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ORIGINAL ARTICLE

Prediction of the effect of varying cure conditions and *w/c* ratio on the compressive strength of concrete using artificial neural networks

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Abstract The present study aims at developing an artificial neural network (ANN) to predict the compressive strength of concrete. A data set containing a total of 72 concrete samples was used in the study. The following constituted the concrete mixture parameters: two distinct *w/c* ratios (0.63 and 0.70), three different types of cements and three different cure conditions. Measurement of compressive strengths was performed at 3, 7, 28 and 90 days. Two different ANN models were developed, one with 4 input and 1 output layers, 9 neurons and 1 hidden layer, and the other with 5, 6 neurons, 2 hidden layers. For the training of the developed models, 60 experimental data sets obtained prior to the process were used. The 12 experimental data not used in the training stage were utilized to test ANN models. The researchers have reached the conclusion that ANN provides a good alternative to the existing compressive strength prediction methods, where different cements, ages and cure conditions were used as input parameters.

Keywords Artificial neural network · Cement · Compressive strength · Cure conditions · Age

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1 Introduction

The high amounts of CO_2 emitted during the Clinker production process should be curbed, for it causes the greenhouse effect, and, hence global warming. What is more, the cement production process consumes too much energy and exhausts raw materials [1, 2]. The recent tendency among cement producers is toward blending or intergrinding mineral additions such as slag, natural pozzolana, sand and limestone [3–5]. Doing so, they prevent excessive amounts of energy from being wasted and CO_2 from being emitted. This also helps preservation of the environment and natural resources, recycling of by-products and efficiency of production.

Portland limestone cement (PLC) falls into two groups: CEM II/A (6–20%) and CEM II/B (21–35%), with respect to limestone replacement ratios. Through various studies, researchers vividly described the physical and mechanical features of these blended cements and obtained sufficient technical data about their performance [6–9].

Viewed chemically, limestone fillers do not contain pozzolanic properties. However, they go into reaction with alumina phases of cement and bring about the AFm phase (calcium monocarboaluminate hydrate), which causes drastic variations in the strength of blended cement [10]. Using limestone in cementitious composites affects the capillary porosity resulting from such physical effects as dilution effect, filler effect and heterogeneous nucleation [11, 12].

One advantage of using ground granulated blast furnace to replace cement is the heightened compressive strength which is partially owing to the fineness of this material and chemical hydration [12, 13].

Replacing slag by weight, to a partial extent, tends to decrease the initial strength. It will subsequently, however, be increased, resulting in significantly improved microstructure and durability of hardened Portland cement and concrete [14].

Curing gains even greater importance provided that it is added supplementary cementing materials and exposed to hot and dry conditions right after the placement and consolidation stages [15].

Artificial neural networks (ANNs) are structures that are inspired by neurobiological studies of the human brain. Artificial neural networks are parallel processing computational structures which are linked to each other by means of weighted connections and which are composed of computation elements with their own memories. To put it another way, ANNs are computer programs that fake the biological neural networks [16]. The recent developments in the field of ANNs technology, a sub-field of artificial intelligence, have been serving to solve various problems encountered in civil engineering processes. What makes this possible in dealing with civil engineering problems is ANN's capability of drawing directly from examples. Their nearly perfect responses to incomplete tasks, their deriving information from data in less than ideal situations (e.g., noise) and their generalizing from the novel cases are also among other important characteristics of ANN [17].

An ANN, which is developed so that problems about which no complete and precise information exists can be better dealt with [18], does not require a truly specific equation form, but rather it calls for sufficient input–output data. In addition, it keeps adapting and readapting to new data.

The growing interest in ANNs stems from their basic property of learning capability. ANNs possess the ability to adapt to any environment. To use ANNs to their fullest potential in the field of engineering, it needs to shorten the adaptation time without losing from the stability of the network's optimal state [19]. The basic rationale behind designing a neural network-based model to predict certain material behavior is training a neural network based on the results of prior experiments with that material. The performance of the trained neural network depends on the extent to which the experimental results contain the required information on the material behavior. If there is access to sufficient information, the trained neural network will provide sufficient information about material's behavior, qualifying thus as a material model. If such conditions are met, it will be more likely that the trained neural network could replicate the experimental results and the generalizibility of the results to other experiments will increase [20].

In the experimental study, the cement samples that were produced using three different types of cement (OPC, PLC and GGSC) and two different *w*/*c* ratios (0.63 and 0.70) were matured in three different cure conditions, and 7, 28 and 90 days compressive strengths were measured. The present paper aims to develop an ANN model to predict the compressive strength of concrete made up of varying cements, ages and cure conditions used as input parameters. To this end, two different ANN models were developed using the "NNTool" of MATLAB program. Furthermore, the data obtained in this study on cement strength, which utilized the ANN's function prediction capability, were compared with the experimental data.

2 Experimental study

So as to produce cement, natural river sand and crushed limestone constituted the fine and coarse aggregates, which can be categorized in three groups by size: 0–5, 5–15 and 15–25 mm. Particle size distribution of aggregates was done by sieve method in accordance with ASTM C33. Tests of specific gravity, water absorption, abrasion resistance, freezing and thawing resistance on the aggregates used in the mixture were performed each.

The cement types used are as follows: ordinary Portland cement (OPC) (CEM I 42.5 N), Portland limestone cement (PLC) (CEM II/A-L 42.5 N) and granulated ground slag cement (GGSC) (CEM III/A 42.5 N).

The concrete used in the study is a mixture of three types of cements (OPC, PLC, GGSC), two distinct *w*/*c* ratios by weight (0.63, 0.70) and cement content (300 kg/m^3). Table 1 shows the approximate concrete composition per one cubic meter of cement. The concrete mixtures were prepared in accordance with the TS EN 206-1 by using a drum mixer in laboratory conditions. The slump cone test was performed to test the feasibility and standardness of the concrete mixes. Concrete was cast in two layers in 150 × 150 × 150 mm cubes and pressed on a vibrating table until all air bubbles disappeared completely. These specimens, covered with plastic sheets so that water would not evaporate, were kept for a period of 24 h under 20 ± 1°C and 60% relative humidity conditions. Upon

Table 1 Approximate concrete composition for a cubic meter

w/*c* ratio	Water (kg/m^3)	Cement (kg/m^3)	Plasticizer (kg/m^3)	Aggregate (kg/m^3)		
				0–5 (mm)	5–15 (mm)	15–25 (mm)
0.7	210	300	–	760	530	530
0.63	189	300	2.4	775	540	540

demolding of the specimens at the end of 24 h, the following approaches were followed to cure them.

Continuous moist curing (L) Lime-saturated water curing was used; the process took place at 23 ± 2°C. This was to avert leaching of Ca $(OH)_2$ from these specimens.

Open-air curing (A) Throughout a period of seven days until the test age, the specimens were watered twice daily, which was followed by air curing at uncontrolled temperature and relative humidity.

In plastic bag curing (B) Specimens were kept in plastic bags up until the test age.

Three values relating to three different specimens in the same conditions were recorded. The average of these three readings was recorded as one value. Each of these values is reported in this experimental study. The samples cured for 3, 7, 28 and 90 days were applied compressive strength.

3 Significance of the study

In this study, so as for it to give concrete strength depending on cement type, *w*/*c* ratio, cure conditions and hardened concrete age, two different artificial neural network models, first one with 4 inputs, 1 output, 9 neurons, 1 hidden layer and, second one with 4 inputs, 1 output, 5, 6 neurons and 2 hidden layers, were developed. Some of the experimental data obtained earlier were given to the network as the training set to train the network. Upon completion of the training of the network, a certain portion of the experimental data that had not been used in the input during the training stage was used in the input of the network. A comparison of the network output and the experimental outputs reveal that the network output produces accurate results at a level just as desired.

4 Artificial neural networks

Adjustment of the synaptic connections between individual neurons is what renders the learning capability of biological nervous systems [21, 22]. The logic behind the ANN modeling is analogous. It enables the training of the network by exposing it to a set of input data where the output values are known. ANN interconnection weights are recursively adapted to correct the finally processed output so that it will match the output of known values. Trained effectively, the network can now solve novel problems similar to the task it was trained on. This is made possible through the knowledge acquired by this learning process and stored in synapses [21].

An ANN is usually composed of an input layer of neurons, also called nodes or processing units, one or several hidden layers of neurons and output layer of neurons. Weights inextricably interconnected the neighboring layers. Neurons in the input layer deliver information coming from the outside environment and send them to the neurons in the hidden layer. In this process, no calculation is performed. The received information then is processed by the hidden layer neurons. This process extracts relevant features to rebuild the mapping from the input space to the output space. Ultimately, the network predictions to the outside world are given by the output layer neurons [23–25].

An artificial neuron is made up of five main components: inputs, weights, sum function, activation function and outputs. Input, sum function, sigmoid activation function and output of a typical neural network are demonstrated in Fig. 1. Each output of the connected neuron is multiplied by the synaptic strength of the connection between them, resulting in the input to a neuron. The following equation is used to calculate the weighted sums of the input components:

$$(\text{net})_j = \sum_{1}^{n} w_{ij} x_i + b. \tag{1}$$

In this equation, $(\text{net})_j$ signifies the weighted sum of the *j*, neuron the input received from the preceding layer with *n* neurons, w_{ij} the weight between the *j*. neuron in the preceding layer, x_i the output of the *i*. neuron in the preceding layer. Also, *b* a fix value as internal addition and $\sum$ symbolizes sum function. Activation function processes the net input obtained from sum function and yields the cell output. Commonly, sigmoid function serves well in multilayer receptive models as the activation function ($f(\cdot)$). To measure the output of the *j*. neuron $(\text{out})_j$, (2) is implemented with a sigmoid function as follows [17, 25, 26]. The counterpart of the tigmoid function in the Matlab program is "Tansig." Sigmoid activation function graph is given in Fig. 2.

$$(\text{out})_j = f(\text{net})_j = \frac{1}{1 + e^{-x(\text{net})_j}}. \tag{2}$$

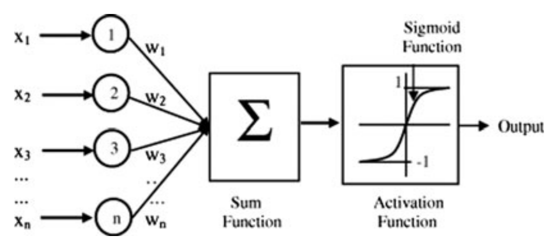

Fig. 1 A simple neuron model

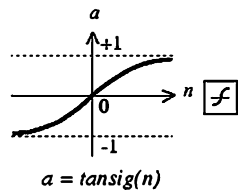

Fig. 2 Sigmoid activation function

4.1 Feedforward back-propagation network

The back-propagation, or its variations, are the most common and powerful learning algorithms in neural networks. The prominent reason for this is that the back-propagation has a high learning capacity and a simple algorithm [16, 27, 28].

This algorithm was named after its feature of minimizing the errors backwards, from output to input [29]. The error-correction learning rule provides the basis of the algorithm. Essentially, the error back-propagation process calls for two passes through different layers of the network: a forward pass and a backward pass. In the former, an activity pattern (input vector) is applied to the sensory nodes of the network, and its effect propagates across the layers. Finally, as part of the actual response of network, a set of outputs is produced. During the latter, there are all fixed-synaptic-weight networks. During the backward pass, on the other hand, the synaptic weights of the network are adjusted according to the error-correction rule. As a matter of fact, an error signal is created by the actual response of network which is subtracted from a desired (target) response. What occurs subsequently is the backward propagation of this error signal [28].

Backpropagation is a form of supervised learning. In supervised learning, information about the characteristics of the data and the observable outcomes is fully included in the training database. The models can learn the interactions between these characteristics and outcomes, i.e., between input and outputs [30]. The structure of feedforward back-propagation network is depicted in Fig. 3.

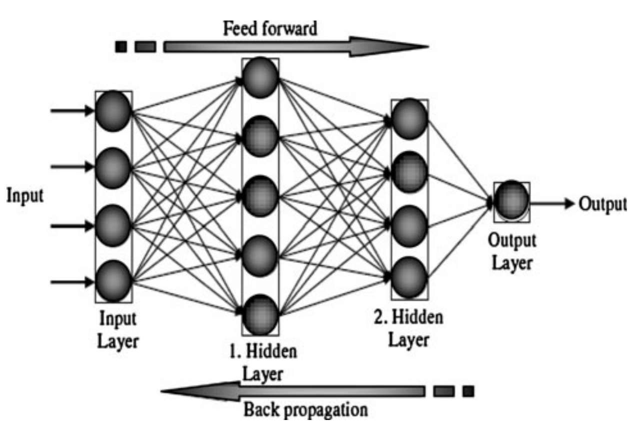

Fig. 3 A typical architecture of a multilayer feed forward neural network

4.2 The structure and the parameters of the artificial neural network developed

In the present study, no experiment was carried out, but rather, in order to measure the compressive strengths of concrete, ANN-I that has 4 inputs, one output and one hidden layer and which uses backpropagation algorithm as the learning algorithm, as well as ANN-II which has two hidden layers, were developed. The number of hidden layers selected for ANN-I is 9, while for ANN-II, it is 5 and 6.

The artificial networks belonging to the ANN-I and ANN-II models are shown in Figs. 4 and 5.

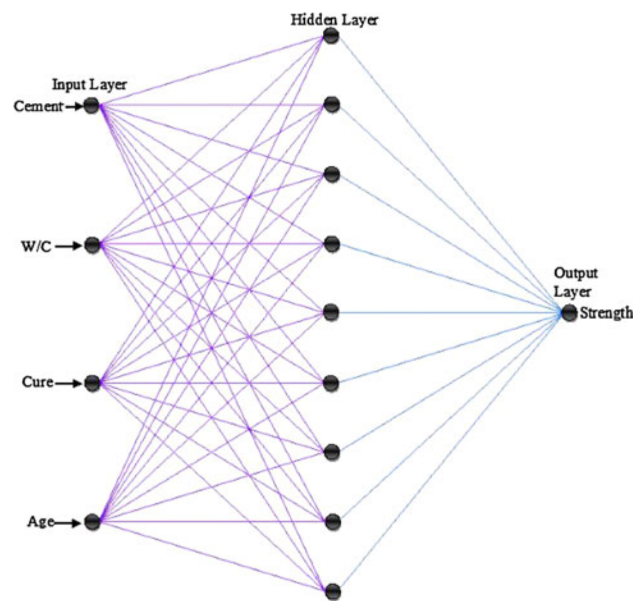

Fig. 4 The system in the ANN-I model

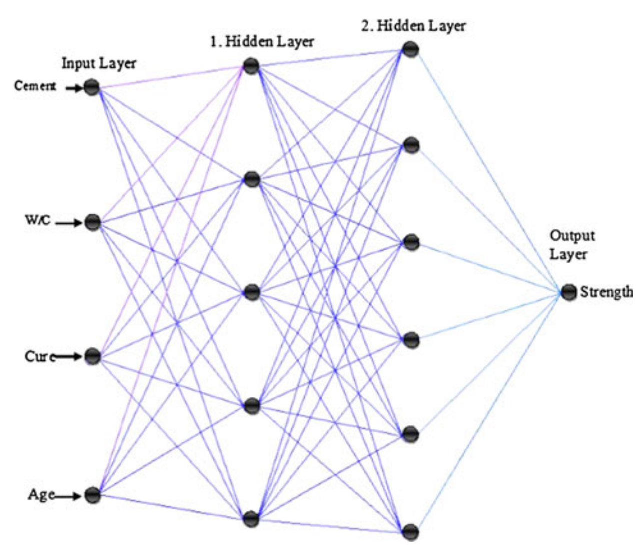

Fig. 5 The system in the ANN-II model

Table 2 Artificial neural network inputs

Inputs	Properties	Input number
Cement	OPC	3
	PLC	
	GGSC	
w/*c*	0.70	2
	0.63	
Cure	B	3
	L	
	A	
Age	3	4
	7	
	28	
	90	

Input layer: 4 neurons. These neurons have the input numbers indicated in Table 2.

Hidden layer: ANN-I and ANN-II models, which are the artificial neural networks developed, have one hidden layer and two hidden layers, respectively. The number of neurons in the hidden layer is a variable affecting the learning performance. The number of neurons in the hidden layer should be neither too small nor too high. A too small number will not provide an optimal value for the network earning procedure, bringing about an oscillatory behavior of the error function. This will make it impossible for the network to discover the relationship between the input–output designs. A too high number of neurons will cause the network to register the input–output list only, resulting in a poor generalization performance. In brief, the optimal ANN size should be just right for the data structure and establish the model definitively related to the problem [31]. Following a series of trials, it was decided that the number of neurons in the hidden layer be 9 for the ANN-I model. For the ANN-II model, on the other hand, the number of neurons was decided to be five in the first hidden layer and six in the second hidden layer, for the optimum result was obtained when the number of neurons in the hidden layers is as indicated.

Output layer: In accordance with the study and the experimental data, the network has a single neuron output, and it gives the cement strength as output.

4.3 Training of the artificial neural network

The present study resorted to MATLAB in establishing and training the artificial neural network. For the testing and training process of 60 experimental data, cement, *w*/*c*, cure and age were applied as input variables in ANN-I and ANN-II models in two distinct architectures; 12 data that the network did not encounter in the training stage were used in the test procedures of ANN-I and ANN-II models.

Table 3 The values of parameters used in models

Parameters	ANN-I	ANN-II
Number of input layer neurons	4	4
Number of hidden layers	1	2
Number of first hidden layer neurons	9	5
Number of second hidden layer neurons	–	6
Number of output layer neuron	1	1
Momentum rate	0.7	0.9
Learning cycle	15,000 epoch	35,000 epoch
Transfer function	Tansig	Tansig
Training function	TRAINGDM	TRAINGDM
Performance function	MSE	MSE

Please find the values related to parameters used in ANN-I and ANN-II in Table 3.

Traingdm algorithm (gradient descent with momentum backpropagation) was used in the Matlab program as the training function. Traingdm was preferred due to its capability to train any network provided that its weight, net input and transfer functions have derivative functions.

Derivatives of performance perf with respect to the weight and bias variables X were calculated by backpropagation. The variables then were adjusted according to gradient descent with momentum, applied with Traingdm.

$$dX = mc * dX\text{prev} + lr * (1 - mc) * d\text{perf}/dX$$

where dXprev is the previous change to the weight or bias.

Training is terminated in case of any one of the following circumstances:

- Reaching the maximum number of epochs (repetitions)
- Exceeding the maximum amount of time
- Reducing performance to the goal
- The performance gradient's getting lower than min. grad.
- Validation performance's being more than max. fail times since it last decreased (when using validation).

5 Results and discussion

For ANN-I and ANN-II models, error occurring in the test and training stages of this study is indicated by mean squared error (MSE), which is calculated as follows (3):

$$\text{MSE} = \frac{1}{N}\sum_{1}^{N}(e_i)^2 = \frac{1}{N}\sum_{1}^{N}(t_i - a_i)^2. \tag{3}$$

In statistical terms, MSE of an estimator is a means of quantifying the extent to which an estimator differs from

Table 4 The statistical values of the proposed ANN-I and ANN-II models

Statistical parameters	ANN-I		ANN-II	
	Training set	Testing set	Training set	Testing set
REG (*R*)	0.9942	0.9870	0.9961	0.9851
MSE	1.0788	2.4560	0.7257	2.9091

the true value of the quantity that is estimated [32]. The learning performance of the network can be assessed based on MSE and *R* (regression value) coefficients. If the MSE value is close to zero, it means the disparity between the network output and the desired output is minimal. If it is zero, there is no disparity whatsoever, thus no error. *R* determines the level of relation between network output and the aimed output. Should this value be 1, then the connection between the network output and the output initially aimed is not coincidental. Table 4 demonstrates the MSE and *R* values calculated after the training for the training and test databases in ANN-I and ANN-II models.

In the ANN-I model, REG and MSE values were found out to be 0.9942 and 1.0788 for the training set and 0.9870 and 2.4560 for the testing set. In the ANN-II model, these values were found out to be 0.99961 and 0.7257, and 0.9851 and 2.9091, respectively.

Overall *R* values manifest that ANN-I and ANN-II models have highly similar values. Despite this, the ANN-II model produces better results for the train set, whereas the ANN-I model does so for the testing set. In fact, what matters more is the results obtained for the training set since the testing set data are not given as the input to the network during the training of the network.

MSE coefficients of the testing set reveal that the error rate in the ANN-I model is approximately 15% less than that in the ANN-II model. Put differently, the ANN-I model can predict the concrete strength with error probability that is 15% less than it would be in the ANN-II model.

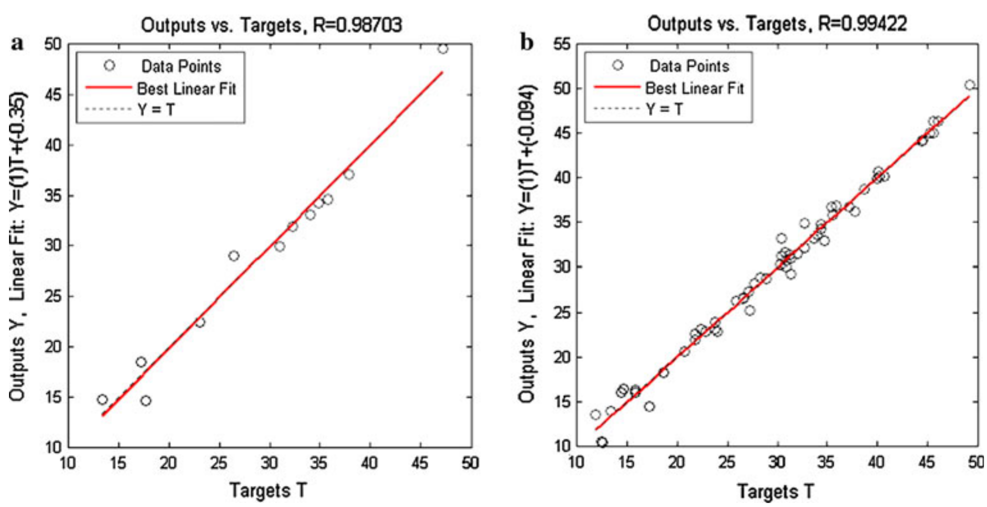

Fig. 6 **a** ANN-I model testing set regression, **b** ANN model-I training set regression

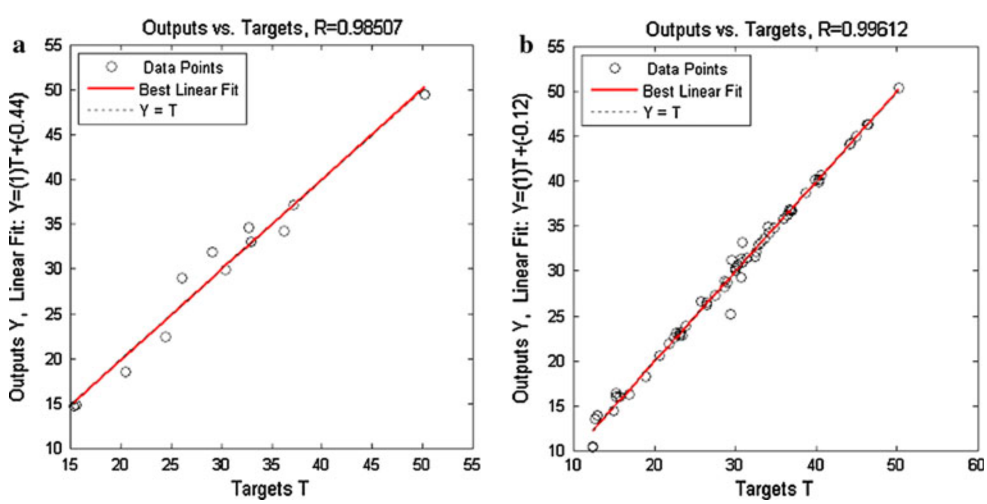

Fig. 7 **a** ANN-II model testing set regression analysis, **b** ANN model-II training set regression analysis

Table 5 The comparison of the experimental results for the training set and the estimated results obtained from the models

Cement	*w/c*	Cure	Age	Experimental results (ER)	ANN-I	Diff.	ANN-II	Diff.
GGSC	0.70	B	3	10.31	12.47	2.16	12.25	1.94
OPC	0.70	B	3	22.79	23.97	1.18	23.40	0.61
PLC	0.63	B	3	27.31	27.10	0.21	27.43	0.11
OPC	0.63	B	3	30.73	30.82	0.09	30.26	0.47
PLC	0.70	L	3	18.26	18.63	0.37	18.91	0.65
GGSC	0.70	L	3	10.48	12.35	1.87	12.28	1.81
OPC	0.70	L	3	23.93	23.73	0.20	23.81	0.13
PLC	0.63	L	3	28.85	28.28	0.57	28.70	0.16
GGSC	0.63	L	3	14.46	17.14	2.68	14.85	0.39
OPC	0.63	L	3	31.59	30.73	0.86	32.42	0.83
PLC	0.70	A	3	16.04	15.83	0.21	15.61	0.43
GGSC	0.70	A	3	13.51	11.82	1.69	12.50	1.01
PLC	0.63	A	3	22.89	22.84	0.05	23.05	0.16
GGSC	0.63	A	3	13.87	13.37	0.50	12.87	PLC
OPC	0.63	A	3	28.76	28.93	0.17	28.87	0.11
PLC	0.70	B	7	22.52	21.74	0.77	22.42	0.10
GGSC	0.70	B	7	16.35	14.60	1.75	15.26	1.09
OPC	0.70	B	7	26.66	26.66	0.00	25.74	0.91
GGSC	0.63	B	7	23.07	22.37	0.69	23.05	0.01
OPC	0.63	B	7	32.15	32.72	0.58	32.53	0.38
PLC	0.70	L	7	23.09	23.77	0.68	22.59	0.50
GGSC	0.70	L	7	15.98	14.38	1.60	15.21	0.77
PLC	0.63	L	7	31.46	31.99	0.53	31.47	0.01
GGSC	0.63	L	7	21.92	21.72	0.19	21.70	0.22
OPC	0.63	L	7	34.95	32.70	2.25	34.12	0.83
PLC	0.70	A	7	20.56	20.71	0.14	20.66	0.09
OPC	0.70	A	7	26.25	25.79	0.46	26.51	0.27
PLC	0.63	A	7	26.51	26.54	0.02	26.38	0.13
GGSC	0.63	A	7	16.28	15.81	0.47	16.75	0.47
OPC	0.63	A	7	30.04	30.85	0.81	29.91	0.13
PLC	0.70	B	28	30.97	31.34	0.36	30.80	0.17
GGSC	0.70	B	28	30.32	30.24	0.08	30.02	0.30
OPC	0.70	B	28	29.25	31.35	2.10	30.71	1.46
PLC	0.63	B	28	39.97	40.00	0.03	40.37	0.41
GGSC	0.63	B	28	40.73	40.16	0.58	40.63	0.10
OPC	0.63	B	28	36.29	37.78	1.49	36.45	0.16
GGSC	0.70	L	28	31.19	30.38	0.82	29.57	1.62
OPC	0.70	L	28	31.36	31.28	0.07	30.76	0.60
PLC	0.63	L	28	40.16	40.25	0.10	39.84	0.32
GGSC	0.63	L	28	40.25	40.65	0.40	40.30	0.05
PLC	0.70	A	28	28.19	27.69	0.50	28.62	0.43
GGSC	0.70	A	28	25.18	27.29	2.11	29.31	4.13
OPC	0.70	A	28	33.16	30.44	2.72	30.85	2.31
PLC	0.63	A	28	33.22	33.73	0.51	33.23	0.01
OPC	0.63	A	28	35.92	35.59	0.34	35.92	0.01
GGSC	0.70	B	90	36.80	37.15	0.35	37.01	0.21
OPC	0.70	B	90	32.98	34.74	1.76	32.93	0.05
PLC	0.63	B	90	45.10	45.58	0.48	45.07	0.03

Table 5 continued

Cement	w/c	Cure	Age	Experimental results (ER)	ANN-I	Diff.	ANN-II	Diff.
GGSC	0.63	B	90	46.38	46.13	0.25	46.41	0.03
OPC	0.63	B	90	44.09	44.47	0.38	44.08	0.01
PLC	0.70	L	90	34.26	34.42	0.16	34.26	0.00
GGSC	0.70	L	90	36.93	35.86	1.07	36.65	0.28
PLC	0.63	L	90	50.42	49.21	1.20	50.21	0.21
OPC	0.63	L	90	46.33	45.64	0.69	46.35	0.02
PLC	0.70	A	90	34.77	34.36	0.42	34.76	0.01
GGSC	0.70	A	90	33.56	34.07	0.51	33.61	0.05
OPC	0.70	A	90	36.78	35.45	1.33	36.77	0.01
PLC	0.63	A	90	38.73	38.71	0.02	38.73	0.00
GGSC	0.63	A	90	45.05	45.24	0.20	45.06	0.01
OPC	0.63	A	90	44.23	44.56	0.33	44.25	0.01

Table 6 The comparison of the experimental results for the testing set and the estimated results obtained from the models

Cement	w/c	Cure	Age	Experimental results	ANN-I	Diff.	ANN-II	Diff.
PLC	0.70	B	3	18.50	17.14	1.36	20.44	1.94
GGSC	0.63	B	3	14.63	17.69	3.06	15.26	0.63
OPC	0.70	A	3	22.44	23.08	0.64	24.42	1.98
PLC	0.63	B	7	29.98	30.94	0.95	30.43	0.44
OPC	0.70	L	7	28.99	26.47	2.52	26.04	2.95
GGSC	0.70	A	7	14.75	13.35	1.40	15.50	0.75
PLC	0.70	L	28	31.95	32.24	0.29	29.04	2.91
GGSC	0.63	A	28	34.30	34.81	0.51	36.25	1.95
OPC	0.63	L	28	37.12	37.91	0.79	37.13	0.01
PLC	0.70	B	90	33.09	34.05	0.96	32.96	0.13
GGSC	0.63	L	90	49.56	47.25	2.31	50.21	0.65
OPC	0.70	L	90	34.61	35.79	1.18	32.70	1.91

Regression analysis for R parameters in ANN-I and ANN-II models is given in Figs. 6 and 7.

Concrete strength, input data and experimental concrete strength data, obtained upon application of the data used for the training of the network as input to the network, are shown in Table 5. The data sets not applied to the network as input during the training of network were then applied to the network which was trained as input. The results are shown in Table 6.

6 Conclusions

ANN-I and ANN-II models based on artificial neural networks were developed to predict, without experimenting, 3-, 7-, 28- and 90-day compressive strengths of concrete samples, in which varying types of cement were used, which had different *w*/*c* ratio and which were matured under different curing conditions. Both models developed in the study were trained by input and output data. Randomly selected 12 experimental data sets were used as test data to test the trained ANN. It was found that, when these testing data sets were applied to both trained ANNs, the concrete strengths were very close to the actual experimental data. However, an analysis of MSE error coefficients reveals that ANN-I model can predict the compressive strength of concrete with much less error.

To conclude, using both ANN-I and ANN-II, it is possible to predict the concrete strength in a short time and with minimum error. Prediction of the compressive strength of concrete by using artificial neural network has proved a practical and effective method.

In the experimental study, the cement samples that were produced using three different types of cement (OPC, LC and GGSC) and two different *w/c* ratios (0.63 and 0.70) were matured in three different cure conditions, and 7, 28 and 90 days compressive strengths were measured. The present paper aims to develop an ANN model to predict the compressive strength of concrete made up of varying cements, ages and cure conditions used as input parameters.

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