Artificial Neural Network Model for Predicting Compressive Strength of Concrete

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Abstract

Compressive strength of concrete is a commonly used criterion in evaluating concrete. Although testing of the compressive strength of concrete specimens is done routinely, it is performed on the 28th day after concrete placement. Therefore, strength estimation of concrete at early time is highly desirable. This study presents the effort in applying neural network-based system identification techniques to predict the compressive strength of concrete based on concrete mix proportions, maximum aggregate size (MAS), and slump of fresh concrete. Back-propagation neural networks model is successively developed, trained, and tested using actual data sets of concrete mix proportions gathered from literature.

The test of the model by un-used data within the range of input parameters shows that the maximum absolute error for model is about 20% and 88% of the output results has absolute errors less than 10%. The parametric study shows that water/cement ratio (w/c) is the most significant factor affecting the output of the model.

The results showed that neural networks has strong potential as a feasible tool for predicting compressive strength of concrete.

Keywords: Artificial neural network, Compressive strength, Concrete, Mixing, Predicting

نموذج الشبكة العصبية الاصطناعية للتنبوء بمقاومة انضغاط الخرسانة

الخلاصة

تعتبر مقاومة انضغاط الخرسانة من المعايير المستخدمة في إنتاج الخرسانة. ان فحص مقاومة الانضغاط لنماذج الخرسانة من الأمور الروتينية لكنه يستحصل بعد 28 يوم من عملية الصب، لذلك فان تخمين مقاومة الخرسانة في وقت مبكر من الأمور المهمة. هذه الدراسة محاولة لاستخدام تقنية الشبكات العصبية الاصطناعية للتنبؤ بمقاومة انضغاط الخرسانة اعتمادا على مكونات المزجة والحجم الأكبر للركام وهبوط الخرسانة الطرية.

تم تكوين نموذج الشبكة العصبية الاصطناعية المعتمدة على خوارزمية التجميع التراجعي بنجاح وتم تدريبه و فحصه باستخدام بيانات حقيقية جمعت من دراسات سابقة.

فحص النموذج ببيانات غير مستخدمة في تدريب النموذج وضمن حدود البيانات الداخلة أظهر أن أعظم خطأ مطلق للنتائج كان بحدود 20% وأن 88% من النتائج فيها خطأ اقل من 10% . أظهرت دراسة أهمية العوامل الداخلة في النموذج أن نسبة الماء إلى الأسمنت(w/c) أهم عامل مؤثر في التنبؤ بمقاومة الخرسانة، كما أظهرت النتائج أن الشبكات العصبية أداة عملية قوية للتنبؤ بمقاومة انضغاط الخرسانة.

الكلمات الدالة: الشبكات العصبية الاصطناعية، مقاومة الانضغاط، خرسانة، مزجة، تنبؤ

Introduction

Most research in material modeling aims to construct mathematical models to describe the relationship between components and material behavior. These models consist of mathematical rules and expressions that capture these varied and complex behaviors. Concrete is a highly nonlinear material, so modeling its behavior is a difficult task.

Concrete is one of the most widely used construction material in the world. Traditionally, concrete has been fabricated from a few well-defined components: cement, water, fine and coarse aggregates, etc. In concrete mix design and quality control, the strength of concrete is a very important property. Many properties of concrete such as elastic modulus, water tightness or impermeability, resistance to weathering agents, etc. are directly related to the strength. The strengths of concrete include compressive, tensile, flexural, shear, bond, etc. A majority of concrete elements are designed to take advantage of the higher compressive strength of the material, since the compressive strength of concrete is usually many times greater than other types of strength[1].

The compressive strength of concrete is related to mix proportions and mix preparation techniques, but the result of the compression test of a specimen can be influenced by the shape, dimension, and the boundary conditions of the specimen. Traditionally, concrete mix is designed based on previous experiences.

The mixture design of concrete targets its 28th day compressive strength which is based on a standard uniaxial compression test and is accepted conventionally as a general index of concrete strength.

Generally, concrete testing procedures are very complicated and time consuming. Furthermore, experimental errors are inevitable. A typical test performed 28 days after concrete placement may be too late to make improvements if the test results do not satisfy the required criterion. Therefore, accurate and realistic strength estimation before the placement of concrete is very important.

Over a period of many years, researchers have proposed various methods for predicting concrete strength. Conventional methods for predicting 28th day compressive strength of concrete are basically based upon statistical analyses, by which many linear and nonlinear regression equations have been constructed to model such prediction problems[2,3]. Such traditional prediction models have been developed with a fixed equation form based on a limited number of data and parameters. If new data is quite different from original data, then the model should be updated not only its coefficients but also its equation form.

Artificial neural network (ANN) does not need such a specific equation form. Instead of that, it needs sufficient input-output data. Also, it can continuously retrain the new data, so that it can conveniently adapted to new data. Modeling with ANN is much simpler because, although a neural network captures the mathematical relationships in its collection of interconnections between its nodes, no formal mathematical rule or formulae are used or observed within the model.

Over the last two decades, different predicting methods based on ANNs has become popular and has been used by many researchers for a variety of engineering applications[4-6].

Yeh[7], Lee[8] and Ahmet et al.[9] applied the ANNs for predicting properties of conventional concrete and high performance concrete. Kim et al.[10] used back propagation neural networks to predict the compressive strength of ready mixed concrete. Hola and Schabowicz [11] developed ANN model to predict the compressive strength of concrete on the base of non-destructive determined parameters. Zarandi et al.[12] applied the fuzzy polynomial neural network to predict the compressive strength of concrete.

This study presents an effort to apply neural network-based system identification techniques to predict the compressive strength of concrete based on concrete mix proportions. For this aim, a computer program is developed using neural network design (NND) toolbox in MATLAB from the MathWorks[13]**.** Using this program, a neural network model with two hidden layers is constructed, trained, and tested using the available test data of 472 different sets gathered from the technical literature[14-18]**.** The data used in ANN model are arranged in a format of six input parameters that cover the cement content, fine aggregate content, coarse aggregate content, water-cement ratio, maximum aggregate size (MAS) and slump of fresh concrete. The proposed ANN model predicts the 28th day compressive strength of concrete.

Neural Network Modeling Background

A number of papers on the application of neural networks in civil and structural engineering revealed that a multilayer feed-forward neural network model is the most widely used network for its efficient generalization capabilities [6,9,12]**.** Fig.(1) presents typical multi-layer feed-forward neural networks used in the current application. This type of neural network consists of an input layer, one or more hidden layer(s) and an output layer. Layers are fully connected, as shown on Fig.(1) by arrows, and comprises number of processing units, the so-called nodes or neurons. The strength of connections between neurons is represented by numerical values called weights. Each neuron has an activation value that is a function of the sum of inputs received from other neurons through the weighted connections[6,19].

The input layer feeds the network with input from outside whereas the output layer produces Neural network (NN) predictions to the outside. The hidden layers link the input layer to the output layer, extract and remember useful features from the input data to predict the output of the network. The optimum number of hidden layers and the number of neurons in each hidden layer is specific problem. Therefore, trial and error procedure should be carried out to choose an adequate number of hidden layers and the number of neurons in each hidden layer[5,6]**.** ANNs are capable of performing a good amount of generalization from the patterns on which they are trained.

Training consists of exposing the neural network to a set of known input–output patterns. The data are passed through the multi-layered feed forward neural network in a forward direction only. As the data moves forward, it is subjected to simple processing within the neuron and along the links connecting neurons. The network performs successive iterations to adjust the weights of each neuron in order to obtain the target outputs according to a specific level of accuracy. The adjusting process of neuron weights is carried out to minimize, to a certain level the network error which is defined as a measure of the differences between the computed and target output patterns. After the NN is satisfactorily trained and tested, it is able to generalize rules and will be able to deal with unseen input data to predict output within the domain covered by the training patterns[6,9].

There are several methods and techniques to train a network. Back propagation is the most successful and widely used in neural network applications. In this method, the input is propagated from the input layer through the hidden layers to the output layer. The network error is then back propagated from the output layer to the input layer in which the connection weights are adjusted. This process is repeated until the error is minimized to a preference level[5]. The ANN based modeling process involves five main aspects: (a) data acquisition, analysis and problem representation; (b) architecture determination; (c) learning process determination; (d) training of the networks; and (e) testing of the trained network for general evaluation.

The error incurred during the learning can be expressed as Mean squared error and is calculated using Eq. (1)

$$\mathrm{MSE} = \frac{1}{nm}\sum_{i=1}^{n}\sum_{j=1}^{m}\left(t_{ij} - y_{ij}\right)^2 \quad \ldots\ldots\ldots\ldots (1)$$

Where t is the target value, y is the output value.

Neural Network Design and Training

In this work 472 sets of 28th day concrete strength data are extracted from experimental tests conducted by Mosul University[14-18]. The range of compressive strength of samples are 13.7 to 50.5 MPa, while those of input data are shown in Table (1).

To train the ANN models, first, the entire training data file is randomly divided into training and testing data sets. 429 sets, are used to train the different network architectures. The remaining 43 patterns are used for testing to verify the prediction ability of each trained ANN model.

The multi-layer feed forward back-propagation technique is implemented to develop and train the neural network of the current study where the sigmoid transform functions are adopted.

The term “ANN prediction” is reserved for ANN response for cases that are not used in the pre-training stages. This is used in order to examine the ANN’s ability to associate and generalize a true physical response that have not been previously “seen”. A good prediction for these cases is the ultimate verification test for the ANN models. These tests have to be applied for input and output response within the domain of training. It should be expected that ANN would produce poor results for data that are outside the training domain.

Preprocessing of data by scaling is carried out to improve the training of the neural network. To avoid the slow rate of learning near the end points specifically of the output range due to the property of the sigmoid function, the input and output data are scaled between the interval 0.1 and 0.9. The scaling of the training data sets is carried out using the following equation:

$$y = (0.8/\Delta)x + (0.9 - 0.8x_{\max}/\Delta) \quad ..(2)$$

Where $\Delta = x_{\max} - x_{\min}$

It should be noted that any new input data should be scaled before being presented to the network and the corresponding predicted values should be un-scaled before use. The back-propagation learning algorithm is employed for learning in the MATLAB program[13]. Each training "epoch" of the network consisted of one pass over the entire 429 training data sets. The 43 testing data sets are used to monitor the training progress.

Different training functions available in MATLAB[13,20] are experimented for the current application. The scaled conjugate gradient (SCG) techniques built in MATLAB proved to be efficient training function, and therefore, is used to construct the NN model. This training function is one of the conjugate gradient algorithms that start training by searching in the steepest descent direction (negative of the gradient) on the first iteration.

The network architecture or topology is obtained by identifying the number of hidden layers and the number of neurons in each hidden layer. There is no specific rule to determine the number of hidden layers or the number of neurons in each hidden layer. The network learns by comparing its output for each pattern with a target output for that pattern, then calculating the error and propagating an error function backward through the neural network. To use the trained neural network, new values for the input parameters are presented to the network.

The network then calculates the neuron outputs using the existing weight values developed in the training process. Table(2) shows the properties (architectures and parameters) of ANN model.

Results and Discussions

Fig.(2) shows actual and predicted compressive strength of regression for training data, the correlation coefficient was found to be 0.961

Table (3) Shows the actual tested values of compressive strength corresponding to ANN predicted values. The maximum errors for 43 test results are about 20%, on the other hand, it can be seen that 88% of the output results has errors less than 10%. The performance of a trained network can be measured to some extent by the errors on the training sets, but it is often useful to investigate the network response in more detail. One option is to perform a regression analysis between the network response and the corresponding targets and finding a correlation coefficient. It is a measure of how well the variation in output is explained by the targets. If this number is equal to 1, then there is perfect correlation between targets and outputs predictions.

Fig.(3) shows a plot of actual compressive strength against corresponding ANN predications for testing data. A linear correlation can be observed and the correlation coefficient is found to be 0.95. Thus it can be concluded that the model successfully predicted the compressive strength of concrete in good manner.

Because of the weight of the backpropagation network cannot be easily understood in the form of a numeric matrix, they may be transformed into coding values in the form of a percentage by dividing the weights by the sum for all the input parameters, which gives the relative importance for each input parameter to output parameter.

The relative importance for various input parameters is shown in Fig.(4) which indicated that the major important parameter is the w/c ratio (75.33%) while the other input parameters have approximately the same (insignificant) importance on predicting compressive strength (3.78%-6.66%)

Conclusions

1. This study shows the feasibility of using the artificial neural networks in building the model for predicting the 28th day compressive strength of concrete using the materials content of mixes, maximum aggregate size and the slump of fresh concrete. The data were extracted from experimental tests conducted by Mosul University.

2. The model is used successfully for predicting the 28th day compressive strength of concrete. The test of the model by un-used data within the range of input parameters shows that the absolute maximum error for model was about 20% and 88% of the output results has absolute errors less than 10%.

3. The parametric study shows that the w/c is the most significant factor affecting the output of the model. On the other hand, the relative importance of values other input parameters are insignificant with respect to the importance of water cement ratio.

4. In constructing, early determination of compressive strength value is very important. Normally, determination of compressive strength takes 28 days but using the proposed ANN model, the compressive strength value can be predicted in shorter time.

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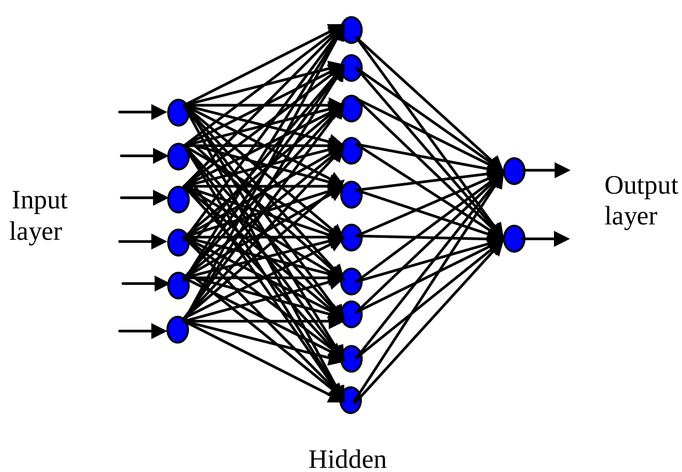

Fig. (1) Typical neural network

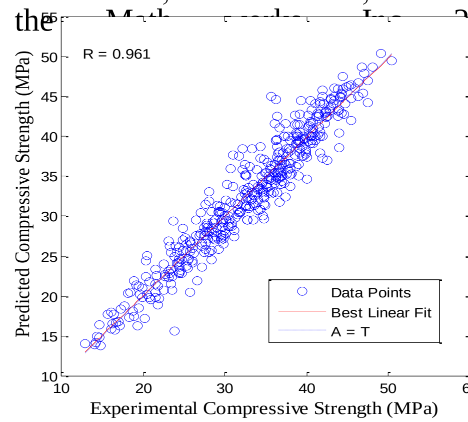

Fig. (2) Actual and predicted compressive strength of regression for training data

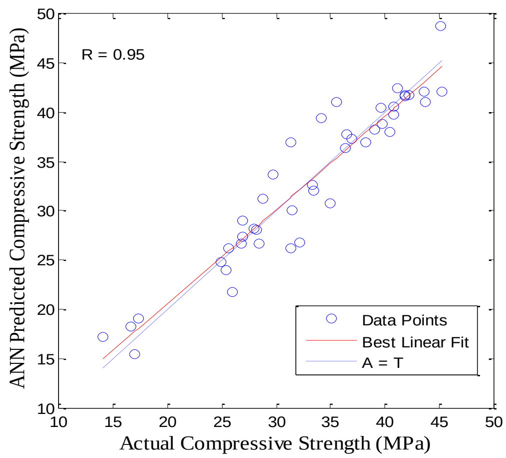

Fig. (3) Actual and predicted compressive strength of regression for testing data

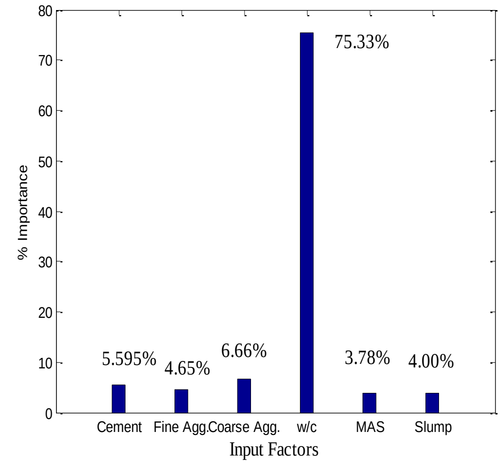

Fig. (4) Relative importance of input parameters for the prediction of compressivestrength of concrete

Table (1) Range of input parameters in database

Input parameter	Min.	Max.
Cement content(kg/m^3)	208	481
Fine aggregate content (kg/m^3)	440.93	1160
Coarse aggregate content (kg/m^3)	186.48	1443.8
Water/cement ratio (w/c)	0.34	0.758
Max. aggregate size (mm) (MAS)	20 and 40	
Slump (mm)	0	191

Table (2) Properties of ANN model

Architecture	6-30-30-1
training function	scaled conjugate gradient
Activation Function	Log sigmoid
Number of Epochs	4369
Mean Squared Error (MSE)	0.0024

Table (3) Compressive strength prediction (test data)

Cement (kg/m^3)	Fine Agg. (kg/m^3)	Coarse Agg. (kg/m^3)	w/c	MAS (mm)	Slump (mm)	Comp. strength (MPa)		% Error
						ANN	Actual	
225	950	225	0.755	20	80	14.081	17.2	18.131
305	1088	305	0.600	20	150	27.967	28.2	0.825
350	686	350	0.460	20	90	41.897	41.6	0.714
350	686	350	0.460	40	100	40.839	40.6	0.588

Table (3) Continued

Cement (kg/m^3)	Fine Agg. (kg/m^3)	Coarse Agg. (kg/m^3)	w/c	MAS (mm)	Slump (mm)	Comp. strength (MPa)		% Error
						ANN	Actual	
400	668	400	0.440	20	100	43.591	42.1	3.541
400	668	400	0.410	40	95	45.297	42.1	7.593
260	715	260	0.690	40	80	25.407	24	5.861
285	912	285	0.620	20	95	28.797	31.2	7.701
359	753.9	359	0.460	40	90	35.520	41	13.367
322	814.66	322	0.540	40	90	29.732	33.7	11.775
481	668.59	481	0.380	20	100	43.722	41	6.638
295	846.65	295	0.590	20	90	32.176	26.8	20.060
302	739	302	0.520	40	90	34.145	39.4	13.337
337	754	337	0.510	40	100	31.396	37	15.146
416	715.52	416	0.440	40	100	39.612	40.5	2.193
258	637.26	258	0.700	40	80	31.324	26.2	19.557
240	720	240	0.600	20	18	28.217	28.12	0.345
425	529.12	425	0.395	20	50	45.183	48.8	7.412
425	881.87	425	0.480	20	90	36.481	37.8	3.491
425	705.5	425	0.440	20	40	40.864	39.8	2.673
375	540	375	0.430	20	20	42.218	41.7	1.243
375	900	375	0.550	20	50	25.623	26.2	2.203
375	720	375	0.425	20	20	41.902	41.8	0.245
375	540	375	0.500	20	110	36.385	36.4	0.042
325	934.37	325	0.510	20	15	26.728	26.7	0.105
325	747.5	325	0.545	20	105	26.842	29	7.441
325	560.62	325	0.510	20	50	33.409	32	4.404
325	934.37	325	0.610	20	95	17.320	19.1	9.317
275	770	275	0.585	20	50	25.926	21.8	18.924
275	577.5	275	0.540	20	15	26.939	27.4	1.684
275	962.500	275	0.660	20	50	16.968	15.4	10.183
425	705.500	425	0.400	40	15	41.223	42.4	2.776
425	529.120	425	0.430	40	95	39.796	38.8	2.567
425	881.870	425	0.415	40	20	38.282	37	3.466
425	705.5	425	0.435	40	90	40.457	38	6.466
375	540	375	0.440	40	45	39.047	38.2	2.217
375	900	375	0.550	40	95	28.410	26.7	6.404
375	720	375	0.500	40	50	33.277	32.6	2.075
325	560.62	325	0.425	40	20	36.928	37.3	0.997
325	747.5	325	0.480	40	25	34.994	30.8	13.616
325	560.62	325	0.510	40	85	31.517	30.1	4.709
275	962.5	275	0.560	40	15	16.652	18.3	9.006
275	577.5	275	0.550	40	50	24.909	24.8	0.441