COMPRESSIVE STRENGTH PREDICTION OF LIGHTWEIGHT SHORT COLUMNS AT ELEVATED TEMPERATURE USING GENE EXPRESSION PROGRAMING AND ARTIFICIAL NEURAL NETWORK

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Abstract. The experimental behavior of reinforced concrete elements exposed to fire is limited in the literature. Although there are few experimental programs that investigate the behavior of lightweight short columns, there is still a lack of formulation that can accurately predict their ultimate load at elevated temperature. Thus, new equations are proposed in this study to predict the compressive strength of the lightweight short column using Gene Expression Programming (GEP) and Artificial neural networks (ANN). A total of 83 data set is used to establish GEP and ANN models where 70% of the data are used for training and 30% of the data are used for validation and testing. The predicting variables are temperature, concrete compressive strength, steel yield strength, and spacing between stirrups. The developed models are compared with the ACI equation for short columns. The results have shown that the GEP and ANN models have a strong potential to predict the compressive strength of the lightweight short column. The predicted compressive strengths of short lightweight columns using the GEP and ANN models are closer to the experimental results than that obtained using the ACI equations.

Keywords: Gene expression programing, artificial neural network, lightweight concrete, short column, elevated temperature.

Introduction

It is recognized recently the beneficial effect of light weight aggregate concrete in reducing the weight of structure, increasing fire resistant capacity, reducing permeability, reducing dead loads and hence dimensions of elements, and solving durability problems (Sturm et al., 2000; Bogas & Gomes, 2013; Kayali, 2008). Furthermore, light concrete is beneficial in seismic regions because seismic loads are linearly dependent on the mass of the structure. However, light weight aggregate concrete has low elastic modulus and most likely suffers from brittle shear characteristics that limit its application in vertical bearing elements such as columns (Wu et al., 2018). Columns performance is significantly influenced the global behavior of reinforced concrete structures. Short columns attract more loads than slender columns due to their high stiffness. It is generally recommended to provide sufficient lateral confinement for lightweight columns to improve their toughness and ductility.

Over the last four decades, several experimental tests (Sheikh & Uzumeri, 1980; Mander et al., 1988; Cusson & Paultre, 1995) have been conducted to investigate the behavior of columns that made using normal weight concrete and light weight concrete. The main parameters that influence the behavior of columns are concrete compressive strength, transverse reinforcement tensile strength, transverse reinforcement configuration, transverse reinforcement spacing, transverse and longitudinal reinforcement ratios and concrete cover. Experimental research has been carried out recently to investigate the behavior of RC short columns made with lightweight concrete aggregate. Anilkumar and Kumar (2016) have carried an experimental program to investigate the load-deflection response of three light weight concrete columns compared to three normal weight concrete columns at normal temperature. The results have shown that the load deflection behaviors of both types of columns are close. Haddad

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and Ashour (2013) have tested 72 light weight aggregate concrete short columns exposed to elevated temperature. Experimental results have shown that columns' compressive load capacity, rigidity have significantly reduced while the peak strain and compressive toughness have increased as exposure temperature exceeded 400 °C. Saatcioglu and Razvi (1992) have shown experimentally that the stirrups increased the ductility of the tested short columns. Li et al. (2018) have shown that the strength of reinforced concrete columns increases when using high-strength steel bars. Esfahani and Kianoush (2005) have shown that FRP wrap can increase the load carrying capacity and ductility of circular reinforced concrete columns significantly. Farghal and Diab (2013) have also shown that carbon fiber reinforced polymer (CFRP) sheets can enhance the compressive strength of the reinforced concrete columns. Al-Thairy (2015) has found that the volumetric ratio of the transverse reinforcement can increase the axial load capacity of the columns significantly. Mostofinejad and Moshiri (2015) have introduced a strengthening grooving method in order to limit the global buckling of columns under compression and to enhance their load carrying capacity.

Most of the experimental programs available in the literature investigate the behavior of RC columns under normal temperature. Few studies have been conducted to investigate the behavior of RC columns under elevated temperature. Although there are some experimental programs that investigate the behavior of lightweight short columns, there is still lack of formulation that can accurately predict their ultimate load at elevated temperature. Empirical modelling based on classical regression techniques are generally used to simulate the experimental behaviour of concrete. Furthermore, modern soft computing applications such as Gene expression programming (GEP) and Artificial neural network (ANN) have been used recently to predict the behaviour of concrete by developing explicit formulations (Cevik & Sonebi, 2008; Sonebi & Cevik, 2009).

Regression techniques work on the basis of predefined functions where regression analyses of these functions are later performed. However, GEP approach does not specify a predefined function but it adds or deletes various combinations of parameters to be considered for the formulation that best fits the experimental results (Cevik & Sonebi, 2008; Sonebi & Cevik, 2009). Therefore, GEP can be considered superior to regression techniques and neural networks. Gene expression programming is an efficient tool in determining explicit formulations for the experimental results including multivariate parameters for the case where analytical expressions are not available (Cevik & Sonebi, 2008; Sonebi & Cevik, 2009).

Gene expression programming is an extension to genetic algorithms (GAs) and genetic programming (GP). The nature of the individuals is different in these three algorithms where it is linear strings (chromosomes) in GAs, nonlinear entities of different sizes and shapes (parse trees) in GP, encoded linear strings of fixed length (the genome or chromosomes) in GEP (Ferreira, 2001). Artificial neural networks can be used to find models from a large amount of data. The development of hybrid methods requires both artificial neural networks and genetic algorithms. In the hybrid methods, genetic algorithms are normally used improve the learning of artificial neural networks and to optimize the inputs and outputs of the neural network model. Gene expression programming and artificial neural networks have been used efficiently in civil engineering applications (Benali et al., 2017; Seifi et al., 2008; Shahrara et al., 2017).

The main purpose of this study is the utilization of ANN and GEP to develop new equations that estimate the compressive strength of short lightweight columns damaged by heat using data available from literature and finite element model (FEM) results. A comparison is also made with the compressive strength predicted using the ACI equation (ACI Committee 318, 2014).

1. Experimental database and FEM results

The proposed ANN and GEP models are built based on the experimental database available in the literature. The models are trained and tested using 83 data test point. The experimental results of fifty specimens are taken from literature (Haddad & Ashour, 2013) while other 33 data points are generated and calibrated using finite element modeling (Obaidat & Haddad, 2016) with the aid of ANSYS, finite element software. Table 1 illustrates a sample of the database. The training and testing data are randomly selected from these data where 70% of the data set is used for training while 30% is used for validation and testing. Table 2 illustrates the statistics of the input and output parameters that used in developing the models. Based on the experimental results available in the literature, the compressive strength of short columns tested under elevated temperature is predominantly controlled by these parameters: temperature (T), concrete compressive strength (f_c'), steel yield strength (f_y), and spacing between stirrups (S). Therefore, the GEP and ANN models are developed using these four parameters.

2. Finite element modeling

Due to the lack of the experimental data that investigates the behavior of lightweight RC columns under elevated temperature, finite element analysis is performed. This section briefly summarizes the finite element modeling of the simulated columns. A three dimensional finite element method is performed using ANSYS (2008). Steel reinforcement is modeled using a beam element 188 that has two nodes with six degrees of freedom including translation and rotation in x, y and z direction. Concrete is modeled using solid 65 element that has eight nodes with three translational degree freedom in x, y, and z directions at each node. Concrete is modeled as a nonlinear isotropic material that associated with Von Mises Criterion with isotropic work hardening method (ANSYS,

2008). The steel reinforcement is assumed to be an elastic perfectly plastic material. The top of the column is restricted against translation in x and z directions but it is free to translate in the y direction while the bottom of the column is restricted against displacement in all directions. Newton Raphson method is adopted with displacement control conditions. The finite element model is validated using the experimental results of the columns' compres-

sive stress capacity, axial stiffness and axial toughness evaluated by Haddad and Ashour (2013). The predicted and the experimental results are close and the absolute error of compressive stress predictions for more than 90% of the columns is smaller than 10%.

3. Gene expression programming

3.1. Overview of genetic programming

Gene expression programming (GEP) is a branch of Genetic programming (GP) that was developed by Ferreira (2002). In GEP, there are five basic components: a function set, a terminal set, a fitness function, control parameters, and a terminal condition. Gene expression programming uses a linear fixed length character string (the genome or chromosomes) to represent the problem solution and is expressed as parse tree called expression tree (ET) with different size and shape (Sarıdemir, 2010; Gandomi et al., 2014; Özcan, 2012; Jafari & Mahini, 2017). Figure 1 shows an example of ET.

Gene expression programming is developed based on two main parameters, chromosomes and expression trees (ETs). The information is translated from the chromosome to the ETs. Chromosomes may contain one or more genes indicating a mathematical expression. The gene in GEP is composed of a head and a tail. The head composed of both function and terminal symbols (constants, variables, functions, and mathematical operators such as (1, a, b, $\sqrt{}$, cos ,*,−, /) (Beheshti et al., 2017). The tail contains only terminals (constant and variables) such as (1, a, b, c). The linking between the genes is by mathematical operator such as addition, subtraction, division, etc.

One of the good advantages of GEP is that the solution is shown as a computer model in tree like structure. It makes possible to infer exactly the phenotype given the sequence of a gene, and vice versa, which is termed as Karva language (Tanyildizi & Çevik, 2010). For example, the ETs shown in Figure 1 which is a chromosome with two genes can be written mathematically as $\left[\sqrt{a+b}+\left(b*a\right)\right]$.

Many recent studies indicated that GEP can be used efficiently in civil engineering applications (Mousavi et al., 2012; Soleimani et al., 2018; Lim et al., 2016; González-Taboada et al., 2016; Gholampour et al., 2017; Gandomi et al., 2014; Nazari & Torgal, 2013). Özcan (2012) used GEP to develop a model for splitting tensile strength of concrete. Beheshti et al. (2017) proposed a model for estimating shear strength of short rectangular reinforced concrete column using Gene Expression Programing.

Table 1. Sample of the database

Specimen identity	Temperature T (°C)	Spacing between stirrups S (mm)	Concrete compressive strength f_c (MPa)	Reinforcement yield strength f_y (MPa)	Column stress (MPa)
1	23.0	60.0	65.0	270.0	62.2
2	23.0	30.0	65.0	270.0	69.2
3	23.0	20.0	65.0	270.0	70.5
4	23.0	10.0	65.0	270.0	72.2
5	100.0	60.0	62.1	261.9	58.2
6	100.0	30.0	62.1	261.9	61.2
7	100.0	20.0	62.1	261.9	65.2
8	100.0	10.0	62.1	261.9	66.7
9	300.0	60.0	50.0	260.0	55.1
10	300.0	30.0	50.0	260.0	58.1
11	300.0	20.0	50.0	260.0	60.3
12	300.0	10.0	50.0	260.0	63.2
13	400.0	60.0	42.0	253.5	44.3
14	400.0	30.0	42.0	253.5	46.3
15	400.0	20.0	42.0	253.5	48.1
16	400.0	10.0	42.0	253.5	50.5
17	500.0	60.0	34.0	203.6	30.4
18	500.0	30.0	34.0	203.6	34.5
19	500.0	20.0	34.0	203.6	38.9
20	500.0	10.0	34.0	203.6	40.7
21	600.0	60.0	26.0	118.5	21.2
22	600.0	30.0	26.0	118.5	24.9
23	600.0	20.0	26.0	118.5	25.8
24	600.0	10.0	26.0	118.5	30.1
25	700.0	60.0	18.0	61.3	15.2
26	700.0	30.0	18.0	61.3	17.2

Table 2. Descriptive statistics of database variables

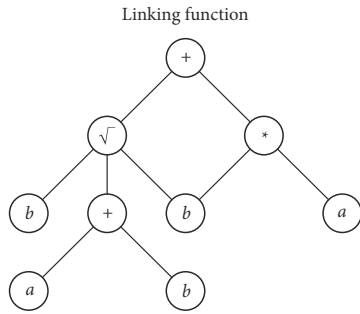| Variable	Unit	Range	Min	Max	Mean	Std. Deviation	Median	Skewness
T	°C	667	23	700	315	233.25	400	0.1
S	mm	50	10	60	30	18.82	25	0.7
F_c	MPa		14.57	65	38.48	16.22	39.5	0.2
F_y	MPa		61.32	590	407.3	187.17	554	0.5
P_o	MPa		15.2	77.5	43.84	18.31	44.4	0.1

Linking function

Figure 1. Example of GEP expression tree

Murad et al. (2019b) proposed predictive models for green concrete using GEP. Gandomi et al. (2014) predict the shear strength of slender RC beams using gene expression programing. Murad et al. (2019a) proposed a GEP model to predict the bond strength of FRP-to-concrete under direct pullout.

3.2. Numerical application

The GEP model that used in the current study is created using GeneXproTools (Gepsoft, 2014). Several trials have been conducted in order to develop the best model that predicts the compressive strength of lightweight short columns damaged by heat. Several GEP models are carried out using the training and testing data. Different GEP models are developed using different number of genes, chromosomes, head size and linking function where the model that best fit the experimental results is selected in this study.

The selected GEP model is developed using two genes with addition as a linking function. The GEP parameters for the models are shown in Table 3 and the expression trees for GEP model are shown in Figure 2.

Table 3. GEP setting parameter

GEP1	
Function set	+, −, *, /
Genes	2
Chromosomes	30
Head Size	8
Tail Size	
Linking Function	Addition
Constant per gene	4
Mutation rate	0.05
Inversion rate	0.1
Transposition rate	0.1
One point recombination rate	0.3
Two point recombination rate	0.3
Gene recombination rate	0.1
Gene transportation rate	0.1

The developed equation that predicts the compressive strength of short columns is generated from the expression trees and is shown in Eqn (1). In the expression tree d_0, d_1, d_2, and d_3 are (T, S, f_c', f_y) respectively and c is constant. It should be noted that the dimensional effects are included in the model. The model predicts the compressive strength in MPa. Thus, the compressive strength P in Eqn (1) is the force / gross column area.

$$P = 7.93 + f_c' - \left(\frac{S^2}{3.99S - 2.08 f_c'} \right) + \left(\frac{f_c' + 3.08S + 7.93}{S^2 - 9.743T} \right).$$

(1)

The developed models are then statistically evaluated using the coefficient of determination (R^2), mean absolute
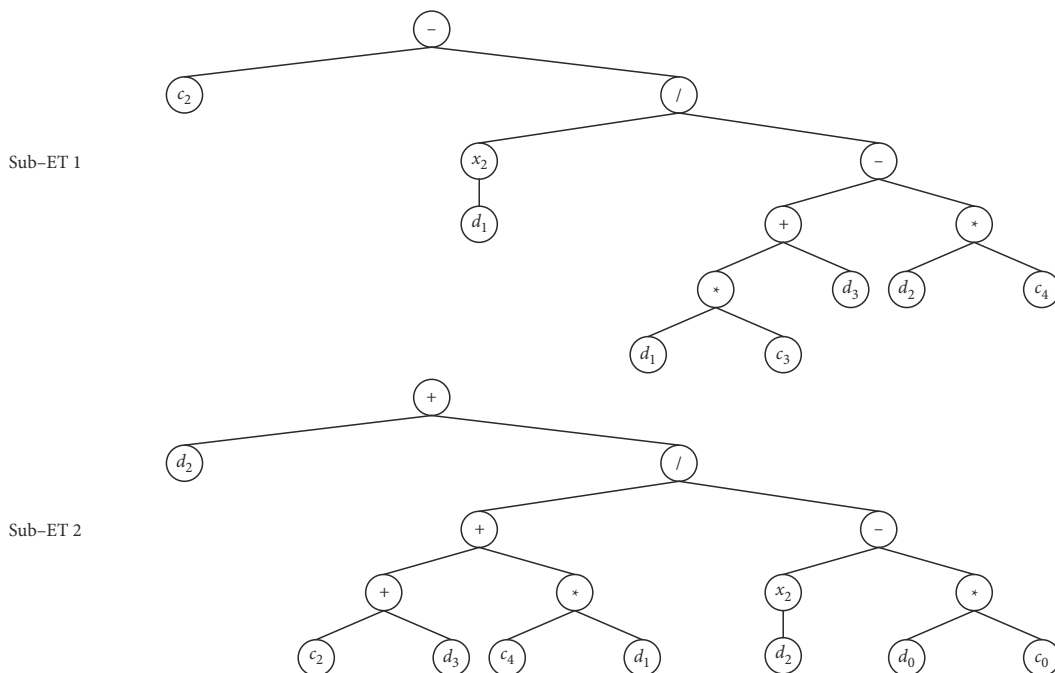

Figure 2. Expression tree of the developed GEP model

error (MAE), and root mean square error (RMSE) that defined in Eqns (2) to (4).

$$R^2 = \frac{\left(\sum_{i=1}^{N}\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)\right)^2}{\sum_{i=1}^{N}\left(X_i - \overline{X}\right)^2 \sum_{i=1}^{N}\left(Y_i - \overline{Y}\right)^2}; \tag{2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|X_i - Y_i\right|; \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(X_i - Y_i\right)^2}. \tag{4}$$

As shown in Table 4 the statistical values of R^2, MAE, RMSE for the training and testing input data are, 94.5, 3.1, 3.76 and 97.2, 2.8, 3.34 respectively. It can be seen that the GEP model has shown an excellent correlation between the predicted and measured values. In addition, the values of R^2 are high and the values of MAE and RMSE are low for testing and validation and this indicates that the GEP model has both prediction ability and generalization performance.

Table 4. Performance of GEP model

GEP1	R^2	MAE	RMSE
Training	0.945	3.1	3.76
Validation	0.972	2.8	3.34
All data	0.9578	3.01	3.63

Comparison between the predicted and experimental values of column compressive strength for the testing, validation and all data are shown in Figure 3 to Figure 5 respectively. It is shown that the distribution of points is close to the ideal fit and hence the model has shown an excellent capability in prediction the compressive strength. The model either under-predicts the experimental strength values by 14.9% or over predicts them by 19.4%.

4. Artificial neural network

4.1. Overview of artificial neural network

Artificial neural network (ANN) is a subfield of artificial intelligence that simulates the human brain and nervous system using computer software and electronic components subjected to certain limitation (Ashteyat & Ismeik, 2018).

Artificial neural network has gain huge interest in the last decade in solving many engineering problems due to it is ability to simulate natural intelligence in the learning from past experience. Artificial neural network is generally relied on experimental data that can be used to evaluate the model.

The structure of ANN is composed of three main parts, input layer, hidden layers, and output layer, as shown in Figure 6. Input layer contains the variables (x_i)
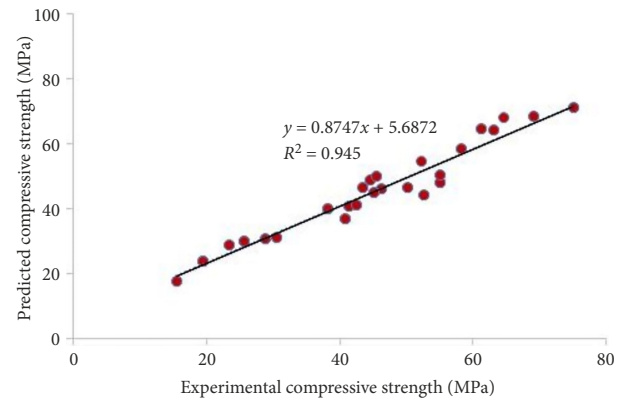

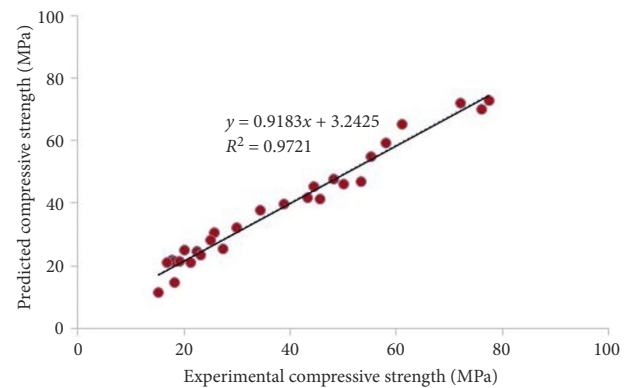Figure 3. Comparison between the predicted and experimental values of training data using GEP model

Figure 4. Comparison between the predicted and experimental values of validating data using GEP model
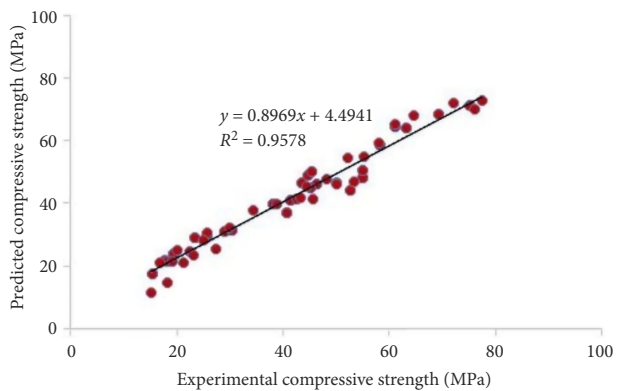

Figure 5. Comparison between the predicted and experimental values of all data using GEP model

and the output layer contains the out parameters. The hidden layer can be one or more and consists of a number of neurons (N_i) that connected to each input and output variable. Each neuron contains a weight w_{ij}, bias b_{ij} and a nonlinear transfer function.

According to Shahin et al. (2009), each input x_i is multiplied by a constant weight w_{ij} then the sum is adjusted by a threshold value θ_j. The combined input I_j is then passed through a nonlinear transfer function $f(I_j)$ to produce the output y_j as shown in Eqns (5) and (6).

$$I_j = \sum w_{ji} * x_i + \theta_j; \tag{5}$$

$$y_j = f\left(I_j\right). \qquad (6)$$

Usually, the transfer function introduces the nonlinearity into the model. It may be of any form, and the one used in this study is sigmoid function.

Artificial neural network has been successfully applied to solve many civil engineering problems. Cascardi et al. (2017) has used ANN to predict the compressive strength of FRP-confined concrete circular column. Ashteyat and Ismeik (2018) predict the residual compressive strength of self-compacted concrete under various temperatures and relative humidity conditions by ANN. Naderpour and Mirrashid (2018) have proposed an ANN model to predict the compressive strength of mortars having calcium inosilicate minerals. One of the difficulties in developing an ANN model is that there is no definite function that can calculate the outcomes using the input variables.

4.2. Numerical application

A multi-layered, feed-forward neural network with back propagation algorithm is used in developing the model to predict the compressive strength of heat damaged lightweight short column.

In ANN, there are number of algorithm that can be used in developing models. Levenberg–Marquardt (LM) algorithm is used in this study as a learning rule in ANN modeling. This algorithm is known for minimizing the error of neural network where it uses layered feed-forward networks, in which, the neurons are arranged in layers, signals are sent forward and errors are propagated backwards (Príncipe et al., 1999; Chithra et al., 2016) as shown in Figure 6.

The neural network models are developed using Neural Network Toolbox in Statistica software. Several configurations for ANN model are generated with different number of neurons in the hidden layer and with different number of hidden layers. The number of neurons in the hidden layer is determined by a training number of networks with different numbers of hidden neurons and then comparing the predicted and experimental values to find the best network structure.

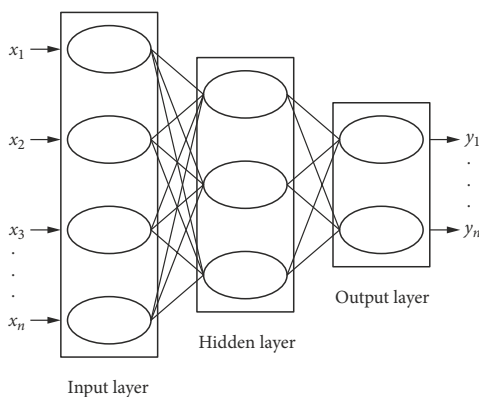The ANN model is developed using 83 test data, approximately 70% of the data has been considered for train-ing, 15% has been considered for testing and 15% has been considered for validation. The best developed ANN model is generated with one hidden layer and two neurons in the hidden layer as shown in Figure 7. The momentum term and learning rate are taken as 0.3 and 0.1, respectively. The input and output transfer functions are logarithmic as shown in Table 5. The model is then evaluated using the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). The values of statistical parameters are shown in Table 5 for training, testing, validation, and total data.

Table 5. Structure and performance of the ANN model

Model properties			
Output	Input	Structure	Function
Σ	T, S, F_c, F_y	4-2-1	sig-sig
Training parameters			
R^2	MAE		RMSE
97.94	2.68		3.77
Validation parameters			
R^2	MAE		RMSE
97.55	2.44		2.89
All datasets parameters			
R^2	MAE		RMSE
95.78	2.65		3.65

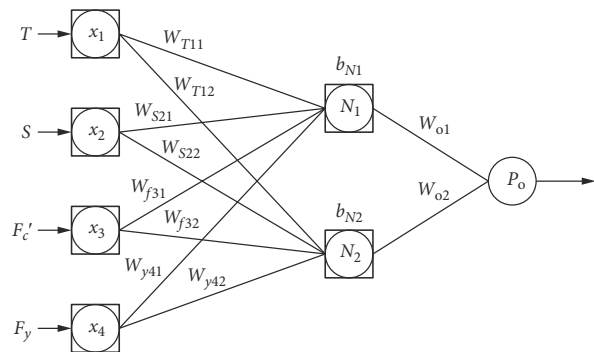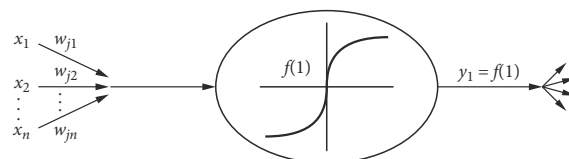Figure 7. The optimal ANN architecture

Figure 6. A typical structure of an artificial neural network

It is shown in Table 5 that the ANN model can accurately predict the experimental strength of columns as verified by the statistical indices. The R^2, MAE, and RMSE, values for the training dataset and validation dataset are 97.94, 2.68, 3.77 and 97.55, 2.44, 2.89 respectively. The RMSE and MAE for the model are very low which means that the errors in predicting column compressive strength using ANN are very low. The ANN model either under-predicts the experimental strength values by 13.4% or over predicts them by 26.3%.

The ANN shows an excellent capability of prediction compressive strength of lightweight short column at high temperature. Figure 8 to Figure 10 show the comparison between the experimental data and predicted values for training, testing and validation and total data. The figures show a good correlation between and predicted data for the training, validation and all data set.

The following equation is proposed to predict the compressive strength of lightweight short columns under elevated temperature using ANN. It should be noted that the dimensional effects are included in the ANN model. The model predicts the compressive strength in MPa. Thus, the compressive strength P in Eqn (7) is the force / gross column area.

$$P = \frac{1.19 + 0.19 e^{-y_O}}{0.01578 \left(1 + e^{-y_o}\right)}. \tag{7}$$

The procedures for calculating the parameter y_o can be summarized in the following steps.
 – Firstly, normalize the input parameters (T, S, F_c, F_y) using the amplitude and offset shown in Table 6. Each input parameter is multiplied by the amplitude and shifted by an offset as ($X_{No} = a_{in}X_n + Of_{in}$).
 – The second step is to calculate the input and output at each hidden layer (N_1 and N_2) using weight and bias as shown in Table 7.

Input at each node in the hidden layer

$$X_n = \sum w_{in} {}^* x_{no} + b_N; \tag{8}$$

Output at each node in the hidden layer $X_o = \dfrac{1}{1 + e^{-X_n}}$. $\qquad$ (9)

 – Calculate the normal value of the output in the output layer

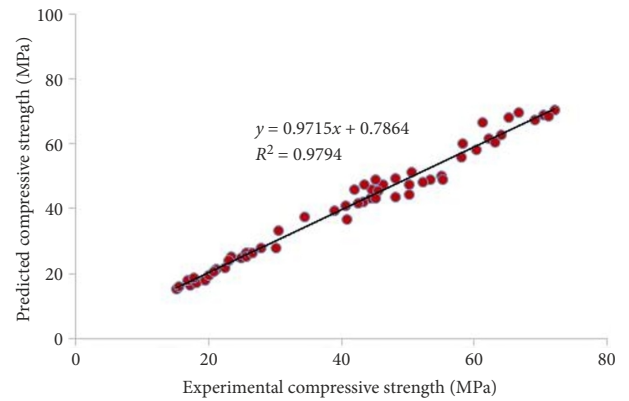$$y_o = \sum w_o {}^* X_o + b_o. \tag{10}$$

Figure 8. Comparison between the predicted and experimental values of training data using ANN model
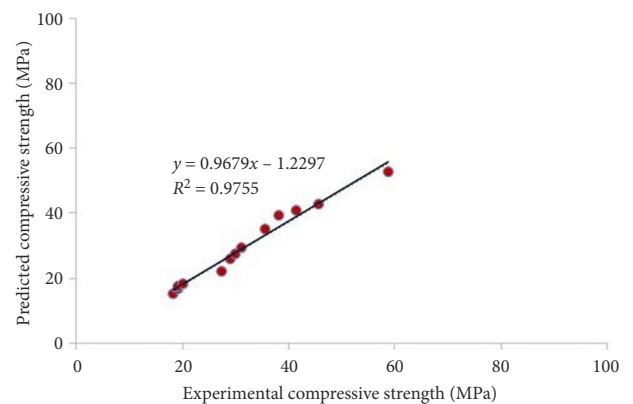

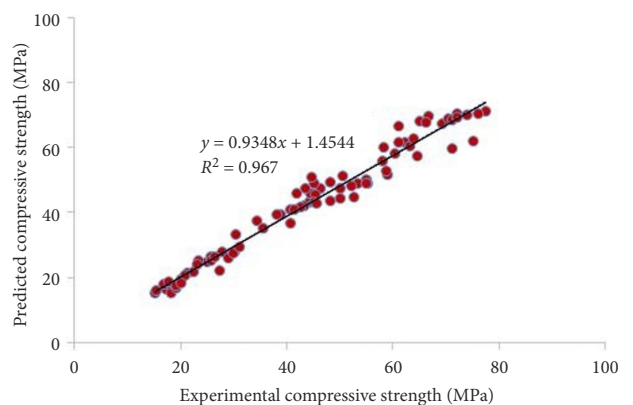Figure 9. Comparison between the predicted and experimental values of validation data using ANN model

Figure 10. Comparison between the predicted and experimental values of all datasets using ANN model

Table 6. Input layer amplitude and offset

Node	Amplitude (a_{in})	Offset (Of_{in})
T	0.00133	0.01942
S	0.018	−0.13
F_c	0.01785	−0.21
F_y	0.0017	−0.0543

Table 7. Weight and bias

w_{T11}	3.833	W_{fc31}	9.966	b_{N1}	−9.428
W_{T12}	0.7592	W_{fc32}	−6.474	b_{N2}	0.2021
W_{S21}	−1.375	W_{fy41}	0.2912		
W_{S22}	0.6681	W_{fy42}	−0.4417		

5. ACI formulation

The compressive strength of short columns under pure axial load is predicted in this research using ACI-318-14 (ACI Committee 318, 2014) formulation and then compared to the values obtained from GEP and ANN models. ACI formulation is shown in Eqn (11). The ACI model either under-predicts the experimental strength values by 36.2% or over predicts them by 131%.

$$P_n = 0.85 f_c' \left(A_g - A_{st} \right) + f_y A_{st}, \tag{11}$$

where: A_g – gross column area; A_{st} – area of longitudinal steel; P_n – nominal compressive load (kN).

6. The sensitivity of the models

The sensitivity of the input parameters to the ACI, GEP and ANN models is investigated in this section in order to further validate the proposed models. It is shown in Figure 11 that the GEP and ANN models are in agreement with the trends of the ACI model. The compressive strength of columns predicted using the ACI, GEP and ANN models decreases by increasing the temperature and spacing. The compressive strength of the columns predicted using the ACI, GEP and ANN models increases by increasing concrete compressive strength and reinforcement yield strength. The results are in agreement with the available experimental results and existing code formulations. These observations confirm the consistency of the GEP and ANN models.

7. Comparison between the predicted strengths of short light-weight columns obtained using GEP, ANN and ACI equations

A comparison is made in Figure 12 between the experimental compressive strength results and the compressive strengths of short light weight columns predicted using
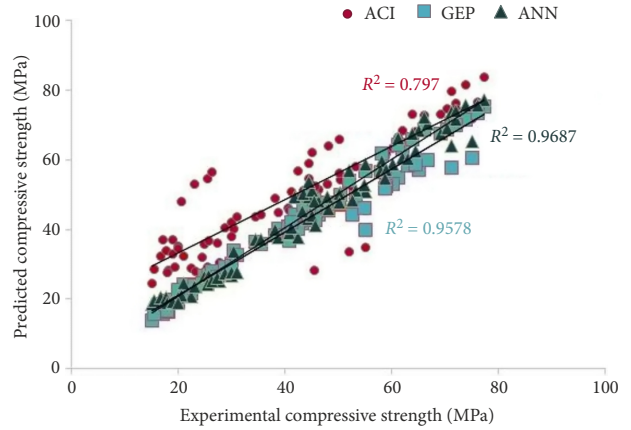

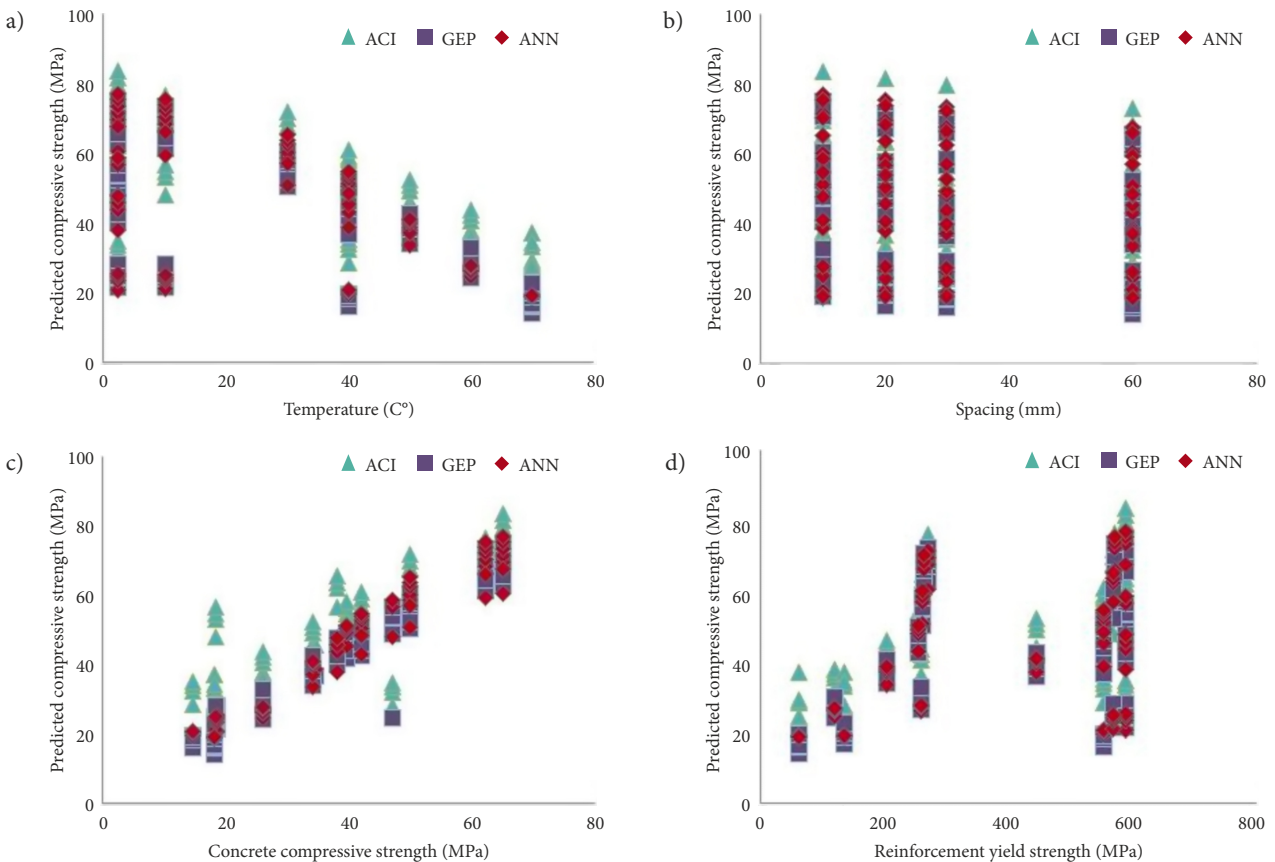Figure 12. Comparison between the ACI, GEP and ANN models

Figure 11. Sensitivity of the models to the input parameters

Table 8. Comparison between the proposed models
and ACI equation

Method	MAE	RMSE	R^2	% Error
ACI	9.1	11.27	79.7	131
GEP	3.01	3.63	95.78	19.4
ANN	2.65	3.65	96.7	26.3

GEP, ANN model and ACI equation. Furthermore, Table 8 illustrates the statistics performance of the GEP, ANN models and ACI equation for the total dataset. Both GEP and ANN models can reasonably predict the compressive strength of short columns and the results obtained using the GEP and ANN models are closer to the experimental results than that obtained using the ACI equations. They have a very high R^2 and low MAE and RMSE compared to the ACI equation. The maximum error in estimating compressive strength of light weight short column was 26.3% for the ANN model, 19.4% for the GEP model compared to 131% for the ACI equation.

Conclusions

Most of the experimental programs available in the literature investigate the behavior of RC columns under normal temperature. Few studies have been conducted to investigate the behavior of RC columns under elevated temperature. Although there are some experimental programs that investigate the behavior of lightweight short columns, there is still lack of formulation that can accurately predict their ultimate load at elevated temperature. Gene expression programming (GEP) and artificial neural network (ANN) are used in this research to predict the compressive strength of lightweight short column at elevated temperature. A total of eighty-three data points are used in developing the GEP and ANN models where 70% of the data are used for training and 30% of the data are used for validation and testing. The input variable parameters are temperature, spacing between stirrups, compressive strength and yield stress of steel. The results predicted using GEP and ANN model are then compared to the results obtained using the ACI equation. The following points summarize the research outcomes:

– Equations are provided to predict the compressive strength of short lightweight column at elevated temperature using ANN and GEP.
– Both GEP and ANN models can reasonably predict the compressive strength of lightweight short columns and the results obtained using the GEP and ANN models are closer to the experimental results than that obtained using the ACI equations.
– The statistical values (R^2, MAE, RMSE) for all data in the GEP, ANN and ACI models are (95.78, 3.01, 3.63), (96.7, 2.65, 3.65), (79.7, 9.1, 11.27) respectively. The proposed GEP and ANN models have high R^2 value and low MAE and RMSE (error). This confirms that the proposed models can predict the compressive strength of columns with reasonable accuracy.

– The ANN, GEP and ACI model either under estimate or overestimate the compressive strength in a margin of (–13.4% to 26.3%), (–14.9% to 19.4%) and (–36.22% to 131%) respectively.
– The model validation results show the high capability of the ANN and GEP models to predict the compressive strength beyond the training domain.
– The proposed GEP and ANN models are expected to be very useful for evaluating the compressive strength of short light weight columns for design and analysis.

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