strain behaviour of the cement-zeolite improved soil. To illustrate, the majority of previous studies that predicted the *UCS* of zeolite cemented sand did not examine the effect of the soil improvement variables and strain concurrently. Therefore, in this research, the mechanical behaviour of cemented and zeolite cemented sand, including the stress-strain behaviour resulting from the unconfined compression tests and unconfined compressive strength, were predicted. This was done using *GMDH* neural network analysis, from which the following results were established:

1) Stress in the lower level as well as the strain increment are important parameters in high-accuracy modelling of stress-strain curves.
2) The optimum modelling for the data of group 1 and group 2 are two hidden layer and three layer modelling, respectively.
3) Stress-strain diagrams of other parameters in this study range can be drawn based on the proposed equations.
4) GMDH modelling is a high-accuracy approach to predict the stress-strain behaviour of materials.
5) Unconfined compressive strength can be estimated based on the assessed stress-strain diagrams.
6) Estimating the unconfined compressive strength based on the approach in this paper is much more accurate than that of previous studies.

Finally, the equations presented in this paper are suggested as optimised equations that are applicable in the scope of this study. It is also suggested to consider soft computing methods. Moreover, the prediction of the triaxial behaviour of zeolite-cemented sand is recommended.

Conflict of Interest Statement

The authors of this paper have no conflict of interest.

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Figure1

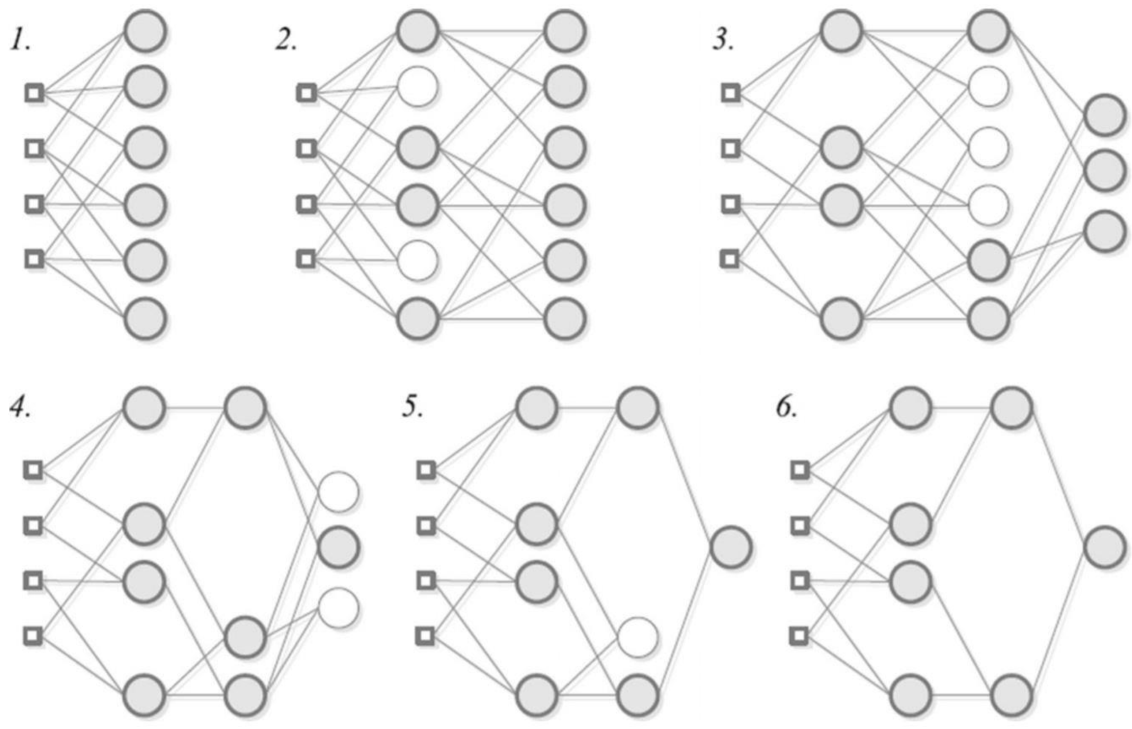


Figure2

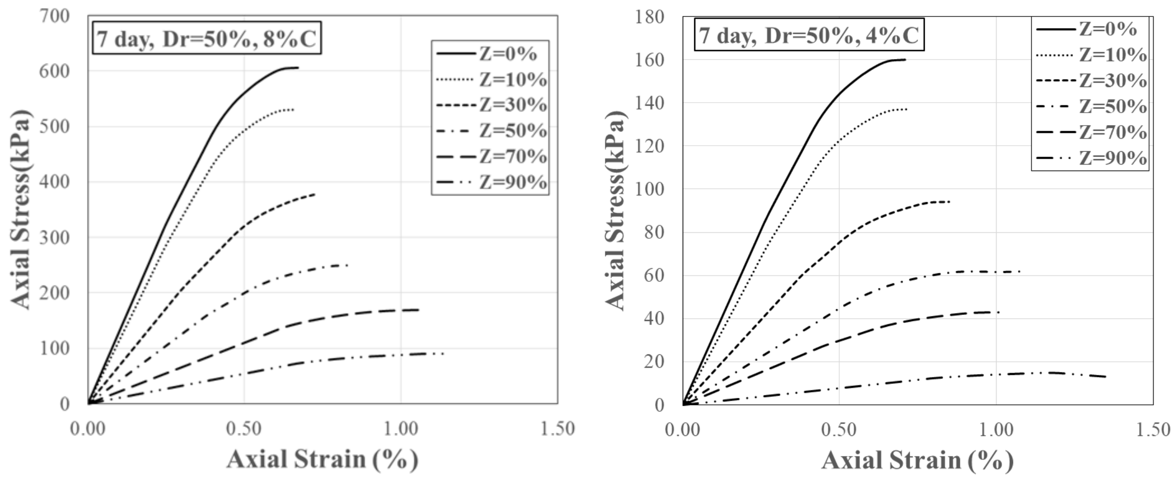

7 day, Dr=50%, 8%C
Z=0%
Z=10%
Z=30%
Z=50%
Z=70%
Z=90%
Axial Stress(kPa)
0
100
200
300
400
500
600
700
0.00
0.50
1.00
1.50
Axial Strain (%)
7 day, Dr=50%, 4%C
Z=0%
Z=10%
Z=30%
Z=50%
Z=70%
Z=90%
Axial Stress(kPa)
0
20
40
60
80
100
120
140
160
180
0.00
0.50
1.00
1.50
Axial Strain (%)

Figure3

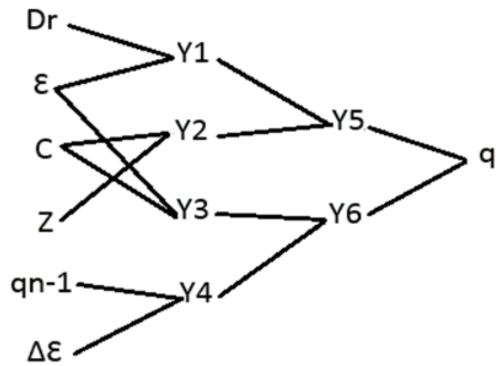


Figure4

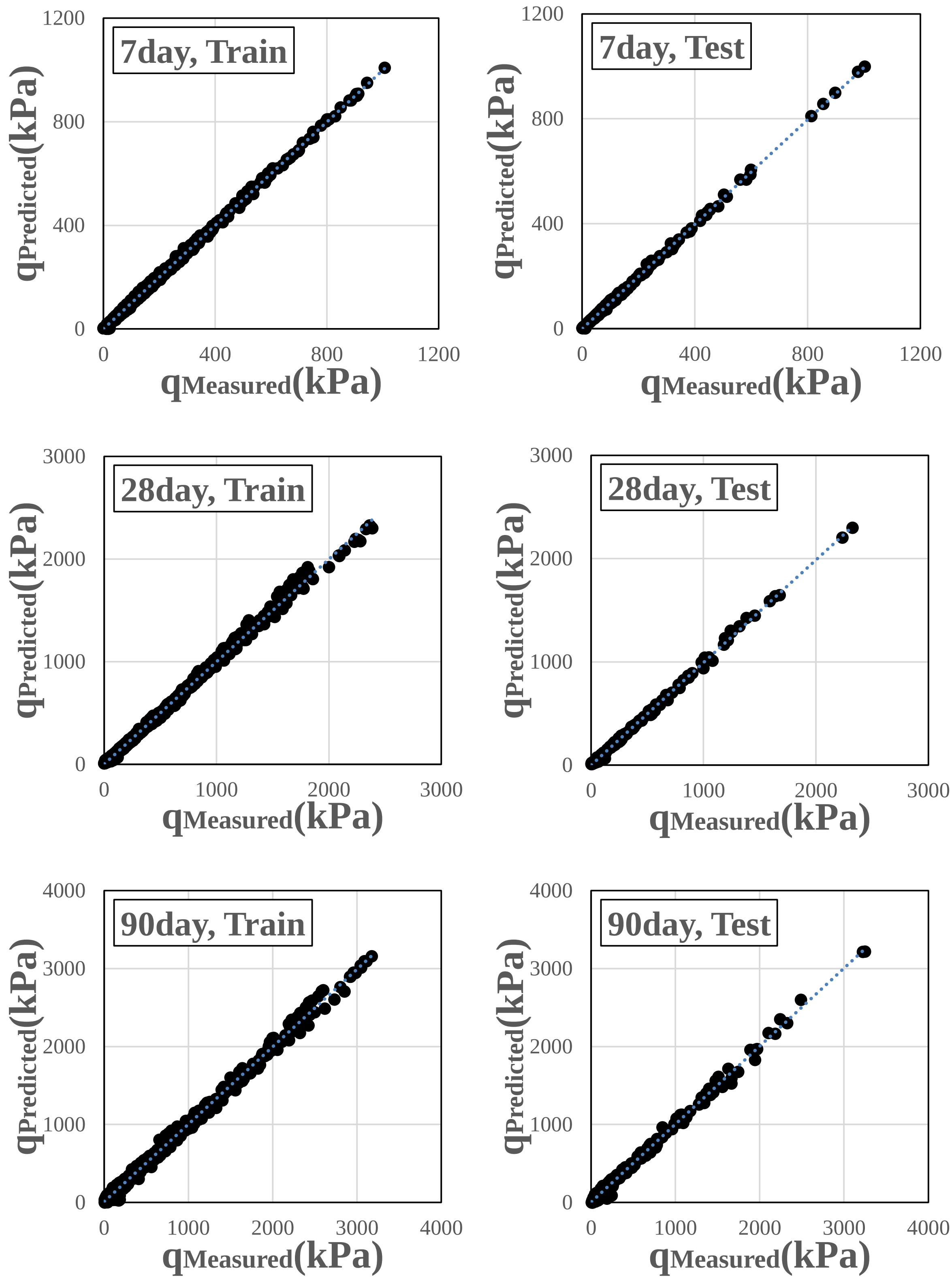

7day, Train
7day, Test
28day, Train
28day, Test
90day, Train
90day, Test
qPredicted(kPa)
qMeasured(kPa)
0
400
800
1200
1000
2000
3000
4000

Figure5

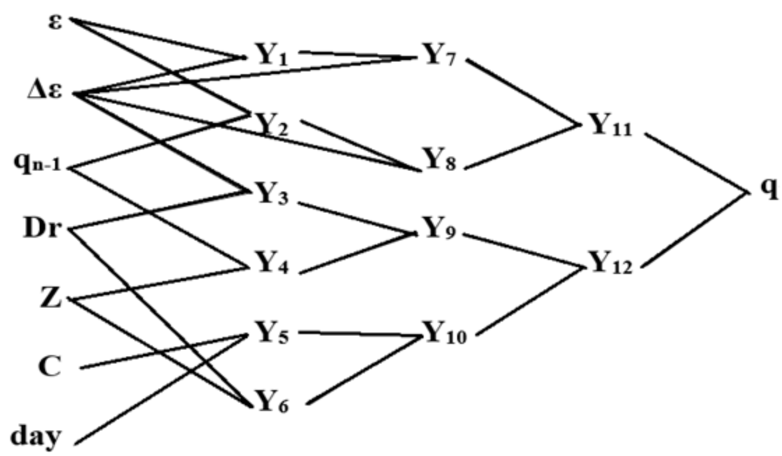


Figure6

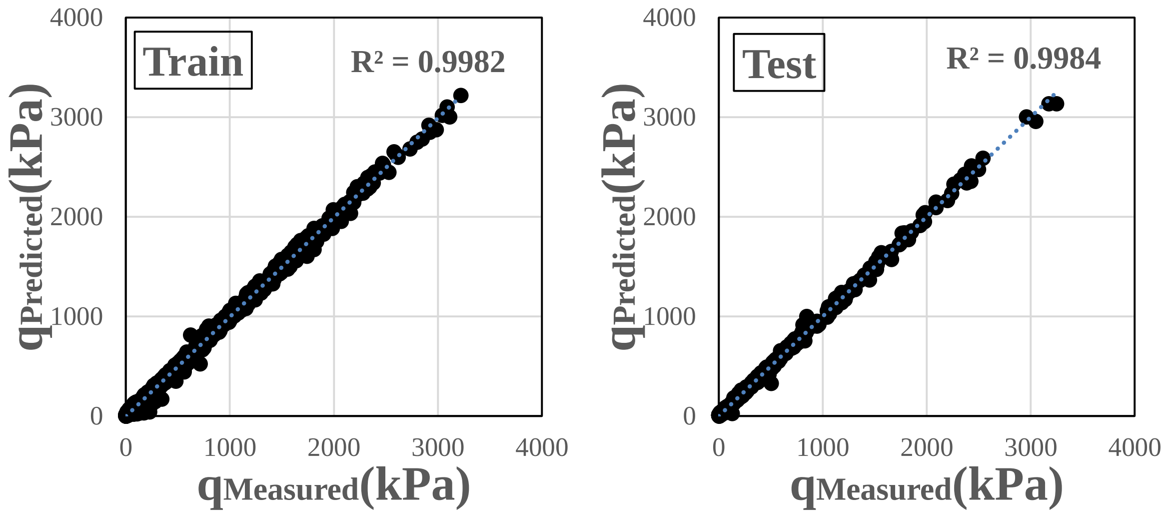
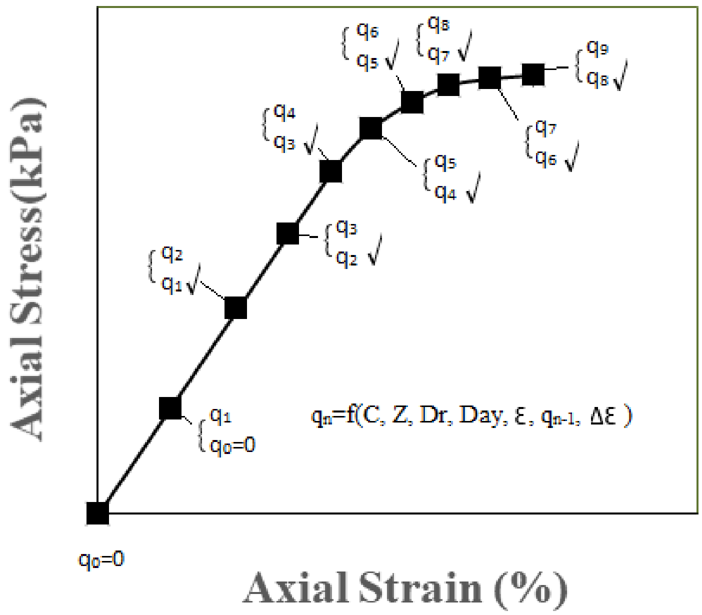
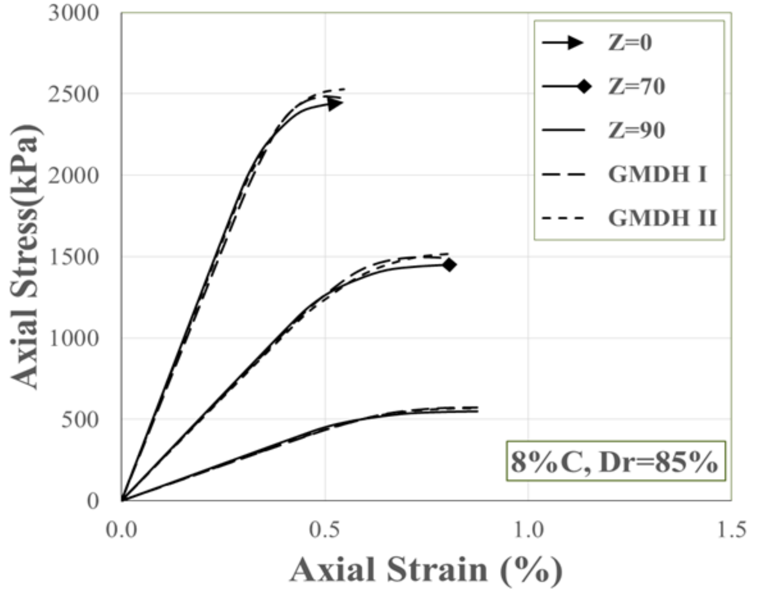

Train
R² = 0.9982
q Predicted (kPa)
q Measured (kPa)
0
1000
2000
3000
4000
Test
R² = 0.9984
q Predicted (kPa)
q Measured (kPa)

Figure7

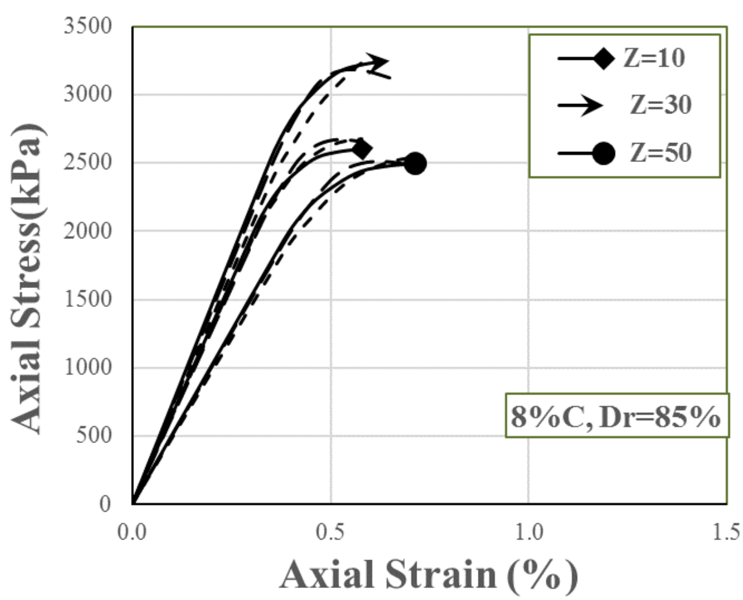


Axial Stress(kPa)
Axial Strain (%)
q_n=f(C, Z, Dr, Day, ε, q_{n-1}, Δε)
q_0=0
q_1
q_0=0
q_2
q_1 √
q_3
q_2 √
q_4
q_3 √
q_5
q_4 √
q_6
q_5 √
q_7
q_6 √
q_8
q_7 √
q_9
q_8 √

Figure8

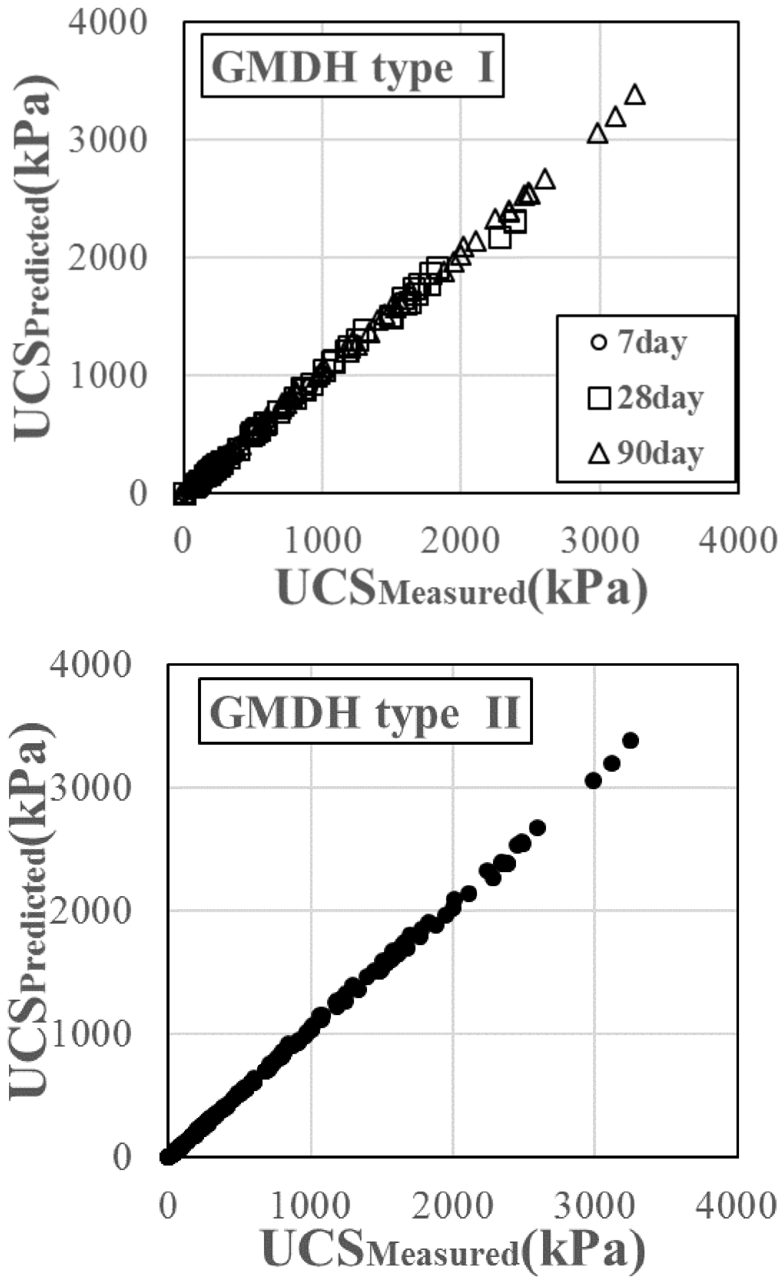


3000
2500
2000
1500
1000
500
0
0.0
0.5
1.0
1.5
Axial Stress(kPa)
Axial Strain (%)
Z=0
Z=70
Z=90
GMDH I
GMDH II
8%C, Dr=85%



3500
3000
2500
2000
1500
1000
500
0
0.0
0.5
1.0
1.5
Axial Stress(kPa)
Axial Strain (%)
Z=10
Z=30
Z=50
8%C, Dr=85%

Figure9



GMDH type I
7day
28day
90day
0
1000
2000
3000
4000
UCSPredicted(kPa)
UCSMeasured(kPa)
GMDH type II
UCSPredicted(kPa)
UCSMeasured(kPa)

Table

No.	Results
1	Addition of zeolite reduced the porosity of the blended cement paste. It also improved the interfacial microstructure properties of the cemented pastes [18].
2	Substitution of zeolite significantly increased the strength of cement because of the pozzolanic reactions with $Ca\ (OH)_2$. Moreover, the addition of zeolite prevented the undesirable expansion due to alkali-aggregate reactions [19].
3	The addition of a clinoptilolite kind of zeolite reduced the specific gravity of the cemented soil [20].
4	The addition of zeolite to the cement-sand mixtures resulted in increasing the strain rate at failure and the ductility of the samples [21].
5	The replacement of cement by zeolite at 30% led to providing the highest *UCS* value of the zeolite-cement-sand blends after 28 days of curing [22].
6	Compared to the cemented sand, the zeolite-cement-sand blends provided stronger adsorptive capacity of Chemical Oxygen Demand (*COD*). In addition, the replacement of cement by natural zeolite resulted in increasing the *PH*. Also, the addition of zeolite in the cemented sand mixtures improved the microstructure of the blends because of filling more pores as well as providing more pozzolanic reactions [25].
7	It was proposed that the porosity/cement content ratio could be considered to be an acceptable parameter for evaluation of the *UCS* of zeolite-cemented sand. Also, a unique relationship was presented to relate the *UCS* to porosity as well as *UCS* to the zeolite and cement contents [1].

Variable and properties	Descriptions and values
Type of soil	Poorly graded sand (SP)
Type of cement	Type II Portland cement
Cement content	2, 4, 6, and 8% (by dry weight of the soil)
Type of zeolite	Natural clinoptilolite zeolite
Zeolite content	0, 10, 30, 50, 70, and 90% of cement
Void ratio	Related to D_r = 50, 70, and 85% of sand
Water content	10% (by dry weight of the soil)
Size of the samples	76 mm height and 38 mm diameter
Curing periods	7, 28, and 90 days

Set	7 days	28 days	90 days	Total
Training	1186	896	831	2914
Testing	297	225	208	729
Total	1483	1121	1039	3643

Group	Statistical parameters	Set	Stress (kPa)	Curing time (days)	Strain increment (%)	Stress in previous strain (kPa) (q_n-1)	Corresponding strain (ε (%))	Relative density (D_r (%))	Zeolite replacement (Z (%))	Cement content (C (%))
Group 1 GMDHI	Mean	Train	110.81	7	0.06	99.80	0.69	68.12	39.10	5.13
		Test	124.46	7	0.06	112.25	0.76	69.79	39.18	5.07
		Total	112.95	7	0.06	101.75	0.70	68.38	39.12	5.12
	Variance	Train	159.64	7	0.02	150.59	0.43	14.37	30.93	2.21
		Test	171.80	7	0.02	161.09	0.42	14.10	30.92	2.12
		Total	161.62	7	0.02	152.30	0.42	14.33	30.92	2.20
	Mean	Train	398.48	28	0.06	351.30	0.53	68.16	39.12	5.09
		Test	348.00	28	0.06	301.83	0.50	69.41	39.71	5.09
		Total	390.82	28	0.06	343.79	0.53	68.35	39.21	5.09
	Variance	Train	487.68	28	0.01	459.36	0.31	14.32	30.60	2.24
		Test	433.34	28	0.02	409.07	0.33	14.50	30.14	2.24
		Total	479.99	28	0.01	452.26	0.32	14.35	30.52	2.24
	Mean	Train	581.10	90	0.06	510.43	0.54	68.58	39.04	5.09
		Test	492.64	90	0.06	435.94	0.51	69.03	38.59	5.00
		Total	567.18	90	0.06	498.72	0.53	68.66	38.97	5.07
	Variance	Train	666.86	90	0.04	630.16	0.30	14.31	30.17	2.20
		Test	634.61	90	0.03	603.72	0.32	13.99	31.65	2.17
		Total	662.10	90	0.03	626.15	0.30	14.26	30.39	2.19
Group 2 GMDH II	Mean	Train	480.84	34.67	0.06	448.52	0.37	14.35	39.14	5.10
		Test	497.61	34.48	0.06	465.20	0.37	14.31	39.01	5.00
		Total	493.65	34.62	0.06	461.12	0.37	14.31	39.10	5.07
	Variance	Train	480.84	34.67	0.02	448.52	0.37	14.35	30.60	2.22
		Test	497.61	34.48	0.02	465.20	0.37	14.31	30.57	2.20
		Total	493.65	34.62	0.02	461.12	0.37	14.31	30.64	2.15

		a_1	a_2	a_3	a_4	a_5	a_6
7 days	Y_1	2.993316	-13.2598	1.436345	8.709119636	-0.0001	-0.29828
	$Y_2/100$	0.082905	-0.37509	1.888064	0.036901252	-1.98379	0.495729
	Y_3	-10.282	11.08636	0.687695	4.418622211	0.004183	-0.52284
	$Y_4/10000$	-0.05414	0.000719	1.29376	-2.8633E-06	-9.7769	-0.00239
	Y_5	0.729246	0.951207	0.010892	-3.1538E-05	-3.9E-05	0.000228
	Y_6	26.24902	-0.26571	-0.0907	0.000102091	-0.00047	0.009367
	q	-0.01297	0.980512	0.012481	-7.4979E-05	-6.7E-05	0.00022
28 days	$Y_1/100$	0.389613	-1.15843	0.013952	0.791759356	-4.9E-07	-0.0036
	$Y_2/100$	-1.5907	-0.49019	9.151163	0.095505468	-9.76299	1.637782
	$Y_3/100$	-2.98565	1.257557	0.132167	0.050231261	-0.00148	-0.01063
	$Y_4/100000$	-0.022	5.1E-05	0.781469	-8.653E-08	-5.8985	-0.00037
	Y_5	-5.79414	0.954868	0.070322	-6.4801E-06	-5.4E-05	4.83E-05
	Y_6	68.88962	-0.77483	0.28929	0.000315706	-0.00095	0.003281
	q	-2.61946	0.956091	0.025773	-2.1089E-05	2.66E-06	6.09E-05
90 days	$Y_1/100$	0.673826	-1.52856	0.013239	0.887138827	-2.5E-07	-0.00291
	$Y_2/1000$	-0.11414	-0.1317	1.525918	0.021511191	-1.56807	0.191593
	$Y_3/100$	-1.73283	0.277275	0.185731	0.261869734	-0.00191	-0.01846
	$Y_4/10000$	0.041988	-0.00046	0.5381	3.81725E-06	-2.26203	0.001311
	Y_5	-20.0219	0.884043	0.166401	1.0326E-05	-6.6E-05	3.87E-05
	$Y_6/100$	1.011643	-0.005	-0.0005	3.10428E-06	6.1E-07	1.77E-05
	q	-15.3777	0.980967	0.025687	8.13625E-05	0.0001	-0.00018

	a_1	a_2	a_3	a_4	a_5	a_6
$Y_1/1000$	-0.07685	1.470297	-0.1705	-0.78328	2.137749	-2.20962
Y_2	31.2116	-68.1412	1.34441	39.5187	-3.5E-05	-0.29896
$Y_3/1000$	1.857377	0.03273	-1.61657	-9E-05	-2.22975	-0.06111
Y_4	13.15049	0.326402	1.135228	-0.00561	-4E-05	-9.9E-05
Y_5	38.22687	-86.4872	9.540386	12.56871	-0.12973	1.865674
$Y_6/100$	1.949455	0.04468	0.035642	-0.00084	-0.00011	-9.9E-05
$Y_7/100$	0.014616	0.005503	3.087246	1.06E-05	0.964806	-0.00829
Y_8	-1.66218	0.839116	-0.10119	-3.2E-06	-0.00747	2.849645
Y_9	0.002415	0.390498	0.863348	-0.00119	-2.3E-06	0.000429
$Y_{10}/100$	1.333315	-0.00324	-0.01079	2.32E-06	2.03E-05	3.39E-05
Y_{11}	-8.66117	-0.00972	1.120966	8.97E-05	1.58E-05	-0.00033
Y_{12}	-10.171	0.943874	0.047539	1.85E-05	0.000101	-7.8E-05
q	-2.76225	0.613628	0.382686	0.00257	0.002393	-0.00496

	Curing time	Data	R^2	MAPE	RMSE	MAD
Group I	7 Day	Train	0.998	24.053	4.904	3.318
		Test	0.999	25.133	5.013	3.500
		Total	0.999	24.852	4.985	3.418
	28 Day	Train	0.998	50.987	7.141	14.345
		Test	0.997	52.111	7.219	15.092
		Total	0.998	51.518	7.178	14.905
	90 Day	Train	0.998	59.409	7.708	16.714
		Test	0.994	60.893	7.803	17.635
		Total	0.997	59.944	7.742	17.343
Group II	Total	Train	0.999	50.534	7.109	14.033
		Test	0.995	51.796	7.197	14.806
		Total	0.998	50.989	7.141	14.560

***q*, Model (stage)**	***R^2***	***MAPE***	***RMSE***	***MAD***
UCS Double* hidden layer *GMDH	0.999	3.350	20.056	13.273
UCS Three* hidden layer *GMDH	0.999	3.212	20.488	12.731
UCS MolaAbasi et al., [23]	0.976	13.791	140.177	93.864
UCS MolaAbasi and Shooshpasha [31]	0.956	20.700	193.236	135.621
UCS MolaAbasi and Shooshpasha [24]	0.968	18.309	174.881	126.676