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ORIGINAL PAPER

ANN, M5P-tree model, and nonlinear regression approaches to predict the compression strength of cement-based mortar modified by quicklime at various water/cement ratios and curing times

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Abstract

This study's goal is to establish systematic multiscale equations to estimate the compressive strength of cement mortar with a high volume of lime (L) and to be used by the construction industry with no theoretical restrictions. For that purpose, a wide tested data and the data gathered in the literature (a total of 392 tested cement mortar modified with lime) have been statically analyzed and modeled. The lime content ranged from 0 to 45% (by cement weight). Depending on literature data the w/c ranged from 0.3 to 0.74, the w/c of 0.5 was selected for this research. The compressive strength of lime-modified cement mortar for up to 28 days ranged from 3 to 75 MPa. The compression strength of the cement mortar reduced with an increasing percentage of lime. The linear and nonlinear regression, M5P-tree, and artificial neural network (ANN) technical approaches were used for the qualifications. In the modeling process, the most relevant parameters affecting the compression strength of cement mortar, i.e. lime (L) incorporation ratio (0–45% of cement's mass), water-to-cement ratio (0.3–0.74), and curing ages (1 to 28 days). According to the statistical assessment such as *R*, *MAE*, and *RMSE*, the compression strength of cement mortar can be predicted very well in terms of water-to-cement ratio, lime content, and curing age using various simulation techniques. The maximum and minimum error between the actual test results and the outcome of the prediction using NLR and ANN (training dataset) were 0.01–21 MPa and 0.012–9 MPa, respectively, and ranged between 0.03 and 14 MPa and 0.02 and 6 MPa errors, respectively, in terms of tested data. The margin of error in using the nonlinear regression-based model (NLR) and ANN for the training dataset was 1.41 and 1.92, respectively, and it was 2.26 and 2.44 respectively in using the tested dataset. The outcomes of this paper suggest that the nonlinear regression-based model (NLR) and ANN are performing better than other applied models using training and testing datasets. The result of the sensitivity investigation was the curing period that is the highest dominating value for the prediction of the compressive strength of cement mortar.

Keywords Water/cement ratio · Quicklime (%) · Curing time · Compressive strength · Statistical analysis · Modeling

Literature review

The advantages of using lime are that it lowers mortar costs, pollution to the atmosphere, early hydration temperatures, and can increase mortar workability. Flowability, bonding strength, and toughness are the three major cement mortar properties (Thongsanitgarn et al. 2012; Yang et al. 2011; Erdem et al. 2016; Ismail et al. 1999; Mohammed 2014; Ghafor et al. 2020). Several scientific research studies were conducted to evaluate the effect of lime on the mechanical behavior of cement mortar modified with lime (Table 1). Compressive strength is a key property of cement and cement mortar, which defines the quality and performance of

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Table 1 Compressive strength of lime-modified cement mortar used in the literature

Sources	Location	Lime content (%)	w/c	Curing time, t (day)	Compression strength, σ_c (MPa)
(Yang et al. 2011)	Canada	0–10	0.33	1, 3, 7, and 28	29–64
(Ismail et al. 1999)	Turkey	0 and 30	0.5	2, 7, and 28	16–60
(Mohammed 2014)	China	0 and 30	0.5	3 and 28	17–60
(Qadir et al. 2019a)	Iraq	0–20	0.5	1, 3, 7, and 28	18–75
(Liu and Vipulanandan 2005)	Ethiopia	0–35	0.5	2 and 28	6.7–62
(Moturi 2010)	Italy	0–20	0.6	3, 7, and 28	3–33
(Mohammed 2017)	China	0 and 30	0.43	3, 7, and 28	46–65
(Mohammed and Mahmood 2018a)	Turkey	0–15	0.5	2, 7 and 28	9–55
(Rai et al. 2014)	China	0–45	0.3–0.5	7 and 28	18–65
(Demircan et al. 2011)	Croatia	0–15	0.5	3, 7, and 28	15–40
(Vipulanandan and Mohammed 2017)	China	0–30	0.74	7 and 28	5–32
(Sarwar et al. 2019b)	Norway	0–35	0.5	1 and 28	14–47.5
Current study	Iraq	0–20	0.5	1, 3, 7, and 28	13.6–45
Comment	9 locations	Ranged between 0% to 45%	Ranged between 0.3 to 0.74	Up to 28 days of curing	Ranged between 3 to 75 MPa

construction work (Vipulanandan and Mohammed 2015a; Qadir et al. 2019a; Mohammed et al. 2018; Liu and Vipulanandan 2005; Moturi 2010; Pakeetharan 2012; Mohammed 2017; Mohammed and Mahmood 2018a; Mohammed and Mahmood 2018b). Also, many other properties of the cement mortar like tensile stress and flexural and shear strengths are strengthened in combination with an improvement in compression strength (Mohammed 2018a; Vipulanandan and Mohammed 2014). In the addition of hydrated lime to cement-based mortar, the compression strength shows that the lime-rich mortar can withstand higher deformations before failure (Bonavetti et al. 2000; Matschei et al. 2007; Lothenbach et al. 2008; Gudissa and Dinku 2010; Corinaldesi et al. 2011; Thongsanitgarn et al. 2012; Yang et al. 2011). The observations indicate that the high lime content compared to the broken failure of cement-rich mortar is high (where the lime volume is twice the cement amount, e.g., 1:2:9 mortar); any elastic-plastic deformation is observed before the brittle failure with decreased lime content. Although the hydrated addition of lime to a mortar can be a negative result of the compressive strength reduction, this provides some accommodation as a result of small movements of the masonry that mitigate the cracking associated with the high-force (cement-rich) monitoring, which is more "brittle" when solid (Sezer 2012; Autier et al. 2013; Nehdi et al. 2003; Erdoğdu 2005; Plank and Hirsch 2007; Zingg et al. 2008; Ferrari et al. 2011; Matias et al. 2013; Liu et al. 2014; Erdem et al. 2016; Ismail et al. 1999). Compressive and bonding strengths are the most critical property of cement mortar that describes its quality and performance for construction works. Sandwiched samples were prepared to study the bonding strengths of the cement mortar modified with polymer and lime. Different samples were prepared by using concrete brick. The bonding material was cement mortar and cement mortar modified with lime content up to 20%. The concrete brick was marked to ensure that the crossed concrete brick is placed in the middle and at right the angle to each other. The second brick was placed on the mortar and the oriented correctly. The specimens were allowed to cure at room condition 25 ± 2 °C and 95% of humidity until the time of the test. The bond strength of cement mortar without lime content was 1.2 MPa at 7 days of curing. The addition of 20% of lime content decreased the bond strength by 131% (Qadir et al. 2019a; Qadir et al. 2019b).

There are several methods for modeling the properties of materials, including computational modeling, statistical techniques, and recently developed tools such as regression analyses and artificial neural networks (ANN) (Qadir et al. 2019b; Mohammed and Mahmood 2020). Multilinear regression analysis, M5P-tree, and ANN are techniques widely used to solve problems in construction project applications (Sihag et al. 2018; Marangu 2020; Vipulanandan and Mohammed 2020a; Mohammed 2018b, c, 2019; Vipulanandan et al. 2018a; Yaman et al. 2017). The most important characteristics of ANN is the ability to learn directly from examples and the great response to imperfect tasks. An ANN is a mathematical model or computational model based on the brain like learning, rather than conventional programmatic computing. The model consists of artificial neuronal groups interrelated to activate the brain structure to store and use information through a connected approach (Sihag et al. 2018; Yaman et al. 2017). Feedforward networks, also known as multilayer perceptron, are the most common ANN models for many applications. According to the extensive review made by the authors of this study on a related matter, despite the wide application of lime, a reliable model to the use of cement mortar to be used by the construction industry is very scarce (Sihag et al. 2018). Most of the attempts have been related to a single scale model without covering a wide experimental data or multiple parameters. Thus, the effect of several parameters such as the lime content, w/c, and curing time of 1 day up to 28 days was quantified using different model techniques, namely, linear and multilinear regressions, M5P-tree, and ANN-based approaches, for predicting the compressive strength of cement mortar using 390 samples from the literature.

Research significant

The main objective of this paper is to develop systematic multiscale equations to estimate the compressive strength of cement mortar containing an either high or low volume of lime. Thus, a wide experimental data (390 tested samples with different lime content, curing period, and w/c) was considered with different analysis approaches (i) to guarantee the construction industry to use the proposed models without any theoretical; (ii) to perform a statistical analysis and understand the effect of the composition of the cement mortar such as lime content, and water-to-cement ratio on the compressive strength of the cement mortar modified with quicklime; (iii) to quantify and propose a systematic multiscale model to predict the compressive strength of cement mortar containing very large volumes of lime (up to 45%) with various w/c and curing time up to 28 days; and (iv) to find the most reliable model to predict the compressive strength of cement mortar from four different model techniques (linear, nonlinear relations, M5P-tree, and ANN models) using statistical evaluation parameters.

Methodology

The tests were conducted following ASTM and British standards. For each case, an average of three samples is considered.

Materials

(i) Cement (OPC)

The chemical composition (%) and mineralogical composition (%) of the cement used in this study are 66.3% of Ca_3SiO_5, 7.67% of Ca_2SiO_4, 2.19% of $Ca_3Al_2O_6$, and 15.5% of $Ca_4Al_2Fe_2O_{10}$. The mineralogical composition includes 63.9% of CaO, 20.1% of SiO_2, 4.08% of Al_2O_3, 5.10% of Fe_2O_3, 1.48% of MgO, 2.20% of SO_3, and 3.41% of LOI.

(iii) Sand

The sand used to measure the compressive strength of cement mortar in all the studies that have been reviewed by the authors was well-graded rounded particles with 97% of silica content according to the EN 196-1 standard specifications.

Methodology

Sample preparation

The cement paste after mixing is lined with cubic molds with a height of (4×4×16) cm^3. The cement paste is placed in one layer in the mold. The mold is then lifted and covered by a plastic bag and stored at 25 °C temperature. After 24 h, the specimens have been removed from the mold and placed in water at room temperature and 95% of the moisture until the test time. The compressive strength samples were tested for 1 day up to 28 days. A flexural testing machine with a rate of 0.06 *MPa/sec* was employed to split the sample into two elements, and each element was compressed at a rate of 0.3 MPa/s. The compression test was conducted based on (BS EN 196-1:2016) (Sarwar et al. 2019a; Vipulanandan and Mohammed 2020b; Yaman et al. 2017; Mohammed et al. 2020a; Vipulanandan et al. 2018b; Mohammed et al. 2020b; Demir et al. 2018; Jung and Kwon 2013; Mahmood and Mohammed 2020).

Collecting data

The total tested and collected data (390 observations) from different research studies were statically analyzed and divided into two groups. The larger group included 260 data used to create models, while the other group included 130 data used to validate models (Rai et al. 2014). Typical examples of the database can be seen in Table 1 that the compressive strength of the cement-based mortar with a diffident w/c and lime content is shown, respectively. The input dataset consists of the water-to-cement ratio (w/c), the curing age (t, days), and the lime content (L, %), while the tested compressive strength (MPa) for the cement mortar was used as a target.

Modeling

Based on the *R* and *RMSE*, there is no direct relationship that was observed between maximum compression stress (compression strength (σ_c)) and the composition of cement mortar such as percentage of lime and water-to-cement ratio to 28 days of curing (Fig. 1). Thus, the following models ("Linear regression model," "Nonlinear regression model," "M5P-tree model," and "Artificial neural network" sections) were used to assess the influence of the mentioned parameters on the compressive strength of the cement mortar.

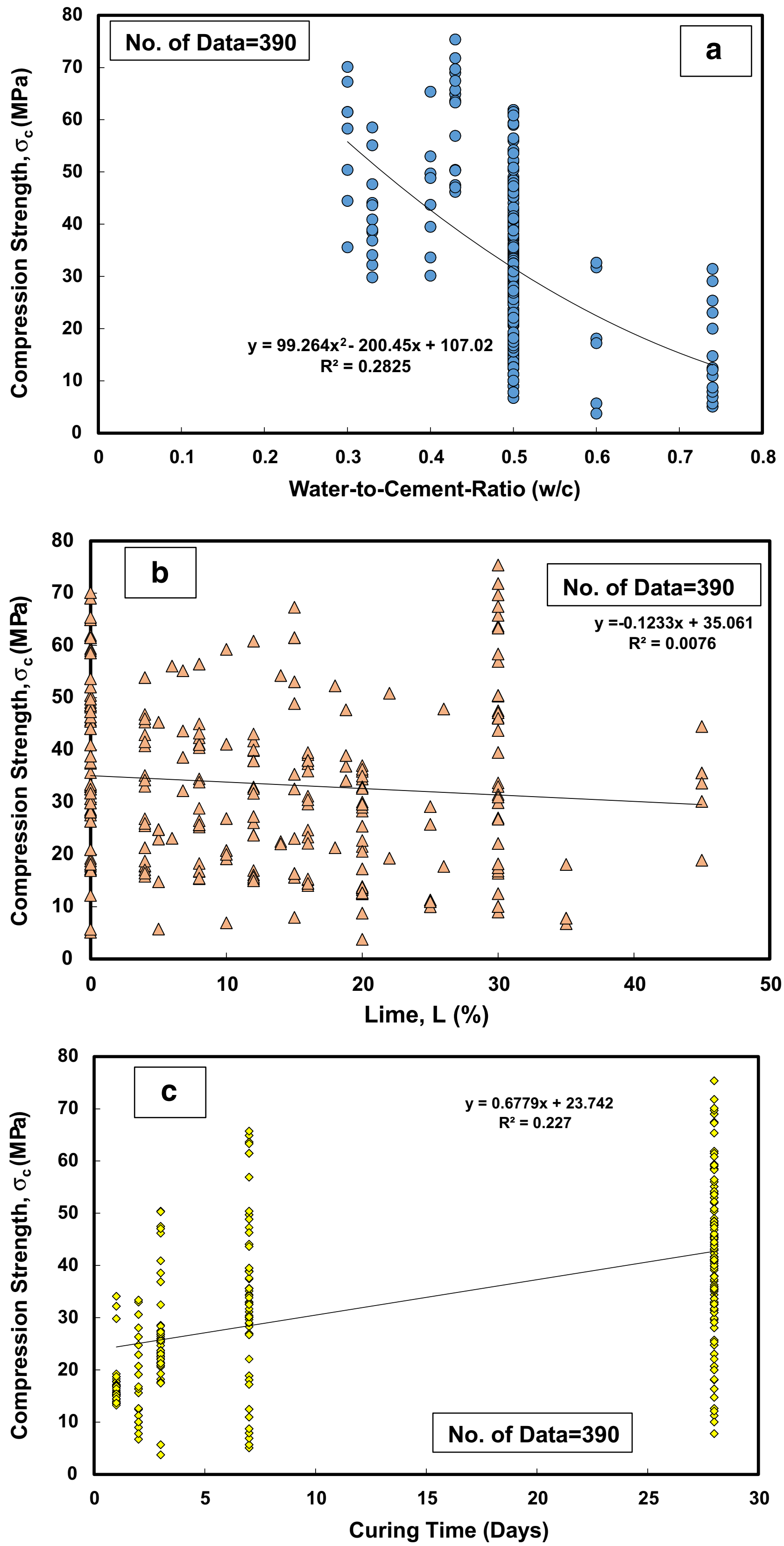


Fig. 1 Variation between compression strength and **a** w/c, **b** lime content (%), and **c** curing age (days) for cement mortar modified with lime

Linear regression model

The linear regression (LR) model can be considered one of the most common regression equations (Eq. 1) for the prediction of cement mortar (Mohammed 2014):

$$\sigma c = a + b(w/c) \tag{1}$$

where σc, w/c, a, and b denote compressive strength of cement mortar (MPa), w/c, and equation parameters, respectively. However, other cement mortar component factors affecting the compressive strength, the type of cementitious materials, and curing time are not included in the equation. To have more reliable results, Eq. 2 is proposed to include other factors:

$$\sigma c = a + b(w/c) + c(t) + d(L) \tag{2}$$

where t is curing age (days) and the lime content (L, %), respectively, and the parameters of the model are a, b, c, and d. In compliance with Eq. 2, all the variables seem to be adapted with linear (Eq. 1) extent. Nevertheless, this may not necessarily be occurred for all cases because the variables involved in a cement mortar mix may affect its compressive strength and interrelate with each other. The model, therefore, needs to always be updated to reliably predict the compressive strength of the cement mortar with an appropriate high precision (Thongsanitgarn et al. 2012; Mohammed 2014). Accordingly, Eq. 2 was converted to a multivariable power equation.

Nonlinear regression model

To develop a nonlinear regression model, the following formula (Eq. 3) can be considered a general form (Rai et al. 2014; Demircan et al. 2011). Equation 3 is representing the interrelation between the variables given in Eq. 2 and Eq. 3 to estimate the compressive strength of the conventional and cement mortar component.

$$\sigma_c = a\left(\frac{w}{c}\right)^b (t)^c + d\left(\frac{w}{c}\right)^e (t)^f (L)^g \tag{3}$$

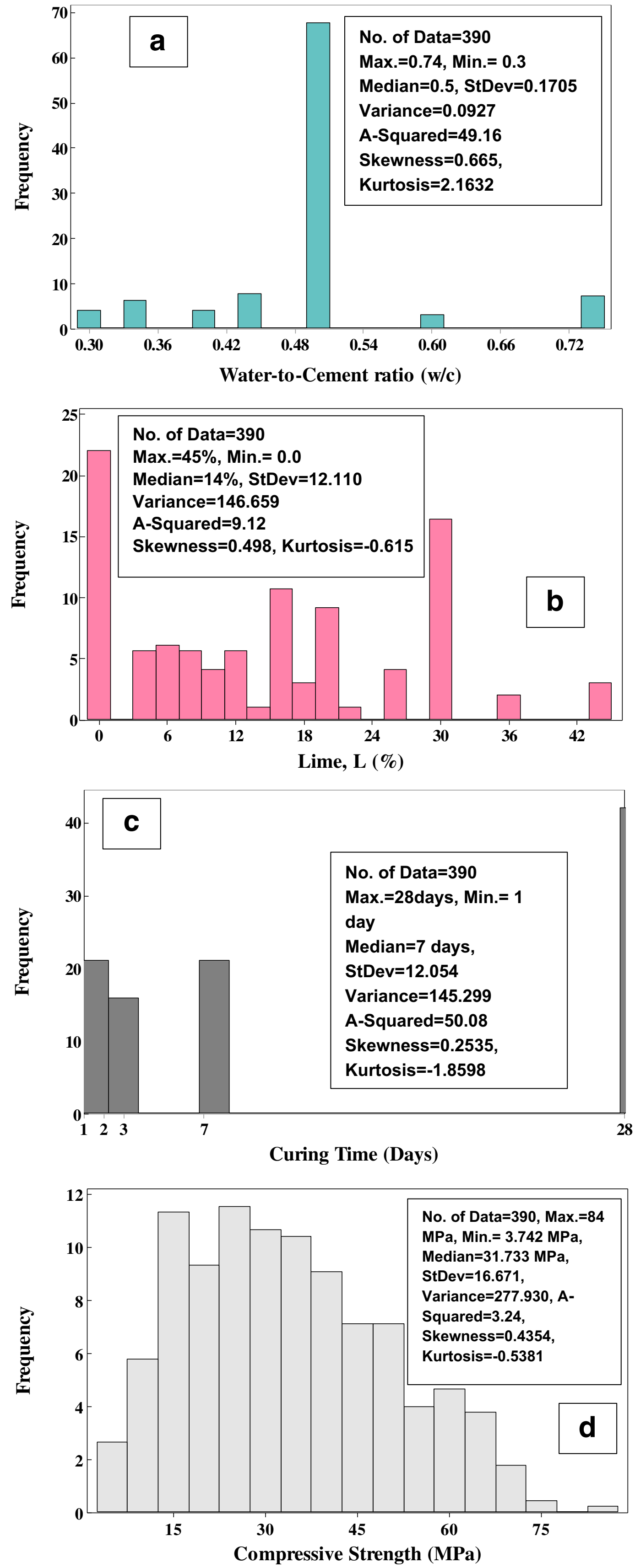
M5P-tree model

M5P-tree is a genetic algorithm learner for regression problems, first introduced by a study (Mohammed and Mahmood 2020). This tree algorithm sets a linearly regression at the terminal node and fits on each sub-location in a multivariate linear regression model by classifying or dividing various data areas into multiple different spaces. Error estimation is presented with information on the M5P-tree model tree division criteria on every node. Errors were measured by the default value variance of the class entering the node. To estimate some features of this node, the attribute maximizes the expected error reduction. Information on the M5P-tree model tree dividing criteria is obtained based on error calculations per node. The standard deviation of the class values in the node decides the M5P error. The function that maximizes the expected error reduction by evaluating each attribute at this node for node division is selected. Due to the branching method, child node data (sub-tree or smaller nodes) have less StDev value. Parent nodes (greater nodes). Select a device with the highest potential error reduction after evaluating all possible structures. This division also creates a large structure similar to a tree that leads to overfitting. In the second stage, the huge tree is cut, and linear regression functions replace the trimmed sub-trees.

Artificial neural network

The artificial neural network is the computing system designed to simulate the way how the human brain processes and analyses. Also, this model is a machine learning system used for various numerical predictions/problems in construction engineering (Thongsanitgarn et al. 2012; Sihag et al. 2018; Marangu 2020). ANN contains the input layer, the hidden layer, and the output layer. The hidden layer is linked to other layers by weight, transfer, and bias. A multilayer feed-forward network was programmed with a mixture of proportions, water-cement ratio, curing age, and lime content like inputs, and compressive strength as output. There is no standard method for designing or selecting a network architecture. Therefore, the maximum number of hidden layers and neurons was calculated by the trial and error test based on the lowest average square error criterion. The second step of the optimal network design process was to choose the optimum number of epochs during the training that gave the minimum *MAE* and *RMSE* and high *R*-value. The same preliminarily designed networks with hyperbolic tangent transfer functions were used to see the effect of several epochs on reducing the *MAE* and *RMSE*. The *MAE* variations with the number of epochs are presented for the preliminarily designed networks. After designing the optimum architecture, the available dataset (total of 390 data) was divided into two parts; the first part was 2/3 of the overall dataset (260) for training the network, and the second part was 1/3 of the total dataset (130) for testing the network (Thongsanitgarn et al. 2012). Several transfer functions and ANN structures with a varied number of hidden layers and neurons were tested to design the optimal network structure to predict the cement mortar compressive strength. Among the networks, two hidden layers with twenty neurons and a hyperbolic tangent transfer function were chosen due to having the minimum mean absolute error (*MAE*). In this part of the research, the ANN model was used to estimate the compressive strength of lime-containing cement mortar as a cement replacement, water-to-cement ratio, curing age, and lime contents.

Fig. 2 Histogram for **a** w/c, **b** lime (%), **c** curing period (days), and **d** cement mortar compression strength modified with lime for up to 28 days of curing



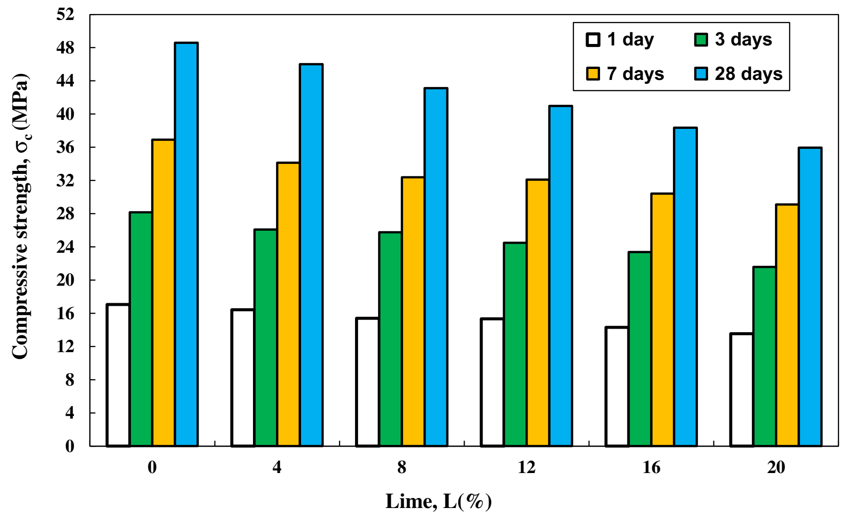


Fig. 3 Current study variation between lime (%) cement mortar compression strength in different curing ages

Performance evaluation and model criteria

R (correlation coefficients), *MAE* (mean absolute error), and *RMSE* (root means square error) values were used to estimate the ability of the above-mentioned modeling methods. Three common statistical measures, *R*, *MAE*, and *RMSE*, were used as evaluation metrics to determine the efficacy of machine learning techniques. Numerous experiments were performed to determine the optimal value of key parameters. High *R* values (Eq. 4) and lower *MAE* (Eq. 5) and *RMSE* (Eq. 6) values show a better model precision:

$$R = \frac{N\sum yi\, xi-(\sum yi)\ (\sum xi)}{\sqrt{N\left(\sum(yi^2)-\left(\sum(yi^2)\right.\right.}\sqrt{N\left(\sum(xi^2)-\left(\sum(xi^2)\right.\right.}} \tag{4}$$

$$MAE = \frac{\sum_{i=1}^{n}|(y_i-x_i)|}{N} \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i-x_i)^2}{N}} \tag{6}$$

where yi = tested data; xi = predicted data; $\overline{y}$ = mean value of yi; and N is the dataset.

Analysis and outputs

Statistical evaluation of cement mortar properties

In this section, the statistical analysis was made to see whether the considered data such as w/c (i), lime content (ii), and (iii) By analyzing the standard Kurtosis and Skewness error, the compression strength is distributed. For the Kurtosis, a large negative value (LNV) means that the tails of the distribution are shorter than that of the normal distribution. The opposite is true (longer tails) for a positive value. Regarding the skewness, and LNV means a long-left tail and the opposite is true (right tail) for a positive value.

(i) Water/cement ratio (*w*/*c*)

Based to the total of 390 data gathered from different published research work, the water-cement ratio for the cement mortar ranged from 0.3 to 0.74 with a median of 0.5, a StDev of 0.1705 and a variance of 0.0927 (Fig. 2a), Skewness which is a function of the asymmetry of the probability of the mean of real-valued distributed variables is 0.665 and A-squared which is the statistical coefficient for Anderson-Darling Normality. Its indicator of how nearly the database fits the

Table 2 Detail of performance assessment parameters for various approaches

Approaches	Training dataset			Testing dataset		
	R	*MAE* (MPa)	*RMSE* (MPa)	*R*	*MAE* (MPa)	*RMSE* (MPa)
LR (Eq. 7)	0.864	5.709	7.063	0.873	5.851	7.131
NLR (Eq. 8)	0.887	4.813	6.469	0.906	4.673	6.197
M5P (Eq. 9)	0.915	5.261	6.848	0.906	3.880	5.702
ANN	0.919	4.037	6.652	0.830	6.562	8.335

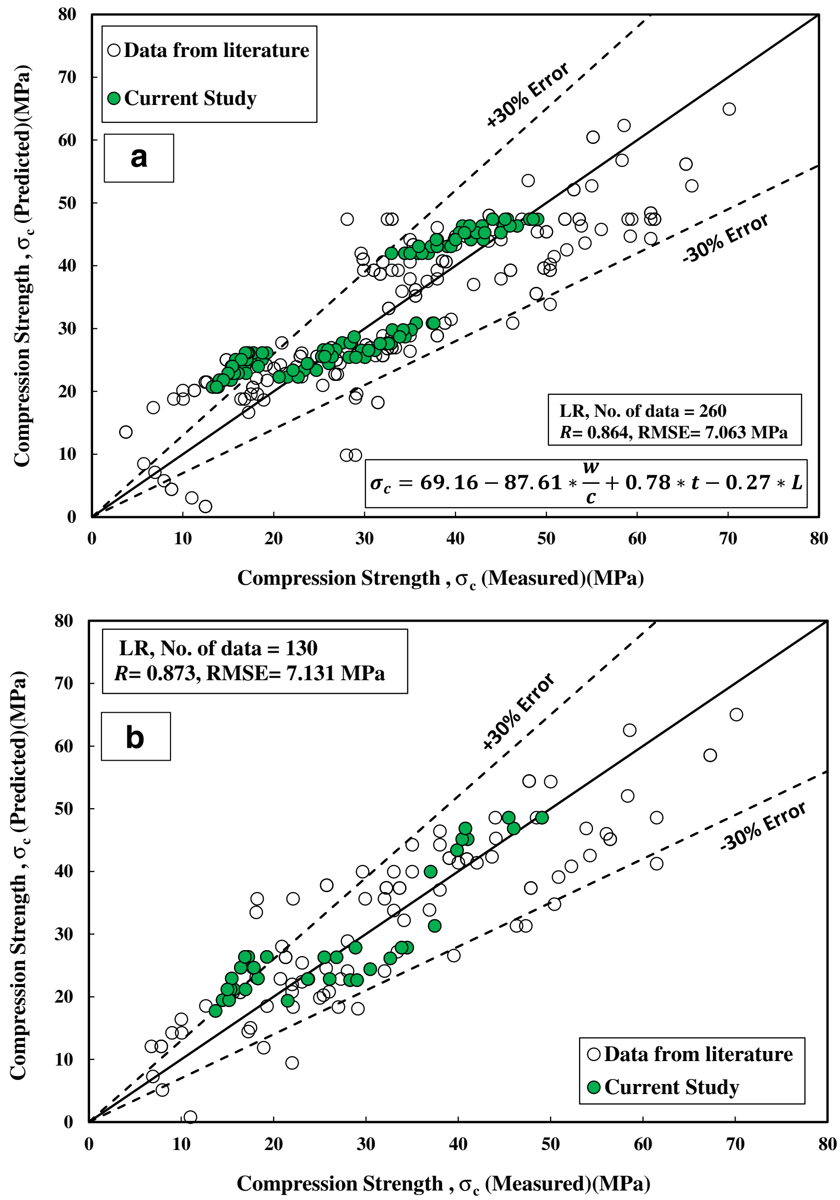


Fig. 4 Comparison between tested and predicted the compression strength of cement mortar modified with lime using linear regression model (LR) **a** training data and **b** tested data

normal distribution is 49.16. The Kurtosis of 2.1632 was also calculated.

(ii) Lime (L %)

According to a total of 390 data of cement mortar mixes, the lime content was varied from 0 to 45% (Fig.2b) with the median of 14%, the StDev of 12.110%, and variance of 146.659. A-squared, Skewness, and Kurtosis are 9.12, 0.498, and −0.615 respectively.

(iii) Compressive strength

The compression strength for up to 28 days of curing ranged from 3.74 to 84 MPa, a median of 31.733 MPa, StDev of 16.671 MPa, and variance of 277.930 according to 390 data from various research studies (Fig. 2d). Thirty-five percent of the total compression strength of cement mortar up to 28 days of curing (Fig. 2c) varied from 15 to 30 MPa as shown in Fig. 2d. A further with lime content of 20% lowered the compression strength of cement mortar by 21.2% after 1 day of curing. An additional 12% of lime decreased the σ_c of cement mortar by 19% at 28 days of curing (Fig.3) (Sarwar et al. 2019b).

The relation between calculated and actual cement mortar compressive strength

(a) The linear model

The model parameter observed that the w/b significantly decreases the cement mortar's compressive strength.

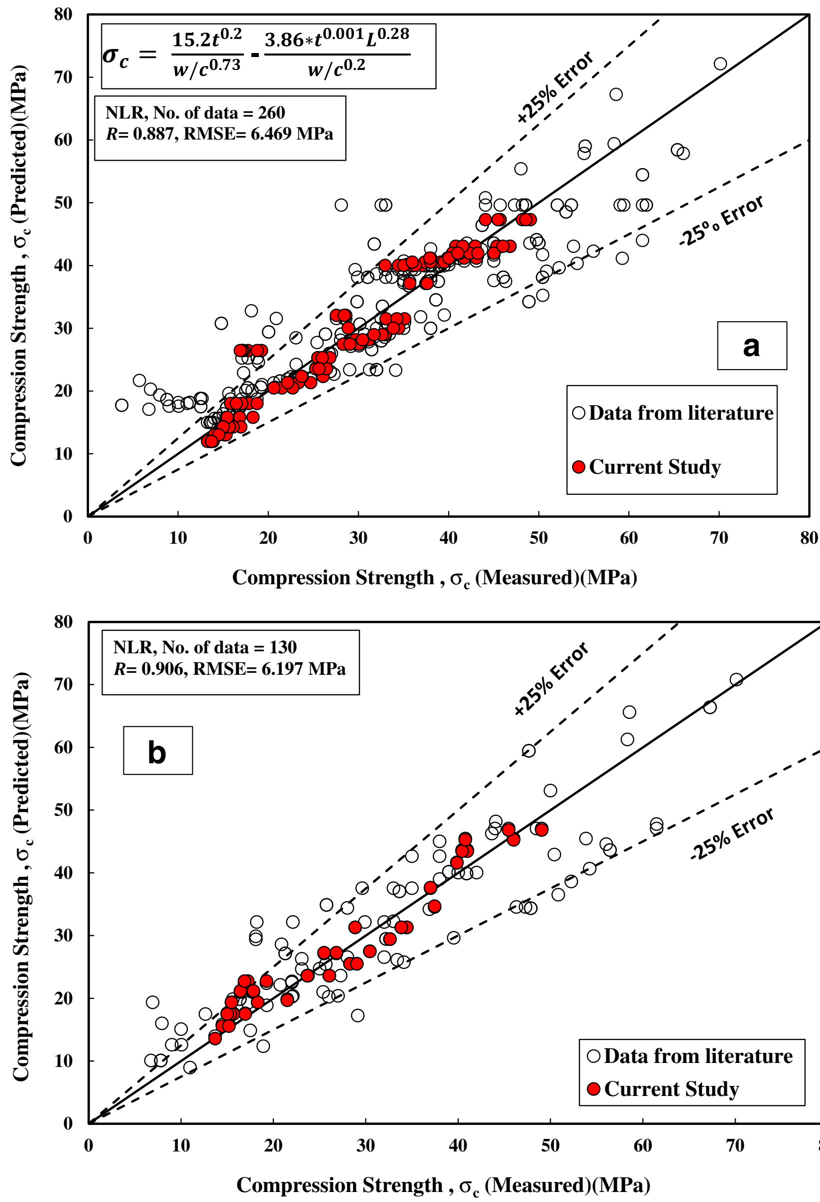


Fig. 5 Comparison between tested and predicted the compression strength of cement mortar modified with lime using non-linear regression model (NLR) **a** training data and **b** tested data

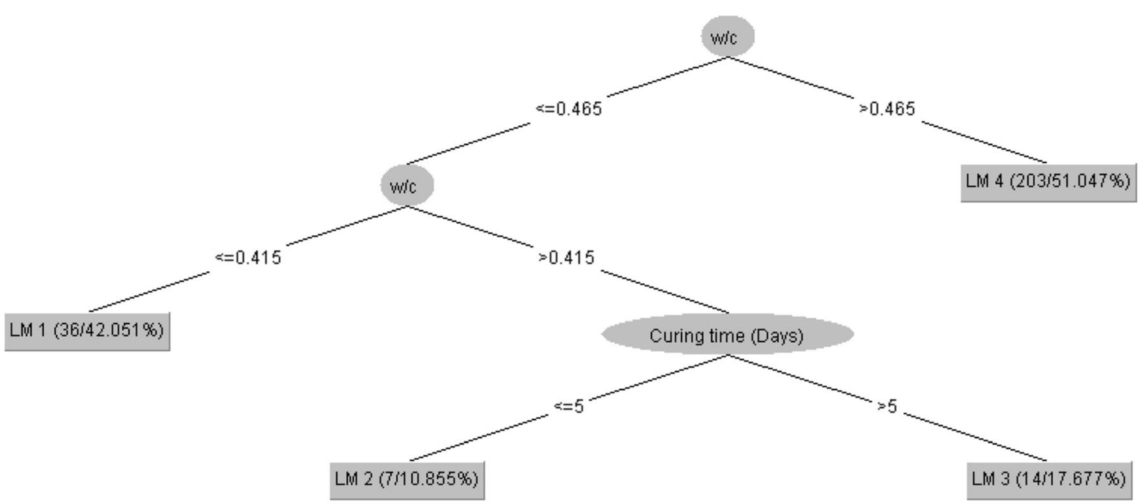


Fig. 6 M5P pruned model tree

Table 3 NLR model parameters for compression strength using M5P-tree model (Eq. 9)

	$(\sigma c = a*\frac{w}{b} + b*t + c*L + d)$				
	LM number	1	2	3	4
Model parameters	a	1.607	11.432	11.432	− 76.105
	b	0.639	0.573	0.596	0.765
	c	− 0.277	− 0.103	− 0.103	− 0.383
	d	43.216	42.887	45.452	62.897

Table 2 summarizes model parameters, *R*, *MAE*, and *RMSE*. The relationships between actual and calculated compression strength of the cement-based mortar are shown in Fig. 4a. The research dataset contains a ± 30% error line, indicating that most checked results are in ± 30% error lines:

$$\sigma c = -87.61w/c + 0.78t - 0.27L + 69.16, \tag{7}$$

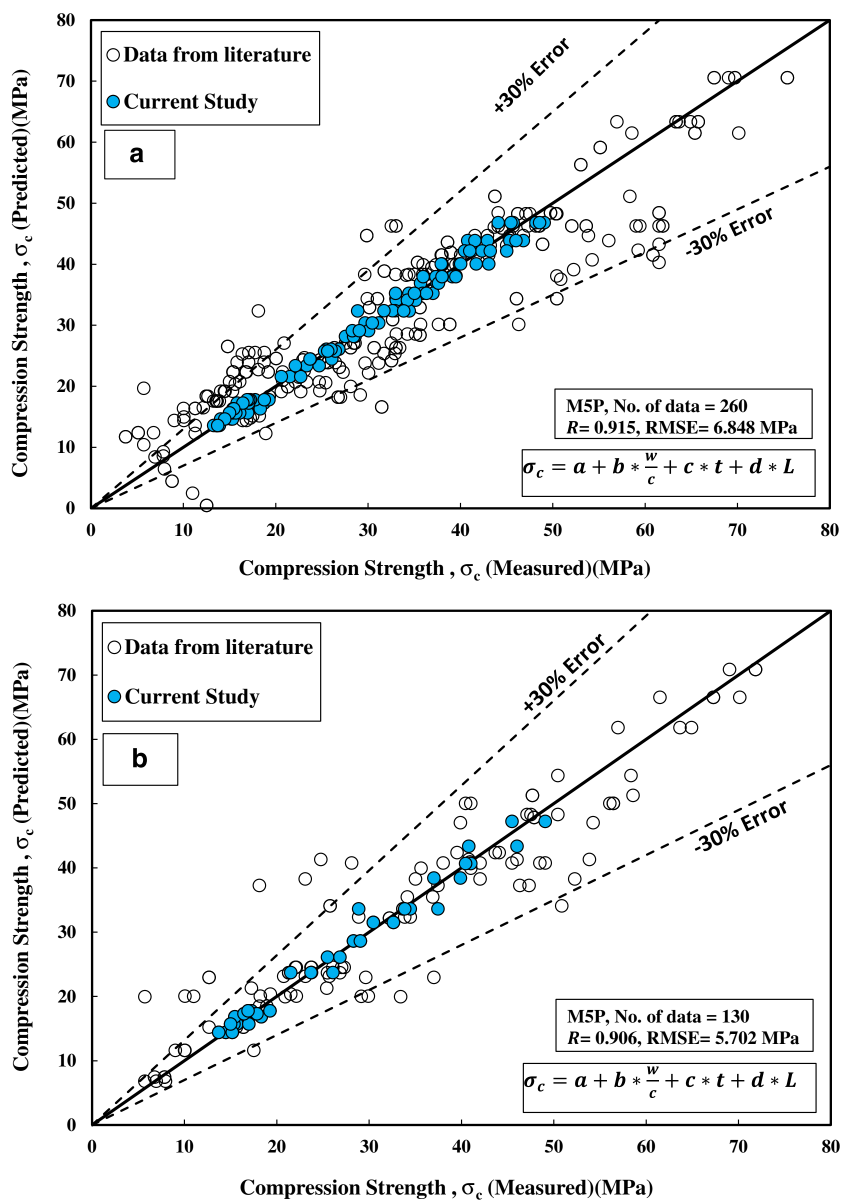


Fig. 7 Comparison between tested and predicted the compression strength of cement mortar modified with lime using M5P-tree model **a** training data and **b** tested data

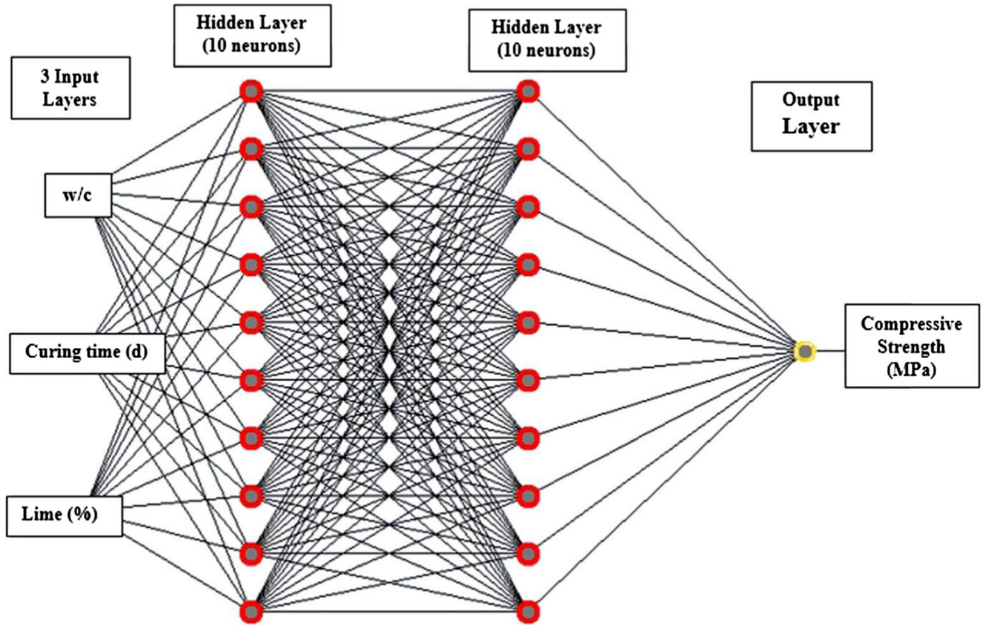


Fig. 8 Optimal network structure of neural network model

where the no. of data = 260, $R = 0.864$, and $RMSE$ = 7.063 MPa.

And from model parameters in the Eq. 7, it can be obtained that the w/c has the highest impact on reducing the compressive strength compared with other cement mortar compositions also based on the parameter (−0.27) the lime content decreasing the compressive strength of the cement mortar as it is comparable with the experimental results in the Fig. 4. Equation 7 has also been validated using the testing dataset as shown in Fig. 4b.

(b) Nonlinear regression model

The study dataset contains an error line of ± 25%, indicating that almost all checked results are in ± 25% error lines (Fig.5a). This model (Sarwar et al. 2019b; Mohammed and Vipulanandan 2015; Abdalla et al. 2019; Burhan et al. 2019; Burhan et al. 2020; Mohammed and Vipulanandan 2018; Vipulanandan and Mohammed 2015b; Vipulanandan and Mohammed 2015c) seems to be more reliable than LR to predict the compressive strength:

$$\sigma c = 15.2w/c^{-0.73}t^{0.2} – 3.86\left(\frac{t^{0.001} \quad L^{0.28}}{w/c^{0.2}}\right) \tag{8}$$

where the no. of data = 260, $R = 0.887$, and $RMSE$ = 6.469 MPa.

Focusing on model parameters (Eq. 8), the maximum impact of w/c on decreasing the compressive strength relative to other cement mortar compositions can be obtained. Equation 8 has also been validated using the testing dataset (Fig. 5b). Equation 8 can be used to estimate the compressive strength of the cement mortar with 0% lime similar to Eq. 7 (Mahmood et al. 2019; Mohammed 2018c; Mohammed and Vipulanandan 2014; Vipulanandan and Mohammed 2018; Mohammed and Mahmood 2019).

(c) M5P-tree model

Figure 8 shows input space division x_1, x_2 (independent variables) by the M5P-tree model algorithm into nine linear tree regression functions (marked LM1 through LM4). The model's general shape is $y = ao + a1x1 + a2x2$, where ao, a_1, and a_2 are linear regression constants. Figure 6 indicates the tree-shaped branch relationship, and the model (Eq. 9) constant is summarized in Table 3. The research dataset contains an error line of ± 30%, indicating that almost all measured results are in ± 30% error lines (Fig. 7a). Furthermore, the output of this model is more reliable than those of the previous models. In other words, the calculated and actual compressive strength of the cement mortar mixes is adapted with the line of equality:

$$\sigma c = \mathrm{a}(w/b) + b(t) + c(L) + d, \tag{9}$$

where the no. of data = 260, $R = 0.915$, and $RMSE$ = 6.848 MPa.

The model constants (a, b, c, and d) are listed in Table 3, and based on the linear tree registration function (LM num), the model variables will be selected. The models (Eq. 9) have also been evaluated using the testing dataset as can be seen in Fig. 7b.

(d) ANN model

The network was equipped with the training dataset, accompanied by the test data to predict the compressive strength values for the correct input parameters (Fig. 8). A sensitivity test for the model predictions was also carried out (Fig. 9). The ANN model based on the predictions over-predicted 130 of the data analyzed. A trial and error cycle is the development of the ANN model (such as the # of hidden layer neurons, # of hidden layers, momentum, learning rate, and iteration). The ANN model contains two hidden layers. Each hidden layer contains ten neurons and three inputs with momentum, and Iteration of 0.2, 0.1, and 2000 respectively. From Table 2, the ANN model was obtained $R = 0.919$, $MAE = 4.037$ MPa, and $RMSE = 6.652$ MPa. The research dataset contains an error line of ± 30%, indicating that all measured results are in ± 30% error lines. The compressive strength values calculated and the ANN expected are compared. Overall, based on the results shown in Table 2 and Fig. 9, the ANN model accuracy is suitable for the prediction of compressive strength. The inter-comparison regression and soft computing-based models, overall comparison among regression and soft computing-based models (Table 2), suggest that the ANN-based model performs better than the other applied models. NLR model is predicting more accurately than the LR model for this dataset. Figure 10 indicates the agreement plot and performance diagram; both figures suggest that the NLR and ANN-based model is outperforming than the other applied models with a minimum deviation from agreement line or actual values. Three statistic parameters including standard deviation, correlation, and root mean square error evaluated the degree of compliance of cement mortar's compressive strength among actual and predicted values.

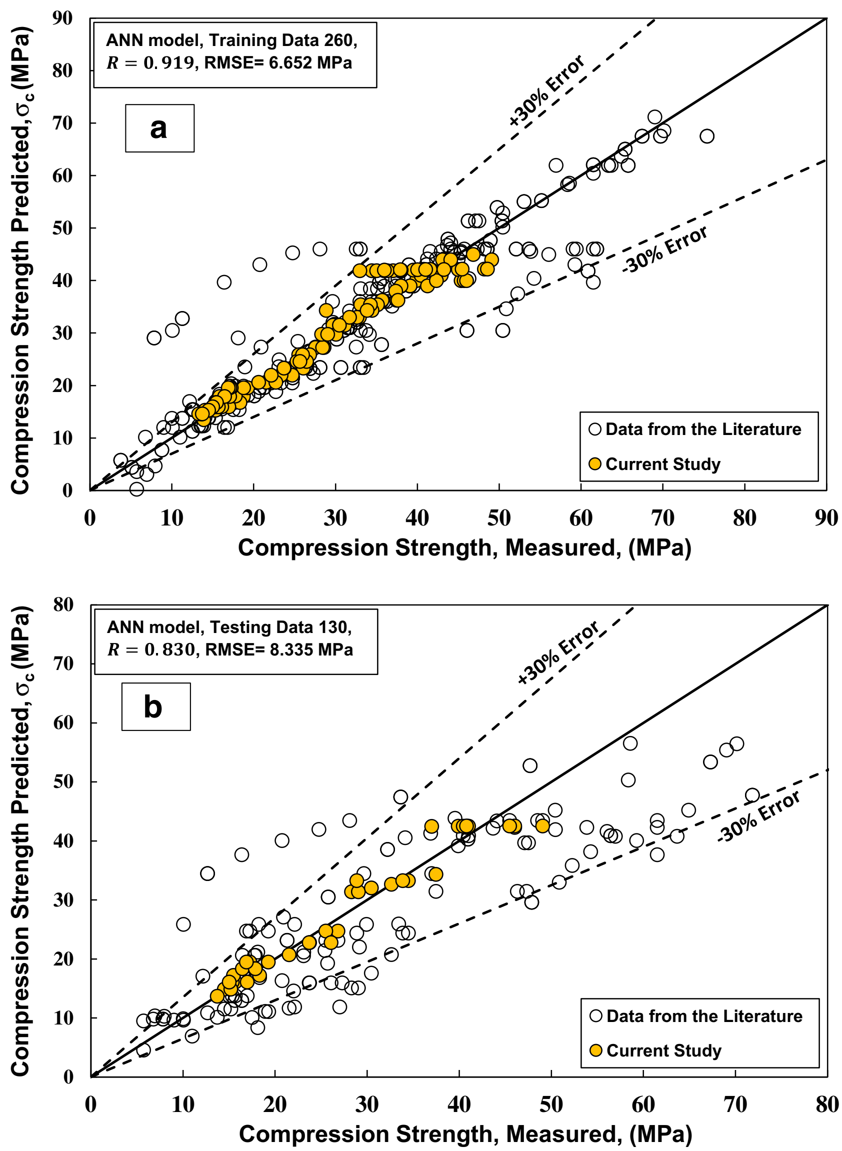


Fig. 9 ANN model prediction **a** training data and **b** tested data (Fig. 10). Variation in predicted values of compressive strength for cement mortar modified with lime based four different approaches in comparison to observed values

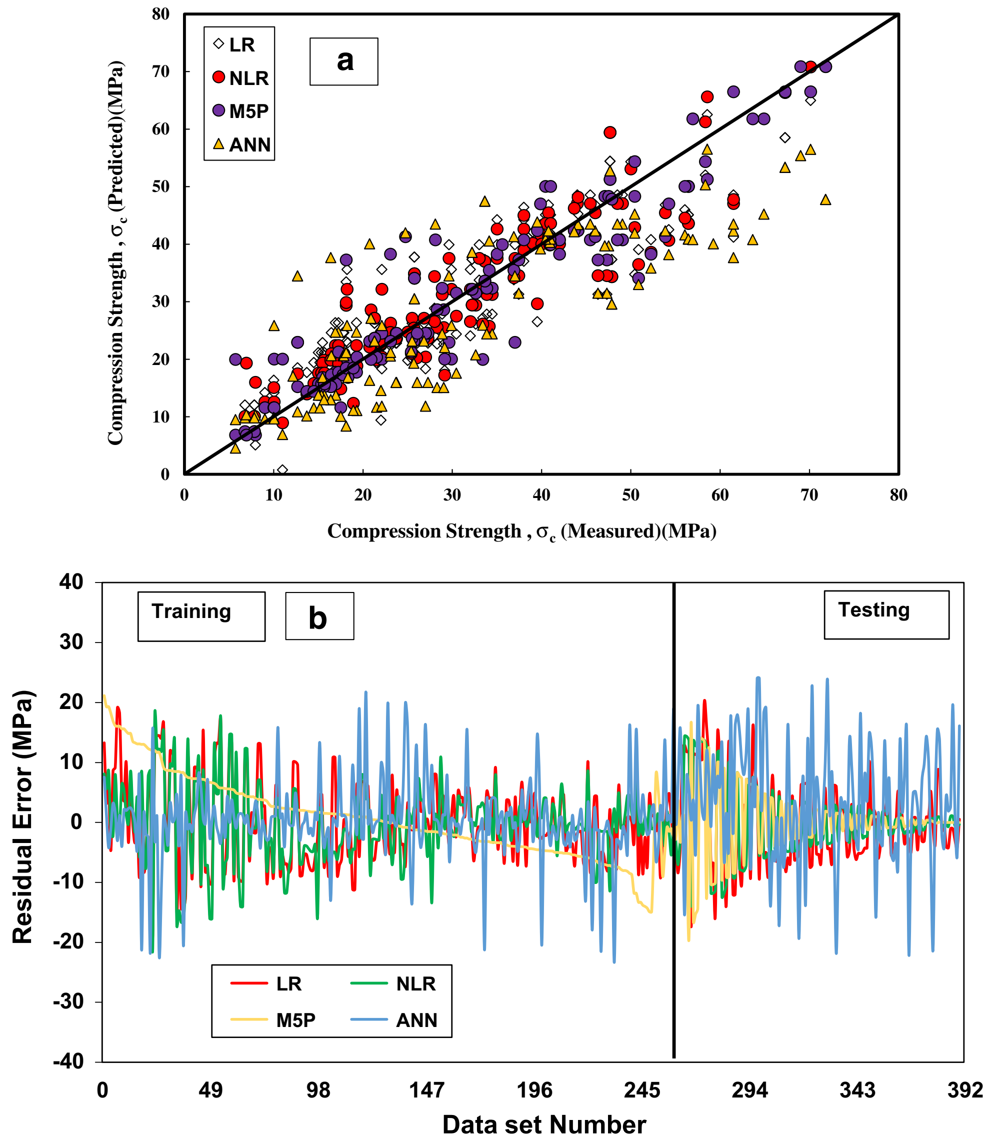


Fig. 10 Variation in predicted values of compressive strength for cement mortar modified with lime based four different approaches in comparison to observed values

Figure 10 a and b indicate the agreement plot and performance diagram; both figures suggest that the NLR and ANN-based model is outperforming than the other applied models with a minimum deviation from agreement line or actual values. Three statistic parameters including standard deviation, correlation, and root mean square error evaluated the degree of compliance of cement paste's compressive strength among actual and predicted values.

Sensitivity investigation

A comparison between the sensitivity of the models was made to assess the most important input variable in the compression strength measurement of the cement mortar. Several training datasets were created by extracting the single input variable at a time, and the test dataset reported the effects of *R*, *MAE*, and *RMSE*. Data set to split into two

Table 4 Sensitivity analysis using the M5P-tree-based model

Sr. no.	Input combination	Removed parameter	*R*	*MAE*	*RMSE*	Ranking
1	Lime, w/c, curing time	–				
2		Lime	0.763	8.951	11.359	3
3		Curing time	0.622	11.157	13.999	2
4		w/c	0.534	10.995	14.324	1

sections for training and testing. The best performing model is selected for the sensitivity analysis. In this research study, the M5P-tree model is used for sensitivity analysis. Results obtained from Table 4 indicate that the w/c is the most influencing parameter for the prediction of compressive strength of cement mortar treated with lime using the M5P-tree-based model.

Conclusions and findings

Based on the data collected from various research studies and the simulation of the compressive strength of cement mortar at 390 different w/c, lime content, and curing ages, the following conclusions are drawn:

1. According to statistical assessment, the median amount of lime used to modify the cement mortar was 14%. The partial replacement of cement with lime ranged from 0 to 45%. The w/c for the lime-modified cement mortar was in the range of 0.3–0.74.
2. Based on the experimental data and model parameters, the compression strength development at the same w/c was decreased with the increasing lime amount, and the strength development was increased with decreased w/c.
3. The designed ANN was used to predict the cement mortar strength after it was trained by 2/3 of the 390 data gathered from the literature. The ANN model predicted the compressive strength of the testing data with a reliable coefficient of correlation (R 0.919). By using the same variables, a nonlinear relation (NLR) was derived, and the parameters were found via multiple regression. Similarly, the ANN model and M5P-tree models have predicted the compressive strength of the testing data with a reliable coefficient of correlation of 0.919 and 0.915 respectively.
4. Apart from the standard curing age, the results of this study have shown that the ANN model can predict the 28-day compressive strength of cement mortar. Based on the training and testing datasets, the ANN and M5P-tree models predicted the compressive strength very close to experimental data, and the predictions were better than other models.
5. Based on the statistical assessment of *R*, *MAE*, and *RMSE*, the compression strength of cement mortar can be well predicted in terms of water/cement ratio, percentage of lime, and curing age using NLR, ANN, and M5P-tree models.
6. By using the M5P-based model, sensitivity analysis showed that water-to-cement ratio is the most important parameter for estimating the compression strength of cement mortar modified with lime.

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