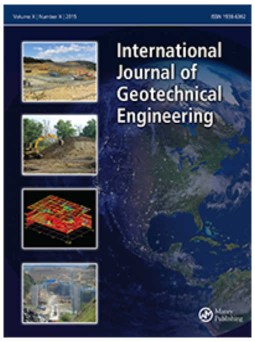

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ABSTRACT

Clayey soils are known as problematic soils for geotechnical engineering since several years. The effect of mineral additives on geotechnical properties of clayey soils has been many times investigated. However, there are a few investigations about the use of artificial neural networks (ANNs) for predicting the geotechnical properties of stabilised soils, all the same, the ANNs can be successfully used in this field. The accurate prediction of plasticity index (PI), maximum dry density (MDD) and optimum moisture content (OMC) is beneficial for the construction engineering in order to avoid the cumbersome tests in the laboratory. The aim of this research is to develop three models with good performances based on ANNs, and to predict all the PI, OMC and MDD values of subgrade soil stabilised with the addition of lime, using basic soil parameters which are always available for engineers. Three different models are developed which each one corresponding to the best architecture for the three properties where these models can be used as a reliable tool to predict the PI, OMC and MDD of clayey soils stabilised with lime.

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Problematic soils; lime; artificial neural networks (ANNs); plasticity index (PI); maximum dry density (MDD); optimum moisture content (OMC)

Introduction

Civil engineering projects located in areas with inappropriate soils is one of the most frequent problems in the world. However, Chemical soil stabilisation has been used for several years in order to render the problematic soils capable of meeting the requirements of specific engineering projects (Kolias et al. 2005). Consequently, the improvement of physico-mechanical properties of these local materials is extremely essential. According to literature, there are different methods which can be selected for soil improvement such as mechanical, hydraulic, dynamical, physical and chemical methods. However, chemical soil stabilisation is the most used by adding mineral additives to the clayey soil such as cement, lime, silica fume, natural pozzolana, slag and fly ash, and it is one of the suitable and economic methods for reducing both plasticity and compressibility but increasing both strength and durability. Indeed, several laboratory investigations were provided in order to assess the effect of these additives on geotechnical properties of soils (Ola 1977; Broms and Boman 1979; Rahman 1986; Locat, Bérubé, and Choquette 1990; George, Ponniah, and Little 1992; Bell 1996; Mathew and Narasimha 1997; Kinuthia, Wild, and Jones 1999; Afès and Didier 2000; Tonoz, Ulusay, and Gokceoglu 2004; Kolias et al. 2005; Stavridakis 2005; Al-Rawas, Hago, and Al-Sarmi 2005; Hossain, Lachemi, and Easa 2007; Manasseh and Olufemi 2008; Harichane and Ghrici 2009; Harichane et al. 2010; 2011, 2011, 2012; McCarthy et al. 2012; Oza and Gundaliya 2013; Khemissa and Mahamedi 2014; Asgari, Dezfuli, and Bayat 2015; Yi, Gu, and Liu 2015; al-Swaidani, Hammoud, and Meziab 2016). On the one hand, these laboratory studies are very beneficial for geotechnical engineers in order to obtain better practical results. On the other hand, laboratory tests are costly and need a long time for each study. For these reasons, the artificial neural networks (ANNs) can be used to develop ANNs models in order to predict different physical and mechanical properties of both untreated and treated soils, and consequently the reduction of both the time consumption and cost. In addition, the ANNs models have been applied as an effective approach with a high performance compared with the statistical models.

There are a low number of works made on computer-based models for predicting the geotechnical properties of stabilised clayey soils where the previous studies showed the capacity of ANNs models in the prediction of different soils characteristics (Lu, Chen, and Zheng 2012). Indeed, ANNs are actually used in almost all the aspects of civil and geotechnical engineering, and their applications and aspects (Yang and Rosenbaum 2002). According to literature, ANNs illustrated their utilisation for predicting response parameters of kinematic soil pile interaction (Ahmad, Hesham El Naggar, and Khan 2007), ANNs as an alternative to pile driving formulas (Chan, Chow, and Liu 1995), prediction of pile bearing capacity (Lee and Lee 1996), simulating the stress–strain behaviour of Georgia Kaolin (Najjar and Huang 2007), soil classification (Cal 1995), identification of

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compaction characteristics (Najjar, Basheer, and Naouss 1996), ANNs as a tool for assessing geotechnical properties (Yang and Rosenbaum 2002), Neuro-fuzzy models as settlement prediction of shallow foundations on granular soils (Shahin, 2013), ANNs for modelling soil correlations (Goh 1995), ANNs for prediction of efficiency factor of ground-granulated ballast-furnace slag of concrete (Boukhatem et al. 2011) and prediction of properties of self-compacting concrete containing fly ash by ANNs (Bellalia-Douma et al. 2016).

However, few ANNs models were developed using a low number of data in order to predict the geotechnical properties of stabilised soil. Hensley (2010) and Das, Samui, and Sabat (2010) have established different ANNs models to predict the maximum dry density (MDD) and compressive strength of stabilised soil where they used the combination of lime+fly ash and cement, respectively. Both researchers have used in their studies a few database (a single experimental study) to make their ANNs models which are difficult to be used and not always with the range of the engineer. Moreover, one of the early works was reported by Chen, Yang, and Fanny (2013) where they have developed an ANNs model based on simple inputs for predicting the unconfined compressive strength of a consolidated soil stabilised with cement and fly ash. In general, through the literature review, the existing ANNs models for applications in geotechnical engineering were established to predict only some geotechnical properties such as the unconfined compressive strength and MDD.

This paper presents the current state of knowledge of the application of ANNs in the field of geotechnical engineering in order to predict some properties of clayey soils stabilised with lime alone. The goal of this investigation is to develop three different ANNs models with easy handling for predicting the plasticity index (PI), MDD and optimum moisture content (OMC) of clayey soils stabilised with lime. It should be noted that the previous ANNs models published in the literature by several researchers for predicting the geotechnical properties of lime-treated clayey soils have been developed by using some results collected from only one or two laboratory studies as maximum data. In addition, the use of these models is severely limited due to the fact that these models have been developed based on few numbers of data. For these reasons, in the present study, all the ANNs models will be developed by using several results collected from various reliable experimental studies published in the literature in order to obtain different ANNs models with extensive and preciseness utilisation. Moreover, this research characterised the previous ANNs models by a comparative study with the experimental values which were carried out by other works that make it possible to ensure a certain precision for the ANNs models, and a devoted parametric analysis for showing the sensitivity of each parameter on the mainly predicted property.

Artificial neural networks (ANNs)

ANNs are one of the most realistic models of the biological brain functions (Ferentinou and Sakellariou 2007), and can be considered as an efficient way for solving the complex problems. Also, ANNs have a classification ability, examination, simulation and decision-making that has given them a wide application in the engineering field, and even in other fields. In general, a multi-layer neural network (NN) consists of a succession of layers where are parallel systems consisting of a large number of units interconnected to each others making elementary processors (Touzet 1992). The capacity of NN to learn from examples is based on both the interconnection and activation models. Thus, the acquired information is stored in the weight of the interconnections; this process can be described in Figure 1.

The operation acts of the connection of these elements between them of such kind, each neuron will be associated the whole of the neurons of the previous layer in order to have a model ensuring the spot wanted to solve the encountered problems, involved by the inputs, weights and transfer function which is equivalent to multiply the vector of entry by a transformation matrix to determine the desired outputs.

The NN is divided into three parts: inputs layer, one or more hidden layers and outputs layer, where the activation of these neurons is interpreted as the network response. For a number from $j = 1$ and a number n, the formal neuron will calculate the sum of its inputs ($x_1, x_1 \ldots, x_n$), weighted by the synaptic weights ($w_1, w_2 \ldots, w_n$), and compared with a threshold theta (θ). Hence, the formula with the transfer function (f), as defined in Equations (1) and (2).

$$y = f(\text{net}) \tag{1}$$

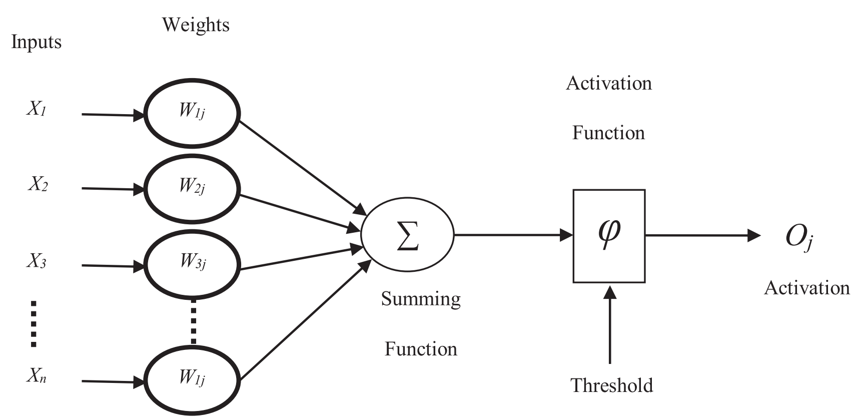

Figure 1. McCulloch and Pitts model of neuron (Parizeau 2004).

Table 1. Database sources of PI property collected from previous works.

Data source	Number of data	Data source	Number of data
Thompson (1967)	16	Ansary, Noor, and Islam (2006)	02
Ola (1977)	05	Nalbantoglu (2006)	03
Rahman (1986)	06	Guney et al. (2007)	06
Tehrani (1988)	03	Khattab, Al-Mukhtar, and Fleureau (2007)	01
Bell (1989)	12	Kavak and Akyarli (2007)	10
Osula (1991)	03	Manasseh and Olufemi (2008)	07
George, Ponniah, and Little (1992)	02	Lasledj and Al-Mukhtar (2008)	06
Attoh-Okine (1995)	05	Eren and Filiz (2009)	04
Frempong (1995)	03	Phanikumar (2009)	03
Bell (1996)	08	Bozbey and Garoisayev (2009)	03
Wild et al. (1996)	01	Harichane and Ghrici (2009)	10
Osula (1996)	03	Unruh (2010)	04
Aytekin and Evin (1998)	06	Ansary and Hasan (2011)	04
Kinuthia, Wild, and Jones (1999)	04	Castro-Fresno et al. (2011)	16
Muntohar and Hantoro (2000)	06	Gueddouda et al. (2011)	09
Okagbue and Yakubu (2000)	06	Kavak and Baykal (2011)	07
Cokça (2001)	04	Elsharief, Elhassan, and Mohamed (2013)	51
Ji-ru and Xing (2002)	03	Asgari, Dezfuli, and Bayat (2015)	04
Mallela et al. (2004)	07	Zhang, Mavroulidou, and Gunn (2015)	01
Al-Rawas, Hago, and Al-Sarmi (2005)	03	Modarres and Nosoudy (2015)	01
Amu, Fajobi, and Oke (2005)	06	Jha and Sivapullaiah (2015)	03
Goswami and Singh (2005)	06		
Total number of data			280

$$\text{net} = \sum_i W_i x_i + \theta \tag{2}$$

where Y, x_i, are the output variables, the input variables are, respectively, θ the bias or the threshold activation of neuron and W_i the synaptic weight of neuron of the input layer. There are several types of the activation function, generally, three functions are the most used: 'threshold', 'linear' and 'sigmoid'.

Data collection and treatment

Usually, the performance of ANNs depends on the width and reliability of data selected. For these reasons, the data collection and selection is the most important step may affect the NN modelling, especially in geotechnical engineering. The performance of NN model is effectively attached to the reliability and division of input data employed and stored in the database. In this study, the databases consist of results collected from several experimental studies of different types of soil stabilised by using lime published worldwide in literature. Both Tables 1 and 2 represent the collected results of both the PI and compaction characteristics database (MDD and OMC), respectively. Based on clayey soils of high and low plasticity improved by different contents of lime in various areas. The data of stabilised clayey soils by using lime were gathered and compiled from a high number of research projects to establish the both databases (39 research projects carried out on the effect of lime on geotechnical properties: IP, MDD and OMC).

The database used for the development of ANNs models make up a total of 80 and 27 types of soil respectively with the PI–ANNs model and compaction characteristics models (MDD–ANNs and OMC–ANNs models). As a total, there are 280 values of PI and 122 values of both MDD and OMC. These data were used to check the reliability of the model for predicting of PI, MDD and OMC of clayey soils stabilised with different contents of lime. The ranges of soil properties of data-sets are shown in Table 3.

The databases were divided into three parts: training (70%), Testing (15%) and validation (15%). The training data-set was used in order to train the ANN model, the validation data-set was used to stop the learning process and all testing data-set was used to assess the ANNs models performance after completion of the training process. Each data-set consists of the factors that affect the stabilised soil properties taking into account the initial Atterberg limits symbolised by LL_0 (%) and PL_0 (%), lime content (%) for forecasting the PI and for the prediction of both compaction characteristics (OMC and MDD), the Atterberg limits (LL (%) and PL (%)) and lime content (%) were chosen as input parameters for MDD and OMC as outputs. The following step is the normalisation of data between −1 and +1 before their introducing to ANNs models to make them consistent with the limits of tangent sigmoid transfer function employed in both hidden layers and output layer.

Development of NN model

The performance of NN models depends on various parameters as the network topology and the learning parameters. The factors linked to the network topology are known as the number of input/output, the number of hidden layers and the number of neurons in each hidden layer, about the learning parameters can be cited as the selected learning algorithm performance function, the transfer function in hidden layers, the maximum error and the number of learning cycles. There are no general rules to define the number of hidden layer and the number of neurons in each hidden layer, it is for that the architecture NN models were determined by using trial and error method, but for earning time in learning phase it is preferable to use a simple architecture of one hidden layer with limited number of neurons.

The models were developed by the most useful mapping scheme back propagation network using the Levengberg–Maquardt algorithm for training hence where was proved as the fastest training algorithm for the multilayer perception the most popular class of ANNs that use the feed-forward architecture (Figure 2). The Mean Square Error (MSE) specifies the

Table 2. Database sources of both MDD and OMC properties collected from previous works.

Data source	Number of data	Data source	Number of data
Ola (1977)	06	Okagbue and Yakubu (2000)	06
Rahman (1986)	07	Ji-ru and Xing (2002)	04
Tehrani (1988)	04	Amu, Fajobi, and Oke (2005)	02
Bell (1989)	06	Guney et al. (2007)	09
Osula (1991)	04	Khattab, Al-Mukhtar, and Fleureau (2007)	01
George, Ponniah, and Little (1992)	04	Kavak and Akyarli (2007)	04
Bell (1996)	04	Phanikumar (2009)	03
Wild et al. (1996)	02	Harichane and Ghrici (2009)	06
Osula (1996)	04	Kavak and Baykal (2011)	02
Aytekin and Evin (1998)	08	Siddique and Hossain (2011)	06
Kinuthia, Wild, and Jones (1999)	04	Modarres and Nosoudy (2015)	20
Muntohar and Hantoro (2000)	07		
Total number of data			122

Table 3. Ranges of components of data-sets.

	Parameters	Unit	Minimum	Maximum	Average
Input	Liquid limit (LL)	(%)	22.8	385	63.70
	Plastic limit (PL)	(%)	10.8	56	27.95
	Lime content	(%)	0	30	5.35
Output	Plasticity index (PI)	(%)	1	158.84	20.35
	Maximum dry density (MDD)	(t/m^3)	1.12	2.07	1.58
	Optimum moisture content (OMC)	(%)	9.2	44	22.81

error generated while learning and can be calculated using Equation (3).

$$\mathrm{MSE} = \frac{1}{N}\sum_{1}^{i=N}\left(\mathrm{O}_{\mathrm{EXP}} - \mathrm{O}_{\mathrm{ANN}}\right)^2 \tag{3}$$

where N is the total number of data, $\mathrm{O}_{\mathrm{EXP}}$ is the experimental values of property and $\mathrm{O}_{\mathrm{ANN}}$ is the predicted values of this last one.

The error values between the experimental results and the predicted results with the present ANNs models are expressed by Equation (4).

$$E(\%) = \mathrm{ABS}\left(\frac{\mathrm{O}_{\mathrm{EXP}} - \mathrm{O}_{\mathrm{ANN}}}{\mathrm{O}_{\mathrm{EXP}}}\right) \times 100 \tag{4}$$

Plasticity index model (PI–ANN model)

The model of the PI prediction corresponds to the architecture of 07 neurons with only one hidden layer (Figure 3) where the regression values of all data were equal to 0.91 (Figure 4). All the parameters chosen for the training of the NN are shown in Table 4.

Maximum dry density model (MDD–ANN model)

The architecture of one hidden layer constituted of 11 neurons makes the better performance model for predicting the MDD (Figure 5). The Atterberg limits and lime content were regarded as inputs parameters in order to obtain the MDD as an output. Table 5 showed the values of training parameters used in NN modelling. As shown in Figure 6, the regression values of all data for the MDD–ANN model were approximately of 0.83.

Optimum moisture content model (OMC–ANN model)

The found architecture which ensures a better model consisted of only one hidden layer of 09 neurons. Indeed, the model was established by taking into account the effect of both lime content and Atterberg limits as defined in Figure 7 and Table 6 which summarised the NN parameters using in modelling. The obtained results showed that regression values of all data for OMC–ANN model reach 0.83 (Figure 8).

Validation of ANNs models

To check the efficiency of trained ANNs models, it is very important to put in test their ability to generalise their forecasting beyond the training data and to perform well when it is nominated with stranger data-sets, inside the range of the input parameters used in the training. Therefore, the capacity of the proposed ANNs models developed for prediction PI, MDD and OMC of new data obtained by other results from other research excluded from the training data must be validated. The more data available, the more reliable the prediction of PI, MDD and OMC by ANNs will be ensured.

Validation of PI–ANNs model

The PI–ANNs model was developed using a total of 20 unseen records including 04 different types of soil. It was also required to predict the PI associated with each set of values within the three influential parameters (Portelinha et al. 2012; Oza and Gundaliya 2013; Ramlakhan, Kumar, and Arora 2013; Siddique and Hossain 2011). The comparison between the predicted values from PI–ANNs model and the validation of new data records is summarised in Table 7. A correlation coefficient of $R^2 = 0.94$ (Figure 9)

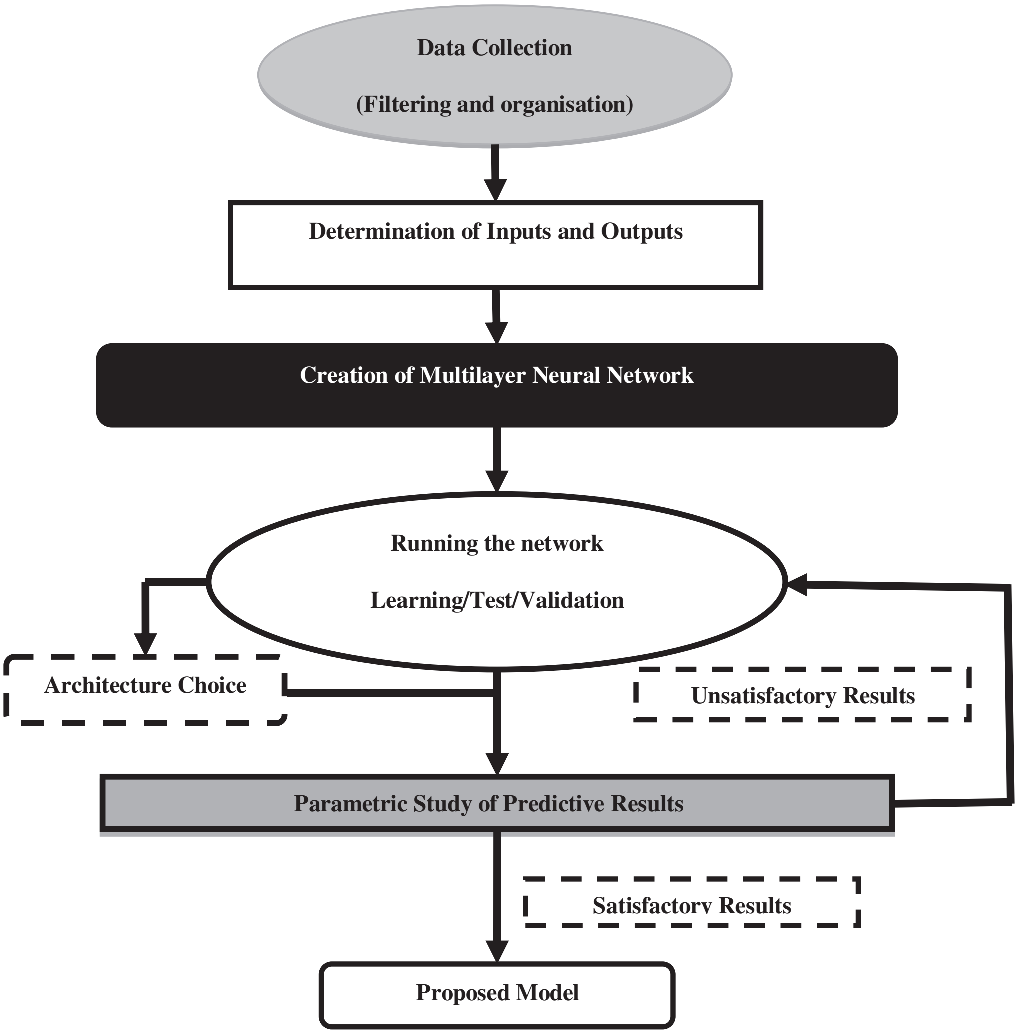

Figure 2. ANNs system development.

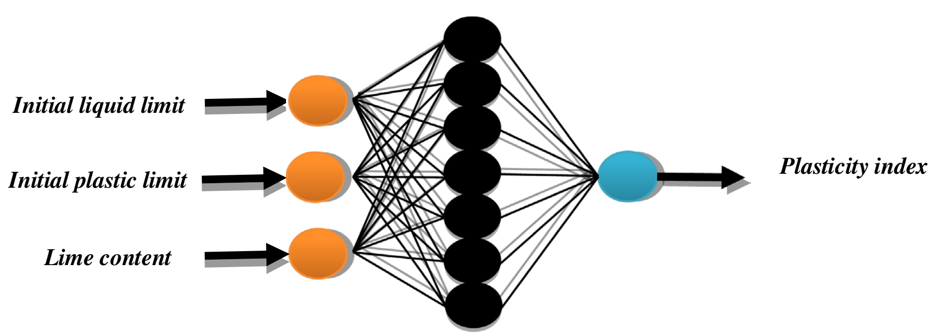

Figure 3. Architecture used in ANNs model for PI prediction.

was obtained between the predicted and the experimental values using the results presented in Table 7, which acts to study the effect of lime on the PI of different types of soil. However, the total average error found between experimental and predicted results of PI equals to 9.16%, this indicates that the proposed model can be used as a reliable tool for prediction of PI of clayey soils stabilised with different amounts of lime. The PI–ANNs model becomes more efficient with clayey soils of high plasticity (CH) where the error is very low (6.89%). This error is deduced from the comparison between the experimental results obtained by Siddique and Hossain (2011) and the values forecasted by the proposed model.

Validation of MDD–ANNs model

The MDD–ANNs model was developed using a total of eight unseen records and was required to predict the MDD associated with each set of values within the three influential parameters (Eren and Filiz 2009; Ramlakhan, Kumar, and Arora 2013). The comparison between the predicted values from

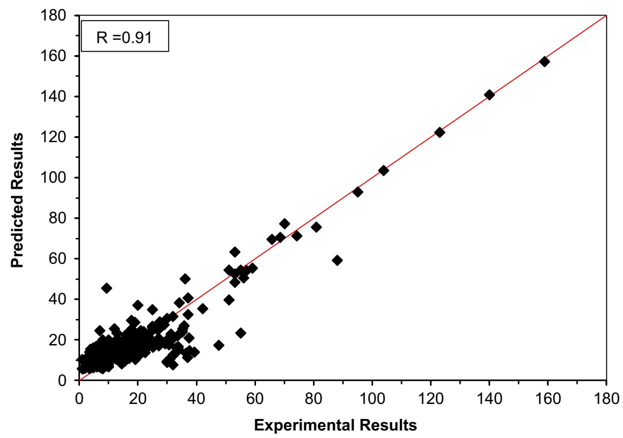

Figure 4. Regression values of all data for PI–ANNs model.

Table 4. Training parameters values used in NN model for PI prediction.

NN parameters	Values and nomination in MATLAB
Train function	'trainlm' (Levenberg Marquardt)
Transfer function	'tansig' (no linear function)
Performance function	'mse' (mean square error)
Error after learning	0.001
Divide function	'dividerand'
Train epochs	1000
Number of input layer neurons	03
Number of hidden layers	01
Number of neurons by hidden layer	07
Number of output layer	01

MDD–ANNs model and the validation of new data records is presented in Table 8. A correlation coefficient of $R^2 = 0.94$ (Figure 10) was obtained between the predicted and the experimental values according to results shown in Table 8, which acts to study the effect of lime on the MDD of two types of soil stabilised with lime. The total average error value obtained between experimental and predicted results of MDD equals to 0.86%. This low error value (0.86%) indicates that the capacity of the proposed model (MDD–ANNs model) is very higher for the prediction of MDD, especially with the stabilised clayey soil of low plasticity.

Validation of OMC–ANNs model

The OMC–ANNs model was developed using a total of 9 unseen records and was required to predict the OMC associated with each set of values within the three influential parameters (Eren and Filiz 2009; Ramlakhan, Kumar, and Arora 2013). The comparison between the predicted values from OMC–ANNs model and the validation new data records is given in Table 9. A correlation coefficient of $R^2 = 0.94$ (Figure 11) was obtained between the predicted and experimental values according to results depicted in Table 9, which acts to study the effect of lime on the OMC of two types of soil stabilised with lime. However, a low total average error value (4.17%) was found between experimental and predicted results of OMC. This reflects that the proposed model (OMC–ANNs model) has a good performance and it can be used as a reliable tool for prediction of OMC of clayey soils stabilised with different contents of lime.

Parametric analysis based on ANNs model results

Through the use of ANNs for the prediction of stabilised soils properties, it was able to stimulate as a parametric analysis the behaviour of these properties when the lime percentage changes; moreover, the effect of some parameters on the mainly predicted property in order to obtain a logical behaviour of stabilised clays of the experimental studies carried out by other searchers in the same field.

Effect of lime on plasticity index (PI)

The results of the changes in the PI of clayey soils by increasing lime content are illustrated in Figure 12. The parametric analysis (as a kind of simulation) presented in Figure 12 was based on three types of fine-grained soils (clay of high plasticity (CH), silt of high plasticity (MH) and clay of low plasticity (CL)) where taking into account the variation of lime content (2, 4, 6, 8 and 10%), but other parameters are considered as constants (Table 10).

According to the literature, the addition of lime as an additive to clayey soils improves their workability which can be reflected by the significant reduction in the PI value of stabilised soils

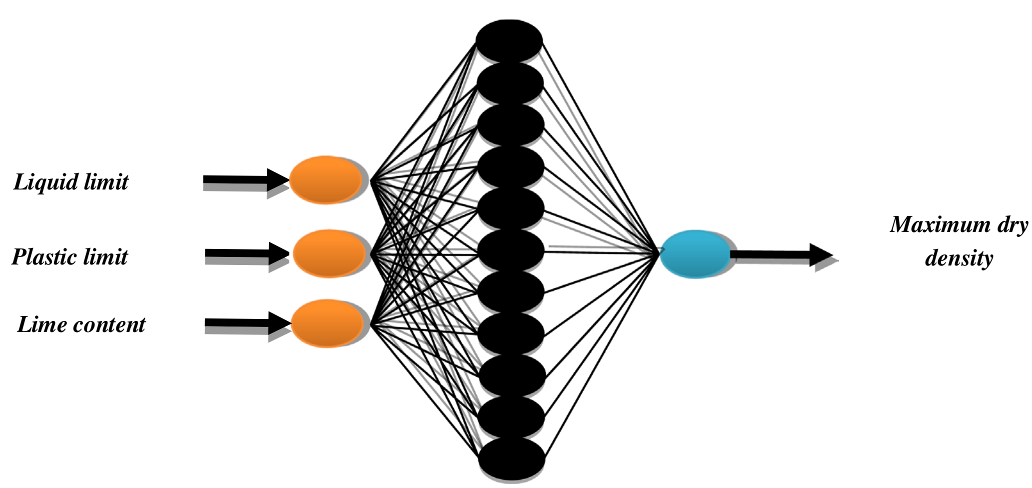

Figure 5. Architecture used in ANNs model for MDD prediction.

Table 5. Training parameters values used in NN model for MDD prediction.

NN parameters	Values and nomination in MATLAB
Train function	'trainlm' (Levenberg Marquardt)
Transfer function	'tansig' (no linear function)
Performance function	'mse' (mean square error)
Error after learning	0.001
Divide function	'dividerand'
Train epochs	1000
Number of input layer neurons	03
Number of hidden layers	01
Number of neurons by hidden layer	11
Number of output layer	01

(e.g. Harichane and Ghrici 2009; Harichane et al. 2010, 2011; Zoubir, Harichane, and Ghrici 2013; Asgari, Dezfuli, and Bayat 2015; Gadouri, Harichane, and Ghrici 2016a, 2016b, 2016c). As shown in Figure 12, for any clay class (CH, MH and CL), the PI considerably decreases with increasing lime content. For example, the PI of CH clay class decreases from 50% to 32.5 and 17% with the addition of 2 and 10% lime, respectively. This corresponds to reductions of 35% and 66% in PI values when using 2 and 10% lime, respectively. However, in the case of the CL clay class, the PI reduces from 15% to only 11 and 6.5% with the addition of the same lime contents (2 and 10%), respectively. This corresponds to reductions of only 26.7 and 56.7% in PI values when using the same lime contents (2 and 10%), respectively. From these both examples, it is quite clear to observe that the sensitivity of the PI reduction to the lime content is more pronounced with the CH clay class than with both MH and CH clay classes. The same behaviour was observed by several researchers when compared their experimental results to predicted PI results obtained by ANNs model. e.g. Gadouri, Harichane, and Ghrici (2016a) reported that the PI of grey clayey soil classified as CH clay decreased from 50.53% to 18.97 and 16.43% when using 4 and 8% lime, respectively. This reflected that the PI values were reduced by 62.46 and 67.49%, respectively, with the same lime contents (4 and 8% lime). However, for the red clayey soil classified as CL clay, the PI decreased from 23.76% to only 20 and 16.9% with the addition of the same lime contents (4 and 8%), respectively. This represented reductions of only 15.82 and 28.87% in PI values when using the same lime contents (4 and 8%), respectively. Similar behaviours were reported by several researchers (e.g. Al-Rawas, Hago, and Al-Sarmi 2005; Bozbey and Garaisayev 2009; Eren and Filiz 2009; Ansary and Hasan 2011).

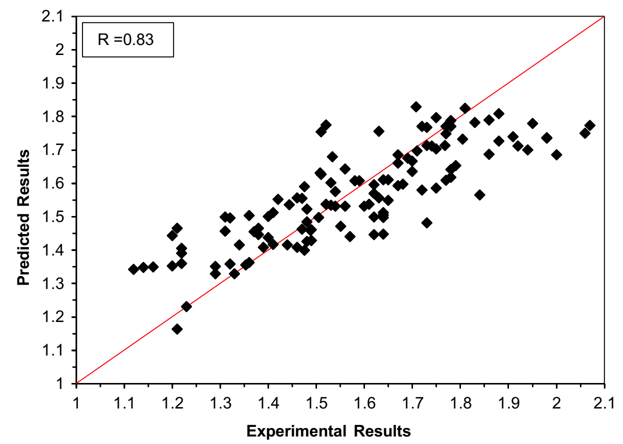

Figure 6. Regression values of all data for MDD–ANNs model.

Effect of lime on compaction characteristics

Effect of lime on the maximum dry density (MDD)

Figure 13 is drawn as a result of parametric study based on the effect of lime variation on MDD, where lime content was considered as a variable and the other parameters were kept constants as shown in Table 11. Figure 13 shows that the MDD decreases with increasing lime content. Several researchers found the same behaviour (e.g. Ola 1977; Rahman 1986; George, Ponniah, and Little 1992; Bell 1996; Aydin and Adnan 2007; Hossain, Lachemi, and Easa 2007; Manasseh and Olufemi 2008; Harichane, Ghrici, and Kenai 2012; Celik and Nalbantoglu 2013; Jha and Sivapullaiah 2015; al-Swaidani, Hammoud, and Meziab 2016). For any clay class (CH, MH and CL), the MDD slightly decreases with increasing lime content whereby the CL clay class presents the high decrease (Figure 13). For example, the MDD of CH clay class decreases from 1.380 t/m^3 to only 1.376 and 1.356 t/m^3 with the addition of 2 and 10% lime, respectively. This corresponds to reductions of 0.28 and 1.74% in MDD values when using 2 and 10% lime, respectively. However, in the case of the CL clay

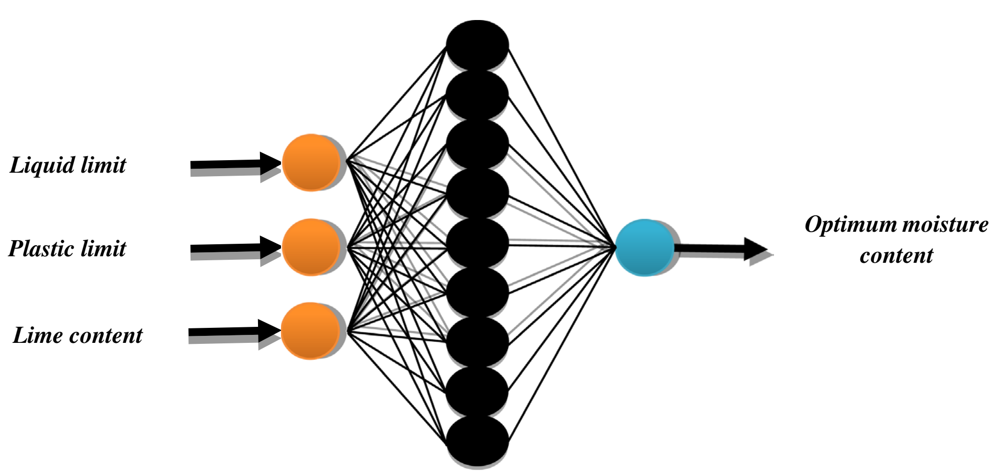

Figure 7. Architecture used in ANNs model for OMC prediction.

Table 6. Training parameters values used in NN model for OMC prediction.

NN parameters	Values and nomination in MATLAB
Train function	'trainlm' (Levenberg Marquardt)
Transfer function	'tansig' (no linear function)
Performance function	'mse' (mean square error)
Error after learning	0.001
Divide function	'dividerand'
Train epochs	1000
Number of input layer neurons	03
Number of hidden layers	01
Number of neurons by hidden layer	09
Number of output layer	01

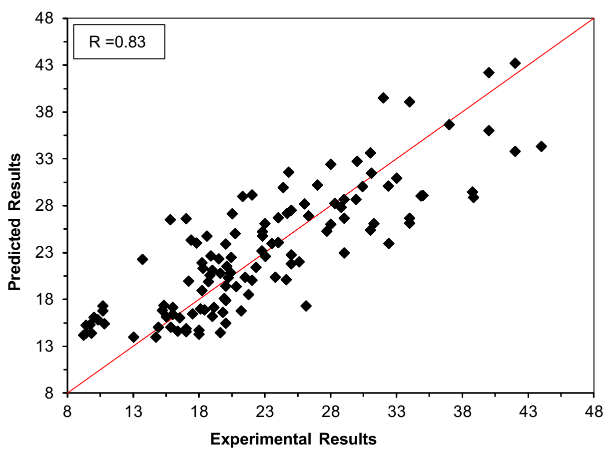

Figure 8. Regression values of all data for OMC–ANNs model.

class, the MDD reduces from 1.489 t/m³ to 1.478 and 1.453 t/m³ with the addition of the same lime contents (2 and 10%), respectively. This corresponds to reductions of only 0.74 and 2.42% in MDD values when using the same lime contents (2 and 10%), respectively. Both examples show that the sensitivity of the MDD reduction to the lime content is more pronounced with the CL clay class than with the CH clay class. The same behaviour was observed by several investigators on comparing their experimental results to the predicted MDD results obtained by ANNs model whereby experimental results present the greatest reduction in MDD values. For example, al-Swaidani, Hammoud, and Meziab (2016) reported that the MDD of clayey soil classified as CH clay decreased from 1.48 t/m³ to 1.41 and 1.35 t/m³ when using 4 and 8% lime, respectively. This reflected that the MDD values were reduced by 4.37 and 8.78% respectively with the same lime contents (4 and 8% lime). However, Harichane, Ghrici, and Kenai (2012) reported that for the red clayey soil classified as CL clay, the MDD decreased from 1.69 t/m³ to 1.64 and 1.62 t/m³ with the addition of the same lime contents (4 and 8%), respectively. This represented reductions of only 2.96 and 4.14% in MDD values when using the same lime contents (4 and 8%), respectively. Practically, it can be observed that the percentages of reductions in MDD values of CH clay class obtained from experimental results are very higher compared to predicted results provided by ANNs model (the differences in MDD values are 15.6 and 5.05 times when using 4 and 8% lime, respectively). This is probably attributed to the lower number of MDD data used in ANNs model due to the few of data published in the literature. However, small differences in percentages of reductions of MDD values of CL clay class between the experimental results and predicted results provided by ANNs model (the differences in MDD values are 4 and 1.7 times when using 4 and 8% lime, respectively). For both CH and CL clay classes, the differences in MDD values between the experimental results and predicted results provided by ANNs model become very small when the content of lime is greater than 8%.

Effect of lime on OMC

Figure 14 presents a parametric study of the effect of lime on the OMC, where lime content was the variable but other parameters were considered as constants (Table 12). Figure 14 shows that the OMC increases with increasing lime content. This behaviour was in concordance with the results obtained by several researchers (e.g. Ola 1977; Rahman 1986; George, Ponniah, and Little 1992; Bell 1996; Hossain, Lachemi, and Easa 2007; Harichane, Ghrici, and Kenai 2012; Siddique and Hossain 2011; Jha and Sivapullaiah 2015; al-Swaidani, Hammoud, and Meziab 2016). For any clay class (CH, MH and CL), the OMC highly increases with increasing lime content (Figure 14). For example, the OMC of CH clay class increases from 29.38% up to 30.05 and 33.52% with the

Table 7. Error between experimental and predicted values of PI.

Author	LL (%)	PL_0 (%)	Lime (%)	PI_{ex} (%)	PI_p (%)	Error (%)	Average (%)
Portelinha et al. (2012)	73.40	40.8	1	28.10	29.11	3.60	12.43
	73.40	40.8	2	2–2,00	17.32	21.26	
Ramlakhan, Kumar, and Arora (2013)	38.90	14.4	3	21.48	19.99	6.93	8.67
	38.90	14.4	6	19.08	19.93	4.46	
	38.90	14.4	9	17.90	19.79	10.58	
	38.90	14.4	12	17.09	19.26	12.73	
Oza and Gundaliya (2013)	59.79	36.8	1	17.13	20.96	22.38	
	59.79	36.8	2	15.57	14.04	9.83	9.91
	59.79	36.8	3	11.37	11.72	3.07	
	59.79	36.8	4	9.56	10.65	11.40	
	59.79	36.8	5	8.63	9.99	15.74	
	59.79	36.8	6	8.93	9.48	6.20	
	59.79	36.8	7	8.74	9.09	3.99	
	59.79	36.8	8	8.35	8.90	6.63	
	59.79	36.8	9	8.50	9.35	9.96	
Siddique and Hossain (2011)	56,00	13,00	3	30,00	30.78	2.61	6.89
	56,00	13,00	6	25,00	26.87	7.47	
	56,00	13,00	9	22,00	24.15	9.78	
	56,00	13,00	12	20,00	21.89	9.43	
	56,00	13,00	15	19,00	19.98	5.16	
Total average error							9.16

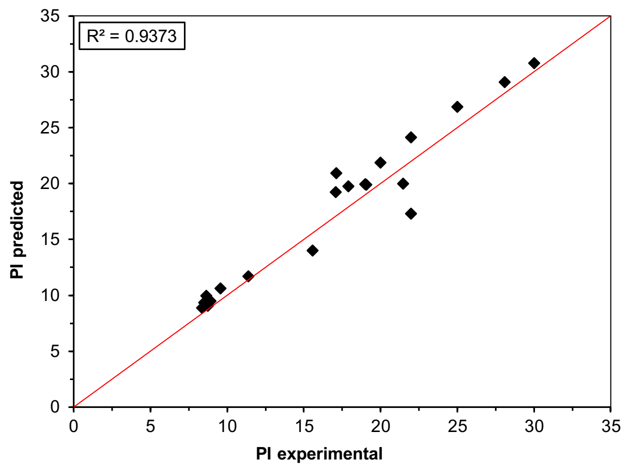

Figure 9. Correlation between experimental and predicted results for PI property according to PI–ANNs model.

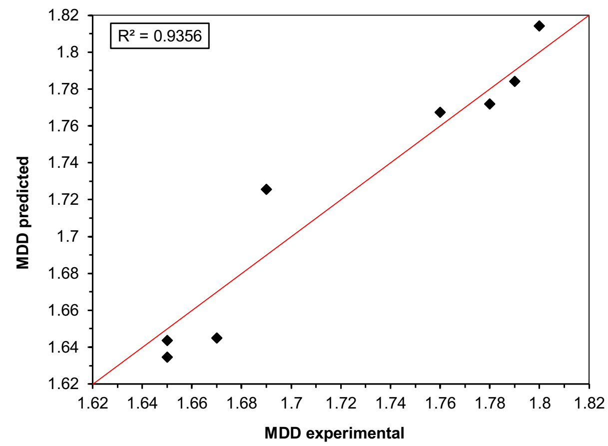

Figure 10. Correlation between experimental and predicted results for MDD property according to MDD–ANNs model.

Table 8. Error between experimental and predicted values of MDD.

Author	Lime (%)	LL (%)	PL (%)	MDD_{exp} (t/m^3)	MDD_p (t/m^3)	Error (%)	Average (%)
Eren and Filiz (2009)	4	31	23	1.69	1.73	2.11	1.23
	6	33	29	1.67	1.64	1.50	
	8	33	31	1.65	1.63	0.92	
	10	33	32	1.65	1.64	0.38	
Ramlakhan, Kumar, and Arora (2013)	3	39.25	17.77	1.8	1.81	0.80	0.50
	6	40.5	21.42	1.79	0.32	0.02	
	9	41.7	23.8	1.78	0.44	0.08	
	12	42.98	25.89	1.76	0.43	0.25	
Total average error							0.86

Table 9. Error between experimental and predicted values of OMC.

Author	Lime (%)	LL (%)	PL (%)	OMC_{exp} (%)	OMC_p (%)	Error(%)	Average (%)
Eren and Filiz (2009)	0	32	17	15	14.50	3.36	6.41
	6	33	29	18	19.68	9.33	
	8	33	31	19.2	20.40	6.23	
	10	33	32	19.5	20.81	6.76	
Ramlakhan, Kumar, and Arora (2013)	0	38.9	14.4	15.73	15.04	4.39	2.38
	3	39.25	17.77	13.83	14.35	3.75	
	6	40.5	21.42	15.80	15.72	0.51	
	9	41.7	23.8	16.90	17.35	2.65	
	12	42.98	25.89	18.27	18.38	0.62	
Total average error							4.17

addition of 2 and 10% lime, respectively. This corresponds to reductions of 2.28 and 14.09% in OMC values when using 2 and 10% lime, respectively. However, in the case of the CL clay class, the OMC increases from 24.26% up to 24.66 and 28.45% with the addition of the same lime contents (2 and 10%), respectively. This corresponds to reductions of 1.65 and 17.27% in OMC values when using the same lime contents (2 and 10%), respectively. It is obvious to observe that the sensitivity of the OMC of all clay classes to the lime content is more pronounced with the high lime content than with the low lime content. The same behaviour was found by several researchers on comparing their experimental results to predicted OMC results obtained by ANNs model whereby experimental results present the greatest reduction in OMC values. For example, Almoghir (2013) reported that the OMC of clayey soil classified as CH clay increased from 18.1% up to 19.9 and 25.6% when using 3 and 9% lime, respectively. This reflected that the OMC values were reduced by 9.94 and 41.44%, respectively, with the same lime contents (3 and 9% lime). It can be observed that the percentages of reductions in OMC values of CH clay class obtained from experimental results are not higher compared to predicted results provided by ANNs model (the differences in OMC values are 4.36 and 2.94% times when considering 2 and 10% lime as references values, respectively). This is probably attributed to the lower number of OMC data used in ANNs model due to the lack of data published in the literature. On the other hand, for a lateritic soil classified as CL clay, Okagbue and Yakubu (2000) found that the OMC increased from 15.5% up to 16 and 19% with the addition of 2 and 8% lime content, respectively. This represented reductions of 3.23 and 22.58% in OMC values when using the same lime contents (2 and 8%), respectively. There are small differences in percentages of reductions of OMC values of CL clay class between the experimental results and predicted results provided by ANNs model (the differences in OMC values are only 1.96 and 1.31%

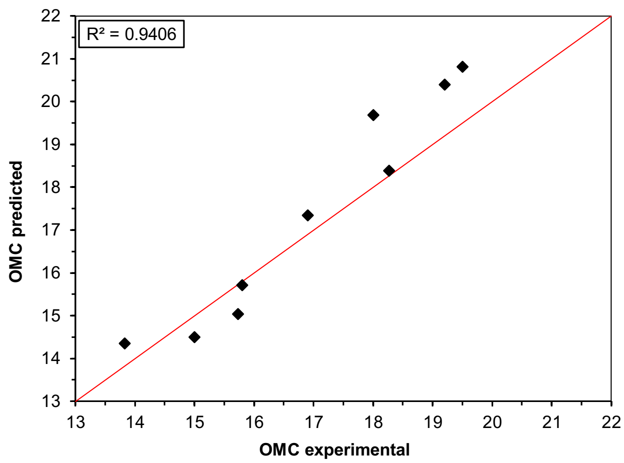

Figure 11. Correlation between experimental and predicted results for OMC property according to OMC–ANNs model.

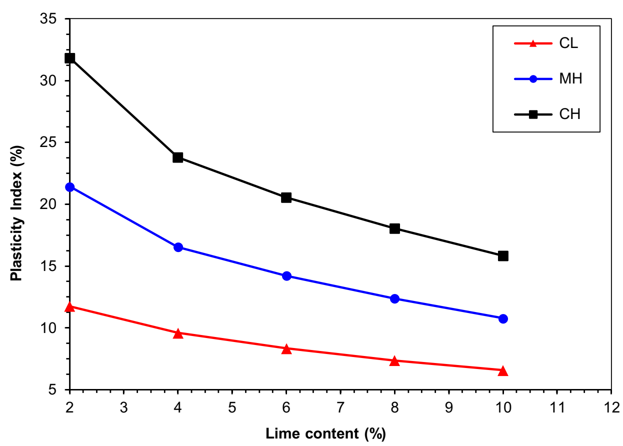

Figure 12. Effect of lime on the PI predected by using PI–ANNs model.

Table 10. Data analysis for parametric study (PI prediction).

Lime content (%)	LL_0 (%)	PL_0 (%)	PI_0 (%)	Soil classification
2, 4, 6, 8, 10	35	20	15	CL
2, 4, 6, 8, 10	55	30	25	MH
2, 4, 6, 8, 10	80	30	50	CH

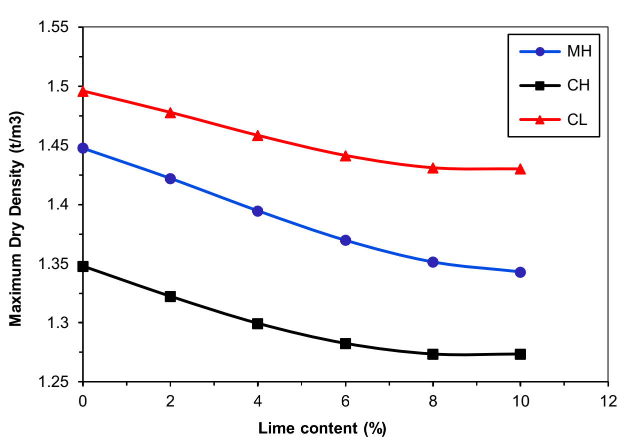

Figure 13. Effect of lime on the MDD predicted by using MDD–ANNs model.

Table 11. Data analysis for parametric study (MDD prediction).

Lime content (%)	LL (%)	PL (%)	PI (%)	Soil classification
0, 2, 4, 6, 8, 10	50	45	15	CL
0, 2, 4, 6, 8, 10	70	45	25	MH
0, 2, 4, 6, 8, 10	85	50	35	CH

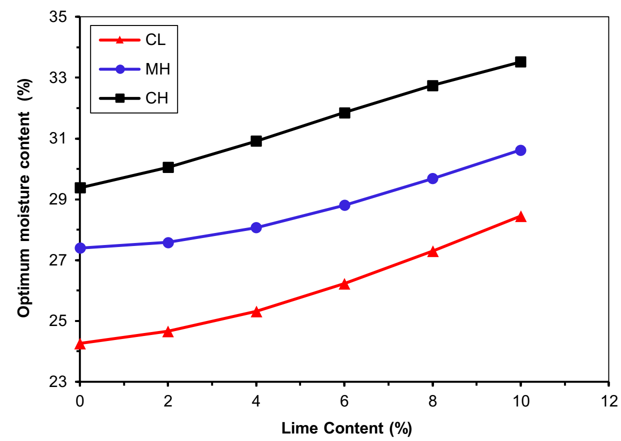

Figure 14. Effect of lime on the OMC predicted by using OMC–ANNs model.

Table 12. Data analysis for parametric study (OMC prediction).

Lime content (%)	LL (%)	PL (%)	PI (%)	Soil classification
0, 2, 4, 6, 8, 10	50	45	5	CL
0, 2, 4, 6, 8, 10	70	45	25	MH
0, 2, 4, 6, 8, 10	85	50	35	CH

times when using 2 and 8% lime, respectively). In general, the ANNs OMC model appears to be more adaptable with the CL clay class than with the CH clay class.

Conclusions

This study was made in order to develop ANNs models used for predicting geotechnical properties of lime-stabilised clayey soils (CH, CL and MH classes). The study carried out in this work showed the feasibility of using a simple ANNs to predict the PI, MDD and OMC of clayey soils stabilised with lime. It was verified that all proposed ANNs models were successfully trained and validated. ANNs is an extremely interconnected system that can discover the nature of complex interrelationships between Atterberg limits and compaction characteristics (MDD and OMC). As a result, all models were able to predict the PI, MDD and OMC. Based on obtained results, the following conclusions can be drawn:

- The better results obtained from different models showed that the ANNs is the most suitable technique for modelling different complex behaviours of clayey soils especially the plasticity which presents a high sensitivity to the lime addition.
- The good performance of ANNs model for the prediction of PI with correlation coefficient $R^2 = 0.94$ corresponding to regression values of all data between experimental and predicted values ($R = 0.91$).

- Low error values corresponded to the comparative study especially for the prediction of MDD.
- The regression of OMC–ANNs and MDD–ANNs models are intermediary affected due to the lack of data.
- ANNs models developed in this paper (IP–ANNs, MDD–ANNs and OMC–ANNs models) can be efficiency used for a rapid prediction of PI, MDD and OMC properties of stabilised clayey soils.
- It is suggested as a perspective to develop ANNs models for the rest of the properties (e.g. strength, compressibility) of clayey soils stabilised with lime. Moreover, it will be very important to develop other models for problematic soils (mainly clayey soils) stabilised by using other additives (e.g. cement, fly ash, slag) with and without sulphates for a better performance, hybridised neural networks with genetic algorithms can be also used in order to minimise the error and also to reduce the learning time.

Disclosure statement

No potential conflict of interest was reported by the authors.

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