Using mathematical models and artificial neural networks for predicting the compressive strength of concrete with steel fibers exposed to high temperatures

Hassiba Belaribi✉**, Mekki Mellas**

Laboratoire de recherché en Génie Civil, Université de Biskra, B.P. 145 R.P. 07000, Biskra, Algeria

Received 16 March 2017
Published online: 26 May 2018

Keywords
Concrete
Compressive strength
Porosity
Mathematical method
Artificial neural networks
Ultrasonic pulse velocity

Abstract: In this study mathematical methods and artificial neural network (ANN) model are used to predict the compressive strength of concrete with steel fibers exposed at high temperatures. The data used in the models construction were obtained from laboratory experiments. The compressive strength was experimentally determined for specimens containing three volume fractions of steel fibers 0.19%,0.25%, 0.5% were used and two different water/cement ratios (w/c of 0.35 and 0.45). Specimens were subjected to various heating-cooling cycles from the room temperature to 200, 400, and 600°C. The inputs models of ANN were temperature, w/c, percentage of porosity, ultrasonic pulse velocity; percentage of steel fibers and percentage superplasticizer, the output was the compressive strength of concrete. Four mathematical models were development to predict the compressive strength. Three mathematical models including a number of functions to express the strength-porosity relationship, and other model used to establish the relationships between strength and ultrasonic pulse velocity. Mathematical methods, artificial neural network and their results were evaluated and compared. The results show that ANN has good potential to be used as a tool for predicting the compressive strength of concrete with steel fibers exposed to high temperatures.

1. Introduction

The compressive strength as the most fundamental mechanical property of concrete and performance indicator for structural design is generally examined, because it usually indicates the overall quality of the concrete (AbdElaty 2014). Early age strength prediction in concrete is very useful in reducing construction cost and ensuring safety (Khademi et al. 2017).

The compressive strength in concrete is affected by many factors like water/cement, aggregates types and their properties (Drissi et al. 2015). This paper introduces a simple mathematical model that can help to predict the compressive strength by two different models. The first prediction of the mathematical models has been compared with those of the artificial neural network (ANN) which is the second model.

The first method of the mathematical models is based on the effect of porosity on the concrete strength which presented some of the more important empirical and theoretical equation for relating compressive strength to porosity. The porous character of the concrete is very important since the strength of the latter is related to its porosity (Mehta 1986) and considered a relevant sustainability indicator for a wide range of degradations, and a number of functions, including the following, have been proposed (Röbler and Odler 1985; Fagerlund 1973):

$f_c = f_{(c,0)}(1-p)^n$ (Balshin) (1)

$f_c = k_s \ln(\frac{P_0}{P})$ (Schiller) (2)

$f_c = f_{c,0} - k_H.P$ (Hasselmann) (3)

$f_c = f_{c,0} e^{-K_r P}$ (Ryshkevitch) (4)

Where fc is the compressive strength, $f_{c,0}$ is the compressive strength at zero porosity, P_o is the porosity at zero strength, (n, k_r, k_s, k_H) are the empirical constants.

The second method is usually based on empirical relations between compressive strength and non-destructive testing (NDT). Ultrasonic pulse velocity was one of non-destructive method to evaluate compressive strength of concrete. The relationship between the ultrasonic pulse velocity (v) and concrete compressive strength (fc) is an exponential function [Tharmaratnam, and Tan 1990; Bungey, and Millard 2004).

$f_c = a\, e^{bV}$ (5)

Where (a, b) are parameters which depend on the properties of the material.

In recent years, there have been new methods to evaluating compressive strength, tensile strength, permeability or other properties of concrete as artificial intelligence based techniques like ANN [Khademi et al. 2015; Nikoo et al. 2015; Sobhani et al.2010).Currently the literature publications interest concerning the application of ANN for predicted compressive strength for different types of concrete composites using artificial neural networks have been compared with the results obtained from several other prediction techniques, like non-linear regression,

✉Corresponding author. E-mail address: belaribi.hass@gmail.com

Nomenclature

fc	Compressive strength
$f_{(c,0)}$	Compressive strength at zero porosity
Po	Porosity at zero strength
v	Ultrasonic pulse velocity
R^2	Coefficient of determination
M	Mass

Greek symbols

φ	Density

Abbreviation

UPV	Ultrasonic pulse velocity
ANNs	Artificial neural networks
MLP	Multilayer perceptron

adaptive network-based fuzzy inference system (ANFIS) model, model tree, statistical analysis, fuzzy logic, genetic based algorithms and factorial design (Duan et al. 2013; Lee 2003; Bingöl et al. 2013; Dias and Pooliyadda 2001; Sbartaı et al. 2009). However, a limited number of works have been published regarding ANN developments in the field of the non-destructive testing of reinforced concrete structures (Atıcı 2011). According to Ref (Hola and Schabowicz 2005a; Hola, and Schabowicz 2005b), they have presented a neural model for the evaluation of concrete compressive strength based on the coupling of different non-destructive techniques. The ref of (Trtnik et al. 2009; Bilgehan and Turgut, 2010) been used ANNs for the estimation of concrete compressive strength based on ultrasonic pulse velocity.

The objective of this paper was compared ANN performance with that of formulae using both linear and exponential models. This comparison was made to establish whether the ANN approach represents a genuine improvement over equations used for predicting the compressive strength. The predicted results were compared with the experimentally determined results. The correlation coefficient was used to judge the models performance in predicting the compressive strength with different data used in present study.

1.1 Artificial neural network

The study of artificial neural networks (ANNs) was an information processing techniques that is inspired by the way biological nervous systems, such as the brain, process information (Pagariya and Bartere 2013; Adhikary and Mutsuyoshi 2006). The multilayer perceptron (MLP) is the most popular network architecture used for approximation, classification and prediction problems. The multilayer perceptron is made up of five main components: inputs, weights, sum function, activation function and outputs. The neural network based modelling process involves five main aspects: (1) data acquisition, analysis and problem representation; (2) architecture determination; (3) learning process determination; (4) training of the networks; and (5) testing of the trained network for generalization evaluation. The most techniques for training were Broyden-Fletcher-Goldfarb-Shanno (BFGS) or quasi-newton is a second order training multilayer perceptron (MLP) (Bishop 1995). They are denoted in Figure 1 illustrates how information is processed through a single neuron. According to (Haykin 1998), in an artificial neural network, the neuron is the unit of information processing, which consists of:

○ Xm refers to input i to the neuron.

○ w_k refers to the weight affected to input i.

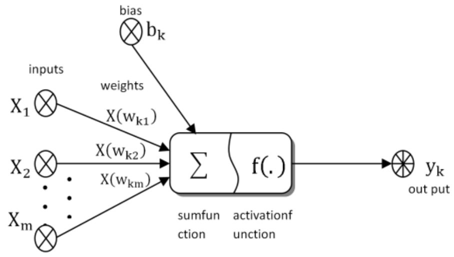

Fig.1. Schematic Artificial Neuron as described by (Haykin 1998).

○ b_k refers to the bias of the neuron.

○ Y_k refers to neuron output.

○ f refers to the activation (or transfer) function that process input information. Usually nonlinear activation functions such as hyperbolic tangent function, step are used.

In this study, the ANN toolbox of the program Statistica13 was used to perform the necessary computations; the problem was proposed to network models by means of five inputs and one output parameter. The parameters such as were w/c ratio, temperature, percentage of porosity, ultrasonic pulse velocity, percentage of steel fibers and super plasticizer, were selected as input variables. The model output variable was the compressive strength of concrete. Nonlinear prediction was studied the neural network whose structure was the simple: multi-layer perceptron (MLP), single hidden layer neural network and quasi-Newton back propagation algorithm were used. The prediction performances were then compared with coefficient of determination (R^2) (Bingol et al. 2013], they are defined as follows:

$$r = \frac{n(\sum actuelpredicted) - (\sum actuel)(\sum predicted)}{\sqrt{[(n\sum actuel^2 - (\sum actuel)^2][(n\sum predicted)^2 - (\sum predicted)^2]}} \quad (6)$$

$R^2 = r^2$ is used to measure the closeness of fit. A perfect fit $R^2 \approx 1$, a very good, fit near 1, and a poor fit would be near 0, this coefficient was used to evaluate the performance of ANN and mathematical models.

2. Experimental details

2.1 Materials

Cement: the cement used was a Portland cement (CPJ CEM II/A 42.5). Chemical composition, mechanical and physical properties of the used cement are given in Table 1.

Aggregates: Three types of aggregates were used in this study. The sand of the river with a diameter below 5.0 mm and two crushed limestone aggregates to sizes (3/8mm) and (8/15mm) were used. The sand density was 2.57kg/dm^3. The gravel density was 2.57kg/dm^3 (3/8mm) and 2.73 kg/dm^3 (8/15mm) respectively.

Table 1. Chemical, physical and mechanical properties of cement (GICA 2013).

Chemical composition(%)	
CaO	56.30
Al_2O_3	4.52
SiO_2	23.88
Fe_2O_3	3.34
MgO	1.08
Na_2O	0.33
K_2O	0.90
CL^-	0.02
SO_3	2.66

Physical and mechanical properties	
Specific gravity (g/cm^3)	3.09
Initial setting (h: mn)	2 h: 06
Final setting (h: mn)	2 h: 56

Compressive strength (MPa)	
2 days	20.98
7 days	32.38
28 days	44.15

Superplasticizer (Sup): SikaViscocrete Tempo 12 superplasticizer was used. It is a high water reducer containing modified polycarboxylate. The superplasticizer density was 1.06kg/dm^3 and the dry extract was 30.2%.

Steel fibers: the used fibers were SIKA FIBRE RL-45/50-BN which are made from steel wire. They comprise a mechanical anchorage consisting hooked ends. They were cylindrical of 50 mm length with a diameter of 1.05 mm. Their tensile strength was 1000 MPa. The choice of steel fiber was according to (CSA A23.1 2004) specifies the quantities for insertion are between 15 to 45 kg/m^3.

2.2. Test methods

Two groups of concrete were made with different w/c ratios (0.35 and 0.45). Three volume fractions of steel fibers were used: 0.19, 0.25 and 0.5% (equivalent to 15, 19.5 and 39 kg/m^3). The type of concrete obtained with the slump test values between 8 and 15 cm ± 1. The percentage of superplasticizer was adjusted in order to keep the workability constant. Concrete formulation was determined according to [Dreux and Festa 1998). The mixture proportions of the different concretes are presented in Table 2. For each concrete mixture, 12 cubes of (100 × 100 × 100 mm) were prepared. The specimens were kept covered in a controlled chamber at (20 ± 2) °C for 24 h until demolding. Thereafter, specimens were placed in water at 20°C until the 28 days. Later, they were kept in air until 56 days in laboratory where the temperature was about 20°C. This choice is to minimize the risk of spalling concrete specimens when subjected to temperature in the furnace, and also to have less interstitial water in the concrete. At the 56 days, the specimens were placed in an electric furnace in which temperature is increased to the desired temperatures at a rate of 10°C/min, the target temperatures were maintained for 1 h to ensure uniform heating throughout the concrete samples and to minimize the thermal gradient between the surface and center of the concrete samples. After this the heating procedure, the specimens were allowed to cool down naturally to room temperature inside the electrical furnace in order to prevent thermal shock. Determination of compressive strength was after one day from heating.

Heating-cooling cycles: Three heating-cooling cycles were carried out in an electric furnace from the room temperature up to 200, 400 or 600°C. The cycles included a phase of rise in temperature, a phase of temperature dwell and a phase of cooling.

Ultrasonic tester: The test equipment (Ultrasound tool Tico) provide a means of generating a pulse, transmitting this to the concrete, receiving and amplifying the pulse and the time taken was measuring. The tests were performed in accordance with the (AFNOR P 18-418, 1989). The UPV is a long-established non-destructive test method that determines the velocity of longitudinal waves through the concrete. The ultrasonic pulse velocity is a popular non-destructive technique to assess the concrete properties. Ultrasonic measurements are also used to determine the changes in the properties of the concrete and to indicate the presence of voids or cracks.

Water porosity (P): We measured the total porosity and not the pore size distribution. Samples resulted from the specimens after the mechanical tests. The samples were oven dried at a temperature of 80°C to constant weight. When the samples were dried, they were immersed in water until complete saturation. After keeping the samples during in water, a weighing in immersed saturated state was carried out on a hydrostatic balance then it was followed by a weighing in saturated state after the specimen was wiped with linen to remove the water in excess at the surface. The test method is slightly different from the AFREM procedures [AFPC-AFREM 1997). The tested samples were those brought up to temperature of 80, 200, 400 and 600°C.The porosity is determined according to below equation:

$$p = \frac{m_{sat} - m_{heated}}{m_{sat} - m_{sat}^{im}} \varphi_e \quad (7)$$

Where: m_{sat} and m_{sat}^{im} the saturated mass of a sample measured in the air and in the water.

M_{heated} is the heated mass (after heating) weighed in the air.

φ_e is the density of water (1000 kg/m^3).

Compressive strength: The compression test was carried out on four cubic specimens (100×100×100 mm) specimens using a hydraulic press in accordance with (AFNOR NF EN 12390-3 2003). The loading rate was 0.5 MPa/s until the failure. The compressive strength of the samples was oven dried at a temperature of 80°C were measured. The data used in the present study are given in Table3.

Table 2. Mix proportions (kg/m^3).

Quantity of steel fibers	0		15		19.5		39	
Volume fractions of fibers (%)	0		0.19		0.25		0.5	
w/c	0.35	0.45	0.35	0.45	0.35	0.45	0.35	0.45
Water	158	180	158	180	158	180	158	180
Cement	450	400	450	400	450	400	450	400
Aggregate 8/15 (mm)	1016.79	1016.79	1016.79	1016.79	1016.79	1016.79	1016.79	1016.79
Aggregate3/8 (mm)	182.91	182.91	182.91	182.91	182.91	182.91	182.91	182.91
Sand 0/5 (mm)	585.44	598.81	598.81	598.81	598.81	598.81	598.81	598.81
Superplasticizer(%)	1.5	1.0	1.7	1.2	1.9	1.4	2.0	1.6

Table3. Data used in this study.

w/c = 0.35

Mixture Steel fibers (%)	T(C°)	Superplasticizer (%)	Porosity (%)	UPV (m/s)	fc Experimental (MPa)
0.00	80	1.50	10.40	4876.33	73.44
	200	1.50	10.80	4663.33	58.34
	400	1.50	13.90	3330.00	41.61
	600	1.50	20.11	2316.67	32.59
0.19	80	1.70	09.80	4987.33	77.33
	200	1.70	11.32	4743.33	59.00
	400	1.70	12.70	3726.67	51.13
	600	1.70	14.70	2233.33	43.30
0.25	80	1.90	09.94	5000.67	78.67
	200	1.90	11.50	4800.00	67.38
	400	1.90	13.41	3980.33	55.70
	600	1.90	17.33	2766.67	44.46
0.50	80	2.00	10.66	5054.67	82.66
	200	2.00	11.52	4833.67	69.74
	400	2.00	13.98	3763.33	61.57
	600	2.00	19.77	3210.00	50.54

w/c=0.45

Mixture Steel fibers (%)	T(C°)	Superplasticizer (%)	Porosity (%)	UPV (m/s)	fc Experimental (MPa)
0.00	80	1.0	13.75	4420.33	50.02
	200	1.0	16.24	4150.00	38.6
	400	1.0	18.85	3330.00	30.71
	600	1.0	22.31	2050.00	24.05
0.19	80	1.2	13.22	4650.00	54.44
	200	1.2	14.40	4450.00	45.86
	400	1.2	15.67	3456.67	36.75
	600	1.2	19.45	2380.00	27.46
0.25	80	1.4	13.66	4720.33	52.55
	200	1.4	14.31	4733.33	46.03
	400	1.4	15.66	3693.33	42.28
	600	1.4	19.82	2566.67	39.64
0.50	80	1.6	14.20	4753.00	54.33
	200	1.6	14.35	4526.67	52.79
	400	1.6	15.66	3574.33	46.59
	600	1.6	20.15	2606.67	39.91

3. Results and discussion

3.1 Relationship between compressive strength and porosity

Equations for the strength-porosity relationship of concrete developed by equations Schiller, Ryshkevich and Hasselmann described before are given in Eqs. (8) to (10) with a correlation coefficient ranges between 0,803 and 0,760:

$$f_c = 71{,}42\ \ln\left(\frac{29.56}{P}\right) \quad \text{with} \quad R^2 = 0.803 \quad \text{(Schiler)} \quad (8)$$

$$f_c = 154{,}2441\ (e^{-0.0771P}) \quad \text{with} \quad R^2 = 0.782 \quad \text{(Ryshkevich)} \quad (9)$$

$$f_c = 106.9788 - 3.7564\ P \quad \text{with} \ R^2 = 0.760 \quad \text{(Hasselmann)} \quad (10)$$

Where fc is the compressive strength (MPa), P is the porosity (%)

The empirical relationship suggested in Eqs.(8) to (10) are plotted in figure 2. It can be seen that the predicted results from Eq.(8) and Eq.(10) showed a relative good relationship between porosity and compressive strength of concrete with steel fibers exposed at high temperatures.

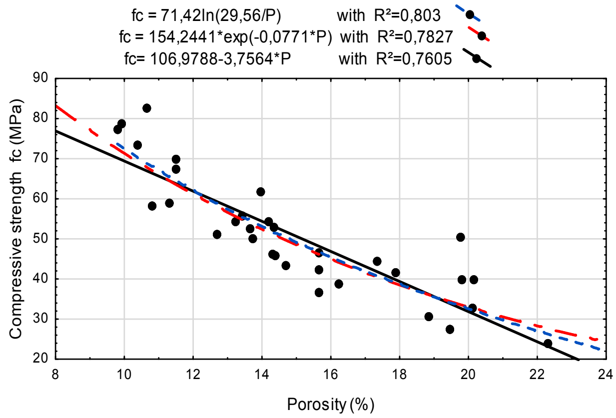

Fig.2. Relationship between compressive strength and porosity for concrete with steel fibers exposed at high temperature defined by equations Schiller, Ryshkevich and Hasselmann.

The performances of each three models mathematical developed using the above mentioned techniques were compared. It can be seen that the correlation coefficient R^2 are 0.803, 0.782 and 0.760 respectively.

The models developed by using equation of Schiller show a better performance than models developed using equations of Hasselmann and Ryshkevich as shown by comparatively high values of R^2.

3.2. Relationship between the compressive strength and UPV

The UPV values as presented in Table 3, the values of ultrasonic pulse velocity decreased for all mixture types after exposure to elevated temperatures. The relationship between the compressive strength and the UPV was developed by exponential are shown in figure 3.

The relationship between compressive strength and UPV of concrete with steel fibers exposed at high temperature is described by Eq. (11) was supported by a correlation coefficient between velocity and compressive strength:

$$fc = 18.2457\ e^{0.0003V} \quad \text{With} \quad R^2 = 0.6549 \quad (11)$$

Where fc is the compressive strength (MPa), V is the ultrasonic pulse velocity (m/s).

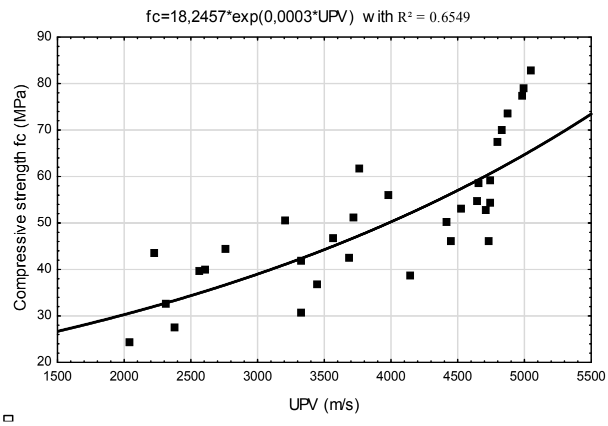

Fig. 3. Relationship between the compressive strength and ultrasonic pulse UPV of concrete with steel fibers exposed at high temperature.

3.3. Artificial neural network model for prediction of experimental results

In this study, the problem is proposed to network models by means of six inputs and one output parameter. The parameters such as were temperature, w/c, percentage of porosity, ultrasonic pulse velocity, percentage of steel fibers and percentage superplasticizer were selected as input variables. The model output variable was the compressive strength of concrete. A data obtained from experimental studies were used for artificial neural networks. The number of neurons in the hidden layer was determined by training several networks with different numbers of hidden neurons and comparing the predicted results with the desired output. The trained model was only tested with the input values and the results found were close to experiment results. To test the accuracy of the trained network, the coefficient of determination R^2 is adopted and choice. The values of network parameters considered in this approach are: Six units in the input layer, one unit in the output layer, number of hidden layers: 1, learning rate = 0.01, learning cycle = 10000, network types MLP, the min hidden unit: 20, the max hidden: 50, network to train: 1000, network retain: 1.From the available data 70% of data were used for training, 15% for validation and 15% for testing. The basic algorithm of quasi-Newton back propagation algorithm is used. The hidden layer used is hyperbolic tangent function (tanh) is a symmetric S-shaped (sigmoid) function. Identity function used is the activation level is passed on directly as the output of the neurons function was used in the output layer.

Many calculations with different geometries of ANNs were carried out. On the basis of the results, the final solution was calculated with the geometry MLP 6-46-1. There were one hidden layers, each of them including 46 neurons. The efficiency of the learning procedure was very good. The coefficient of correlation from training, testing and validation was presented in table 4. The Predicted and measured values are presented in Figure 4. While the statistical values R^2 from training, testing and validation in ANN model were found 0.9885, 0.9933, and 0.9999 respectively, is indicating a perfect fit.

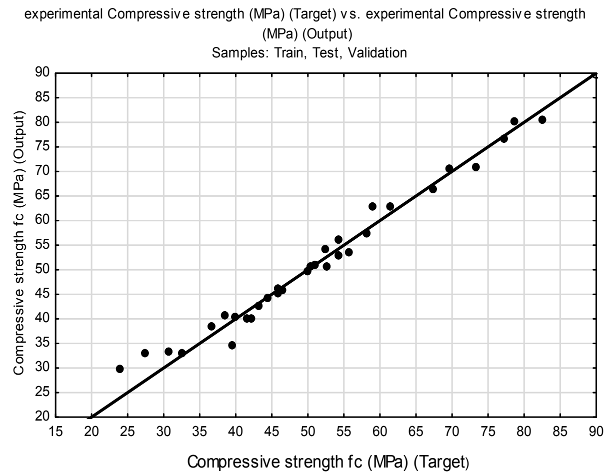

Fig. 4. Linear relationship between measured and predicted compressive strengths by MLP 6-46-1.

Table 4. Coefficients of determination from training, testing and validation.

Statistical parameters	Training	Testing	Validation
R^2	0.9885	0.9933	0.9999

Sensitivity analysis technique was used to evaluate the effect of input layer on the output layer. The technique is used to determine the output parameter in the certain network has higher sensitivity relative to which input parameter, sensitivity analysis was done to determine more effective feature on the output of system model. The results presented in Table 5 indicate that all of the parameters considered in the analysis were important in achieving the desired accuracy and reliability in the estimation of the residual compressive strength of concrete. Nonetheless, sensitivity analysis is extremely useful in helping you to understand how important variables are. However, the temperature was importance of variables in the context of a particular neural model.

3.4. Comparison results obtained using different models

It has been clearly observed that compressive strength values of concretes exposed to elevated temperatures can be predicted by using developed models in the ANN and equations developed by Schiller Eq. (8), Hasselmann Eq. (9), Ryshkevich Eq. (10), the relationship between UPV and the compressive strength Eq. (11). Experimental results together with testing results obtained from ANN and the others models are given in Table 6.

Figure 5 shows the Predicted concrete strengths with steel fibers exposed to high temperature for all models developed in this study with R^2 coefficients. All of the statistical values demonstrate that the proposed ANN model is suitable and it predicts the compressive strength values very closely to the experimental value.

Table 5. Sensitivity analysis of compressive strength of concrete for input parameters in MLP model (MLP 6-46-1)

Sensitivity analysis (Spreadsheet ANN) Samples: Train, Test, Validation					
T(C°)	UPV (m/s)	w/c	Superplasticizer (%)	Porosity (%)	fibers (%)
36.261	8.427	7.640	4.059	3.084	2.988

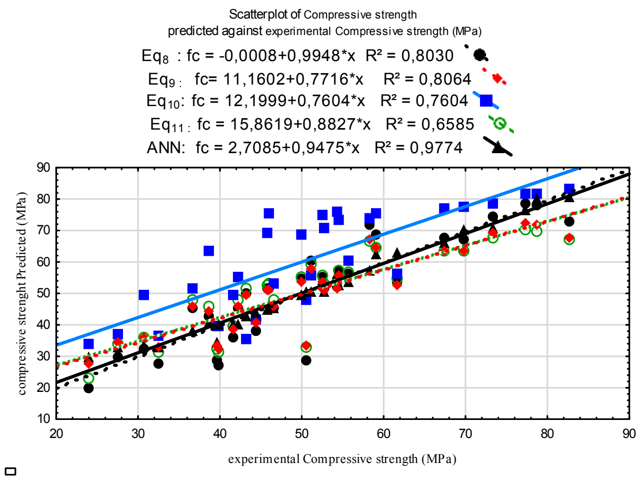

Fig.5. Correlation of compressive strength predicted values and experimental of concrete with steel fibers exposed to high temperatures obtained from different models of this study.

Table 6. Comparison of experimental results with testing results obtained from different models used in this study.

fc	Predicted outputs for compressive strength fc (MPa)				
(Experimental)	fc(Eq_8)	fc(Eq_9)	fc(Eq_{10})	fc(Eq_{11})	fc(Eq_{ANN})
73.44	74.61	69,18	67.91	78.79	70.80
58.34	71.91	67.08	66.41	73.92	57.24
41.61	35.83	38.80	39.74	49.55	39.96
32.59	27.51	32.72	31.44	36.56	32.89
77.33	78.85	72.45	70,17	81.46	76.55
59.00	68.55	64.44	64.46	75.71	62.73
51.13	60.34	57.94	59.27	55.81	50.81
43.30	49.89	49.66	51.76	35.66	42.55
78.67	77.84	71.68	69.64	81.79	80.13
67.38	67.43	63.55	63.78	77.01	66.33
55.70	56.45	54.85	56.60	60.22	53.52
44.46	38.14	40.54	41.88	41.84	43.96
82.66	72.84	67.81	66.93	83.12	80.47
69.74	67.30	63.46	63.70	77.79	70.53
61.57	53.48	52.49	54.46	56.43	62.86
50.54	28.73	33.59	32.71	47.80	50.48
50.02	54.66	53.43	55.33	68.72	49.60
38.6	42.78	44.10	45.97	63.37	40.54
30.71	32.13	36.06	36.17	49.55	33.29
24.05	20.10	27.62	23.17	33.75	29.62
54.44	57.47	55.66	57.32	73.62	52.66
45.86	51.36	50.82	52.89	69.33	44.95
36.75	45.33	46.08	48.12	51.47	38.23
27.46	29.89	34.43	33.92	37.26	32.85
52.55	55.13	53.80	55.67	75.19	54.05
46.03	51.81	51.17	53.22	75.48	46.04
42.28	45.37	46.12	48.15	55.25	39.99
39.64	28.55	33.46	32.53	39.41	34.54
54.33	52.36	51.61	53.64	75.93	56.05
52.79	51.61	51.02	53.07	70.95	50.53
46.59	45.37	46.12	48.15	53.32	45.55
39.91	27.37	32.62	31.29	39.88	40.23

The accuracy of the prediction for each approach has been evaluated by the coefficient of determination.

As shown in table 6, performances of each model developed using the above mentioned techniques were compared, In each of the models developed, ANN shows a better performance than models developed than those produced by all the mathematical functions. A comparison between models depicts that artificial neural networks can be used to predict the compressive strength of concrete with steel fibers exposed to high temperatures effectively. Figure 5 shows the correlation of models developed using both Artificial neural network, equations Schiller, Ryshkevich and Hasselmann, also relationship between UPV and the compressive strength, they coefficient R^2 was given equal to 0.9774, 0.8030, 0.8064, 0.7604 and 0.6394 respectively. It should be note that Figure 5 is related to the prediction results of models used in this study and testing data (experimental). The old method for mathematical relationship using compressive tests and ultrasonic pulse on this study through regression analysis was not effective compared with other models used.

4. Conclusion

The objective of this study was to apply data-driven models, artificial neural network and models by the equations Schiller, Hasselmann and Ryshkevich, also Relationship between UPV and the compressive strength for prediction of compressive strength of concrete with steel fibers exposed to high temperatures and compare their results with each other. As a result, compressive strength fc values of the concrete with steel fibers exposed to elevated temperatures can be predicted in ANN and other models mathematical used in this study. The modeling is carried out for the data from experimental test in laboratory. The correlation coefficient for ANN is much greater than the models mathematical. Results demonstrated that artificial neural network has better predictions of the experimental compressive strength values than those of Mathematical models used in this study. In other words, results from establishing an artificial neural network illustrate a good degree of coherency between the target and output values as confirmed by correlation coefficient R^2. The values of coefficient R^2 was given equal to 0.9774, 0.8030, 0.8064, 0.7604 and 0.6394 for ANN, equations Schiller, Ryshkevich, Hasselmann, and relationship between UPV and the compressive strength respectively. Therefore, using ANN model, the compressive strength of concrete with steel fibers exposed to high temperatures can be predicted both accurately and easily.

References

AbdElaty, M.A.A. (2014) Compressive strength prediction of Portland cement concrete with age using a new model, Housing and Building National Research Center HBRC Journal 10(2): 145-155.

Adhikary, B.B., H. Mutsuyoshi (2006) Prediction of shear strength of steel fiber RC beams using neural networks, Construction Building Materials 20(9):801-811.

AFNOR, NF EN 12390-3 (2003) Essai pour béton durci - Partie 3: Résistance à la compression des éprouvettes, Indice de classement: P 18-455; Février 2003.

AFNOR, P 18-418 (1989) Association française de normalisation-Auscultation sonique, mesure du temps de propagation d'ondes soniques dans le béton, Tour Europe cedex 792080, Paris la défense

AFPC-AFREM (1997) Sur la durabilité des bétons, Méthodes recommandées pour la mesure des grandeurs associées à la durabilité des bétons, INSA-LMDC, Toulouse.

Atıcı, U. (2011) Prediction of the strength of mineral admixture concrete using multivariable regression analysis and an artificial neural network, Expert Systems with Applications 38(8): 9609–9618.

Bilgehan, M., P. Turgut (2010) Artificial neural network approach to predict compressive strength of concrete through ultrasonic pulse velocity, Research in Nondestructive Evaluation 21(1) 1–17.

Bingöl, A.F., A. Tortum, R. Gül (2013) Neural networks analysis of compressive strength of lightweight concrete after high temperatures, Materials and Design 52: 258-264.

Bishop, C. (1995) Neural Networks for Pattern Recognition, Oxford: University Press.

Bungey, J.H., S.G. Millard (2004) Testing of concretes in structures, Taylor&Francis e-Library.

CSA A23.1/.2 (2004) Béton : constituants et exécution des travaux/Essais concernant le béton. Association canadienne de normalisation, Canada, 453 p.

Dias, W. P. S., S. P. Pooliyadda (2001) Neural networks for predicting properties of concrete with admixtures. Construction and Building Materials 15(7): 371-379.

Dreux, G., J. Festa (1998) Nouveau Guide du Béton et de ses Constituants, Editions Eyrolles, 8ème Edition, Paris.

Drissi, M., B. Mezghiche, L.K. Khouadjia (2015) Influence of concrete composition parameters on Its compressive strength, Courrier du Savoir 20: 73-78.

Duan, Z.H., S.C. Kou, C.S. Poon (2013) Prediction of compressive strength of recycled aggregate concrete using artificial neural networks, Construction and Building Materials 40: 1200–1206.

Fagerlund, G. (1973) Strength and porosity of concrete, Proc. Int. RILEM Symp. Pore Structure, Prague D51–D73 (Part 2).

GICA (2013) Caractéristiques physico-mécaniques et composition chimiques, Fiche technique, Société des ciments de AinTouta Groupe GICA.

Haykin, S. (1998) Networks-A Comprehensive Foundation, McMillan College Publishing, New York.

Hola, J., K. Schabowicz (2005a) Application of artificial neural networks to determine concrete compressive strength based on non-destructive tests, Journal of Civil Engineering and Management 11 (1): 23–32.

Hola, J., K. Schabowicz (2005b) New technique of nondestructive assessment of concrete strength using artificial intelligence, NDT&E International 38 (4): 251-259.

Khademi, F., M. Akbari, S.M. Jamal (2015) Prediction of compressive strength of concrete by data-driven models, i-Manager's Journal on Civil, 5(2): 16-23.

Khademi, F., M. Akbari, S.M. Jamal, M. Nikoo (2017) Multiple linear regression, artificial neural network, and fuzzy logic prediction of 28 days compressive strength of concrete, Frontiers of Structural and Civil Engineering 11(1): 90-99.

Lee, S.C (2003) Prediction of concrete strength using artificial neural networks. Engineering Structures; 25(7):849-857.

Mehta, P.K. (1986) Concrete structure, properties and materials, Prentice-Hall, Englewood Cliffs.

Nikoo, M., T.F. Moghadam, L. Sadowski (2015) Prediction of concrete compressive strength by evolutionary artificial neural networks, Advances in Materials Science and Engineering. ID 849126: 8pages.

Pagariya, R., M. Bartere (2013) Review Paper on Artificial Neural Networks, International Journal of Advanced Research in Computer Science, 4(6): 49-53.

Röbler, M., I. Odler (1985) Investigations on the relationship between porosity, structure and strength of hydrated Portland cement pastes: I. Effect of porosity, Cement and Concrete Research 15(2): 320-330.

SbartaI, Z.M., S. Laurens, K. Viriyametanont J.P. Balayssac, G. Arliguie (2009) Non-destructive evaluation of concrete physical condition using radar and artificial neural networks, Construction and Building Materials 23(2): 837–845.

Sobhani, J., M. Najimi, A. R. Pourkhorshidi, T. Parhizkar (2010) Prediction of the compressive strength of no-slump concrete: a comparative study of regression, neural network and ANFIS models, Construction & Building Materials 24(5): 709–718.

Tharmaratnam, K., B.S. Tan (1990) Attenuation of ultrasonic pulse in cement mortar, Cement and Concrete research 20 (3): 335-345.

Trtnik, G., F. Kavcic, G. Turk (2009) Prediction of concrete strength using ultrasonic pulse velocity and artificial neural networks, Ultrasonics 49 (1): 53-60.