Int.J.Curr.Res.Aca.Rev.2022; 10(07): 70-80

EXCELLENT PUBLISHERS

International Journal of Current Research and Academic Review

ISSN: 2347-3215 (Online) Volume 10 Number 07 (July-2022)

Journal homepage: http://www.ijcrar.com

doi: https://doi.org/10.20546/ijcrar.2022.1007.004

Modelling of Concrete Strength Properties using the Artificial Intelligence tool of MATLAB

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Abstract

Two developing data mining approaches, Artificial Neural Networks (ANNs) and Genetic Programming, are used in this study to construct compressive strength prediction models (GP). Experiments were conducted in the laboratory under standard controlled settings at 7th, 14th and 28th day curing periods to collect data for analysis and model building. The created models were also put to the test using in-situ data from the literature. A comparison of the prediction results obtained using both models is studied, and it can be concluded that the ANN model with the training function Levenberg-Marquardt (LM) is the best prediction tool for the prediction of concrete compressive strength. Cement, water, and aggregates are the three main ingredients in concrete. The main goal in proportioning these elements is to make concrete that is strong enough. Because concrete is such a complex material, predicting compressive strength is a complex process. This research proposes an Artificial Intelligence model for predicting concrete strength at various ages, which will undoubtedly save time, material, and money. Cement, sand, water, coarse aggregates, fine aggregates, and fineness modulus are all inputs to the suggested model. The data used in this study was collected, and the network was trained using a backpropagation approach.

Article Info

Received: 04 June 2022
Accepted: 28 June 2022
Available Online: 20 July 2022

Keywords

Artificial Intelligence,
Genetic Programming,
Properties of Concrete,
Concrete compressive strength.

Introduction

It is important to know the compressive strength of concrete during the construction phase. Specimen testing is the standard approach for ensuring concrete strength. The characteristic strength of concrete is represented by 28th day strength of concrete cubes that has been prepared and cast to form the concrete work (Khashman and Akpinar, 2017). The 7th day or 14th day tests are done to assess the gain of concrete strength. However, according to the design/construction Code, 28th day testing are required. Waiting for 28 days is inconvenient, but it is necessary to verify the quality control procedure (Oreta and Kawashima, 2003). Based on the nature of strength gain, a simple mathematical model was constructed to forecast the compressive strength of concrete at 28 days from the findings.

The model is a straightforward rational polynomial equation. The suggested model has a high potential for accurately predicting concrete strength at various ages (Akhmad Suryadi and Trimilan Pujo Aji, 2011; Flood and Kartam, 1994; Hola and Schabowicz, 2005). Concrete is commonly utilised to construct protective structures that are subjected to a variety of harsh stress situations (Namyong *et al.*, 2004; Kamalloo *et al.*, 2010). The most commonly utilised construction material produced on the site is concrete. Cement, water, and aggregates are combined to make this composite material. Its manufacture entails a variety of activities that are dependent on the current site conditions (Diab *et al.*, 2014; Faruqui *et al.*, 2010). Concrete of acceptable quality can be made from ingredients with significantly varied qualities. Concrete's strength, durability, and other features are determined by the properties of its constituents, the quantities of the mix, the compaction method, and other factors (Mannan and Ganapathy, 2001; Mukherjee and Despande, 1995).

Concrete's popularity as a construction material stems from the fact that it is created from readily available components and can be customised to meet specific functional requirements. The water-cement ratio law governs the concepts of workability of fresh concrete, desired strength and durability of hardened concrete (Muthupriya *et al.*, 2011). The properties of the mortar, coarse aggregate, and the interface determine the strength of concrete. Variable types of coarse aggregate with different form, texture, mineralogy, and strength may result in different concrete strengths for the same quality mortar (Palika Chopra *et al.*, 2016).

The strength of nominal fixed volumetric cement-aggregate ratio mixtures results in under- or over-rich mixes (Gupta, 2013). As a result, many specifications contain a minimum compressive strength requirement. These mixes are called as Standard mixes. The proportions of materials in a concrete mix are commonly expressed in terms of parts or ratios of cement, fine and coarse aggregates. For example, a 1:2:4 concrete mix means that the proportions of cement, fine aggregate, and coarse aggregate are 1:2:4, or that the mix comprises one part of cement, two parts of fine aggregate, and four parts of coarse aggregate. The proportions are either by volume or by mass, giving you two options for design.

The IS standard code or the US system of units can be used to design the concrete mix. Compressive strength tests are often performed seven, fourteen, or twenty-eight days after the concrete is placed. Testing at 28 days is typical and hence required, although it can also be done at other times if necessary. Many researchers have employed artificial neural networks in structural engineering to construct multiple neural network models among the numerous properties of concrete, the most notable of which is its compressive strength. The workability of concrete, on the other hand, is critical in the mix design. Other elements such as the W/C ratio, aggregate fineness modulus, and cement specific gravity all play a role in mix formulation (Suryadi *et al.*, 2011; Yeh, 1998; Alilou and Teshnehlab, 2010; Aggarwal and Aggarwal, 2011).

Software Used

In this study MATLAB (MATrix LABoratory), a fourth-generation programming language is used. It has a numerical computing environment. Matrix manipulations, graphing of functions and data, implementation of algorithms, construction of user interfaces, and interfacing with programmes written in other languages, such as C, C++, Java, and Fortran, are all possible with MATLAB, which was developed by Math Works.

It is difficult to model a closed-form equation. The MATLAB Neural Network Toolbox contains functions and apps for modelling complex nonlinear systems that are difficult. With feed forward, radial basis, and dynamic networks, Neural Network Toolbox provides supervised learning. With self-organizing maps and competing layers, it also facilitates unsupervised learning. Neural Network Toolbox is used for data fitting, pattern recognition, clustering, time-series prediction, and dynamic system modelling and control, among other things.

For constructing, training, and simulating neural networks, Neural Network Toolbox provides command-line tools and programmes. The programmes make building neural networks for tasks like data fitting (including time-series data), pattern recognition, and clustering a breeze.

Objectives

The objectives of present study are as follows:

To select parameters to be used in Artificial Neural Network by concrete mix design of M35 grade concrete by ACI Method.

To apply a proper AI tool for generating training data for the network. A suitable collection of mix proportions with associated characteristic strength, water content, and fineness modulus of aggregate are necessary for training the neural network in order to construct an Artificial neural Network model for concrete mix design.

To run test problems and establish the network. Training the network for supervised learning after generating the test data and to compare them with actual experimental data. To compare the Neural Network predicted data to actual experimental data.

Methodology for Neural Identification of concrete strength

The formulation of concrete mix designs is based on empirical correlations between design parameters. After multiple attempts on the mix proportions, a standard concrete mix with the requisite strength can be achieved. An artificial neural network (ANN) is a network made up of multiple neuron nodes. Weights are carried via the connections between these neurons, defining the relationship between input and output data.

ANN is a technology that can be used to solve problems for which there is no known solution algorithm. Concrete mix design falls under the same category of issues. Concrete development, which necessitates a vast number of trials, is a complex challenge in and of itself.

A methodology for concrete strength prediction through neural identification has been developed.

Figure 1 shows the three blocks to explain methodology schematically. The experimental results which create a set of data on concrete that is used to train and test the neural network are represented byBlock-1. The trial results were saved as a set of patterns in a computer file, which was then used as the network's input data in Block-2. The data was separated into two categories: data for training and data for testing the neural network. The training patterns are fed into the network at random:

70% of total data is used to train the neural network

15% of total is used for validation of the neural network

15% of total data is used to test the neural network

ANN Modelling of Concrete Mix Design

The relationship between the input parameters and the related output parameters can be mapped using ANN. The capacity of the neural network approach to train a given data set and then forecast missing data and maybe normalise it makes it an excellent proposition for knowledge acquisition in problems where no acceptable theory exists. In the present study Back Propagation Neural Network has been used for finding out the ratio of fine aggregate and coarse aggregate. All of the input and output data has been normalised by the maximum value, referred to as the normalising factor, for each parameter, ensuring that the values remain within the range of 0 to 1. The network's output is produced as normalised output, which is then translated to actual values by multiplying each value by the same normalising factor that was used to prepare the training set. The initial weights were set to be a random value between –0.3 and +0.3.

Selection of Learning Parameter Rate and Momentum constant

Throughout the network's training, the learning rate parameter and momentum coefficient were kept constant. The learning rate parameter is fixed at 0.15, and the momentum constant is set at 0.75.

Architecture of Network

The network's architecture was chosen through trial and error in order to minimise error and attain fast convergence.

Network for Predicting Compressive Strength of Concrete

Network-I

This network has two hidden layers: an input layer and an output layer. As an activation function, a non-linear sigmoid function was used.

An input layer has six neurons namely:

Cement content

Fine aggregate

Coarse aggregate

Water content

Fineness modulus

Water cement ratio.

The output layer has three neurons namely:

7^{th} day compressive strength

14th day compressive strength

28th day compressive strength.

Network-II

To test Network-I another network is generated. This network consists of 2 hidden layers.

An input layer has 4 neurons namely:

Water cement ratio,

Water

Fineness modulus

28th day's strength of concrete specimen

The output layer has three neurons namely:

Cement content,

Fine aggregate

Coarse aggregate.

The architecture of the network model consists of input layer, hidden layer and output layer corresponding to the compressive strength. Figure 2 shows the ANN Architecture.

Results and Discussion

After developing the network, the next step is to train network. As mentioned earlier we have opted for supervised learning. The learning rule is based on a set of examples (the training dataset) of paper network behaviour in supervised learning.

The network outputs are then compared to the targets as the inputs are applied to the network. The learning rule is then implemented to the network's weights and biases in order to get the outputs closer to the targets. The target pairs are then formed for the training data.

ANN Program

The concrete mix design is done for M35 grade concrete. The ACI design approach was used to design the concrete mix in this study. Sands with a fineness modulus of 2.4 and 2.6 are selected since they are locally available. In total volume, coarse aggregates of 20mm are used. OPC Cement of 53 grade is used.

For total mix proportion twenty-eight cubes of 150 mm size were casted in the laboratory and tested in Compression Testing Machine for 7th, 14th and 28th days. Concrete mix proportioning and its compressive strength are given in Table 1 and are discussed in the following paragraphs.

Comparison

Difference between actual experimental data and predicted data which is generated by Artificial Intelligence tool of MATLAB are shown in Figure 2, Figure 3 & Figure 4.

Effect of water cement ratio

Variations of compressive strength by changing the water cement ratio have been plotted in figure. Compressive strength is found to diminish when the water cement ratio increases, regardless of the amount of cement, fineness modulus, or aggregate ratio utilised. Compressive strength is found to be higher at lower w/c ratios than at larger w/c ratios.

The graphs show how the actual and anticipated values differ. Because the approach is approximate, this difference is acceptable. The model's output is significant from the engineer's perspective on the following counts: it gives a mechanism to capture inherent vagueness in the design.

The percentage error in the Prediction of concrete strength has been observed between 2%-4.50% for this network (Maximum error can be allowed 10%).

Though this error cannot be eliminated, can be further reduced by increasing the number of test problems for training of network including variety of test problem for training network including verity of mix design parameters.

In comparison to the new IS approach, the ACI method has a higher fine aggregate content. The IS technique produces significantly more coarse aggregate. As a result, the ACI mix will improve workability. Because the spaces are filled with fine aggregate, it should contribute to greater strength. Fine aggregate content decreases when the design strength requirement rises in the case of IS.

Table.1 Following parameters are used for concrete mix design

A	**Water-Cement ratio**	**0.42-0.52**
B	Water	185 – 190 kg/m^3
C	Fineness modulus	2.4 – 2.6
D	Cement	355.77-462.5 kg/m^3
E	Fine aggregate	707.25-833.3 kg/m^3
F	Coarse aggregate	1024.12-1056.97 kg/m^3

Table.2 Concrete mix proportioning and its compressive strength

S. No.	W/c ratio	Cement	FA	CA	Water	F.M.	7 Days	14 Days	28 Days
1	0.4	462.5	711.97	1056.13	185	2.6	22.22	28.08	32.17
2	0.4	462.5	743.85	1024.04	190	2.4	27.68	32.71	38.4
3	0.4	452.38	707.25	1056.03	190	2.6	24.66	26.68	29.88
4	0.4	452.38	739.13	1024.04	185	2.4	27.35	28.68	35.88
5	0.42	440.45	730.2	1056.24	185	2.6	18.04	26.17	24.64
6	0.42	440.45	762.08	1024.26	190	2.4	19.86	27.91	28.68
7	0.42	452.38	707.25	1056.13	190	2.6	24.33	30.6	32.66
8	0.42	452.38	739.13	1024.97	185	2.4	26.15	32.62	34.2
9	0.44	420.45	747.2	1056.14	185	2.6	17.55	21.95	24.77
10	0.44	420.45	779.08	1024.89	190	2.4	20.64	22.46	26.95
11	0.44	431.82	724.48	1056.32	190	2.6	23.77	27.11	34.68
12	0.44	431.82	756.36	1024.31	185	2.4	27.35	31.71	34.68
13	0.46	402.17	762.52	1056.29	185	2.6	18.97	22.02	23.84
14	0.46	402.17	794.4	1024.63	190	2.4	19.22	25.55	28.55
15	0.46	413.04	740.22	1056.59	190	2.6	22.33	25.82	25.97
16	0.46	413.04	772.09	1024.24	185	2.4	23.48	26.42	28.97
17	0.48	385.42	776.57	1056.15	185	2.6	14.44	19.06	23.06
18	0.48	385.42	808.45	1024.12	190	2.4	20.8	24.75	31.95
19	0.48	395.83	754.64	1056.98	190	2.6	16.11	21.77	26.84
20	0.48	395.83	766.52	1024.96	185	2.4	20.4	22.73	32.55
21	0.5	370	789.49	1056.74	185	2.6	13.91	17.93	21.82
22	0.5	370	821.37	1024.24	190	2.4	21.6	21.82	24.88
23	0.5	380	767.91	1056.52	190	2.6	16.11	21.77	26.84
24	0.5	380	799.99	1024.55	185	2.4	20.04	22.73	32.55
25	0.52	355.77	801.42	1056.32	185	2.6	15.08	20.26	24.84
26	0.52	355.77	833.3	1024.99	190	2.4	17.13	23	28
27	0.52	365.38	780.16	1056.9	190	2.6	17.82	23.2	25
28	0.52	365.38	812.04	1024.45	185	2.4	24.31	27.57	28.9

Table.3 Actual Data, Predicted Data and Error

S. No.	Actual data			Predicted data			Error		
	7 Days	14 Days	28 Days	7 Days	14 Days	28 Days	7 Days	14 Days	28 Days
1	22.22	28.08	32.17	22.17	29.69	32.27	0.05	-1.61	-0.1
2	27.68	32.71	38.4	23.28	32	22	4.4	0.71	16.4
3	24.66	26.68	29.88	24.36	26.67	27.11	0.3	0.01	2.77
4	27.35	28.68	35.88	27.32	28.72	31.36	0.03	-0.04	4.52
5	18.04	26.17	24.64	18.1	27.89	32.38	-0.06	-1.72	-7.74
6	19.86	27.91	28.68	19.93	28.88	22	-0.07	-0.97	6.68
7	24.33	30.6	32.66	24.13	3.09	26.59	0.2	27.51	6.07
8	26.15	32.62	34.2	26.14	32.27	31.1	0.01	0.35	3.1
9	17.55	21.95	24.77	17.38	27.22	32.55	0.17	-5.27	-7.78
10	20.64	22.46	26.95	20.61	22.14	21.99	0.03	0.32	4.96
11	23.77	27.11	34.68	23.57	27.12	26.87	0.2	-0.01	7.81
12	27.35	31.71	34.68	24.96	31.71	31.7	2.39	0	2.98
13	18.97	22.02	23.84	17.67	22.01	32.86	1.3	0.01	-9.02
14	19.22	25.55	28.55	20.73	20.9	22.03	-1.51	4.65	6.52
15	22.33	25.82	25.97	19.43	25.35	26.08	2.9	0.47	-0.11
16	23.48	26.42	28.97	23.44	23.92	30.45	0.04	2.5	-1.48
17	14.44	19.06	23.06	15.21	18.26	32.99	-0.77	0.8	-9.93
18	20.8	24.75	31.95	20.85	24.76	22.11	-0.05	-0.01	9.84
19	16.11	21.77	26.84	16.14	21.78	25.42	-0.03	-0.01	1.42
20	20.4	22.73	32.55	20.62	22.76	30.2	-0.22	-0.03	2.35
21	13.91	17.93	21.82	14.13	18.32	33.89	-0.22	-0.39	-12.07
22	21.6	21.82	24.88	21.69	21.81	22.25	-0.09	0.01	2.63
23	16.11	21.77	26.84	16.06	21.26	24.8	0.05	0.51	2.04
24	20.04	22.73	32.55	19.98	22.71	30.42	0.06	0.02	2.13
25	15.08	20.26	24.84	14.15	20.17	34.46	0.93	0.09	-9.62
26	17.13	23	28	22.19	21.07	22.4	-5.06	1.93	5.6
27	17.82	23.2	25	17.88	23.19	24.28	-0.06	0.01	0.72
28	24.31	27.57	28.9	16.75	23.38	30.41	7.56	4.19	-1.51

Table.4 Comparisons of actual data and predicted data for 28 days Strength

S. No.	Actual Data			Predicted Data			Error		
	C kg/m3	FA kg/m3	CA kg/m3	C kg/m3	FA kg/m3	CA kg/m3	C kg/m3	FA kg/m3	CA kg/m3
1	462.5	711.97	1056.13	456.43	768.75	1056	6.07	-5.78	0.13
2	462.5	743.85	1024.04	451.75	728.56	1024	10.75	15.29	0.04
3	452.38	707.25	1056.03	454.46	718.92	1056	-2.08	-11.67	0.03
4	452.38	739.13	1024.04	453.6	748.31	1024	-1.22	-9.18	0.04
5	440.45	730.2	1056.24	436.48	774.63	1056	3.97	-44.43	0.24
6	440.45	762.08	1024.26	442.27	757.78	1024	-1.82	4.3	0.26
7	452.38	707.25	1056.13	448.59	723.7	1056	3.79	-16.45	0.13
8	452.38	739.13	1024.97	448.14	760.7	1024	4.24	-21.57	0.97
9	420.45	747.2	1056.14	423.1	795.88	1056	-2.65	-48.68	0.14
10	420.45	779.08	1024.89	423.75	772.5	1024	-3.3	6.58	0.89
11	431.82	724.48	1056.32	432.05	742.25	1056	-0.23	-17.77	0.32
12	431.82	756.36	1024.31	435.64	770.15	1024	-3.82	-13.79	0.31
13	402.17	762.52	1056.29	400.39	806.03	1056	1.78	-43.51	0.29
14	402.17	794.4	1024.63	401.6	789.23	1024	0.57	5.17	0.63
15	413.04	740.22	1056.59	408.48	729.39	1056	4.56	10.83	0.59
16	413.04	772.09	1024.24	412.5	777.83	1024	0.54	-5.74	0.24
17	385.42	776.57	1056.15	382.42	810.86	1056	3	-34.29	0.15
18	385.42	808.45	1024.12	384.4	808	1024	1.02	0.45	0.12
19	395.83	754.64	1056.98	392.48	749	1056	3.35	5.64	0.98
20	395.83	766.52	1024.96	392.3	777.35	1024	3.53	-10.83	0.96
21	370	789.49	1056.74	368.07	812.97	1056	1.93	-23.48	0.74
22	370	821.37	1024.24	371.58	819.98	1024	-1.58	1.39	0.24
23	380	767.91	1056.52	375.49	819.98	1056	4.51	-52.07	0.52
24	380	799.99	1024.55	377.49	778.76	1024	2.51	21.23	0.55
25	355.77	801.42	1056.32	366.67	814.76	1056	-10.9	-13.34	0.32
26	355.77	833.3	1024.99	363.26	824.95	1024	-7.49	8.35	0.99
27	365.38	780.16	1056.9	364.79	789.97	1056	0.59	-9.81	0.9
28	365.38	812.04	1024.45	367.22	783.27	1024	0.52	0.22	0.8

Fig.1 Block diagram for Neural Identification

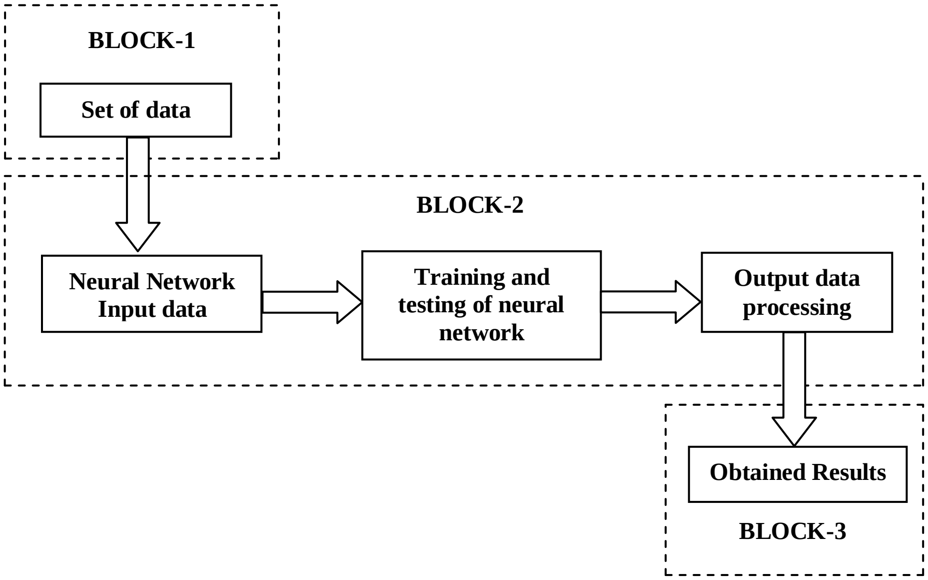


Fig.2 ANN Architecture

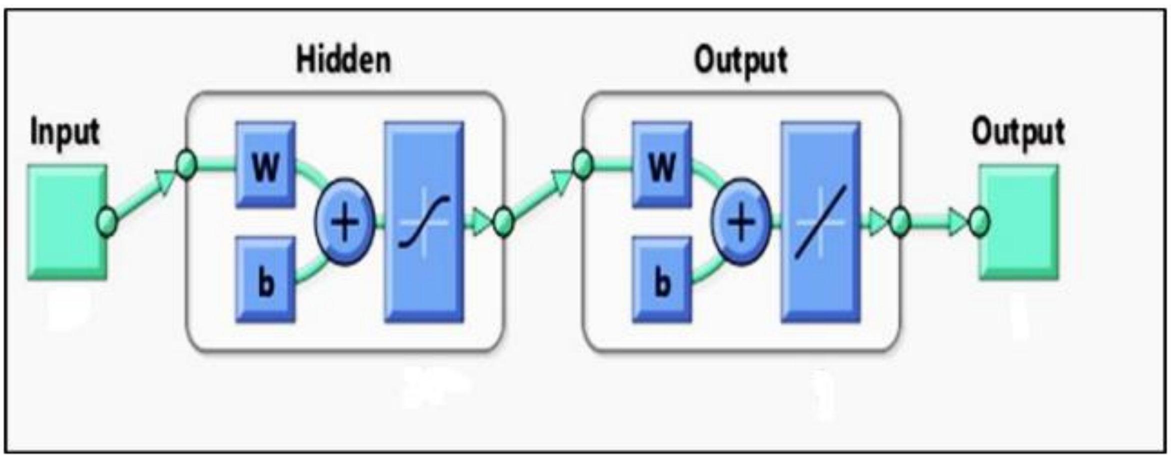


Fig.3 Difference between Actual data & Predicted data of 7 days strength.

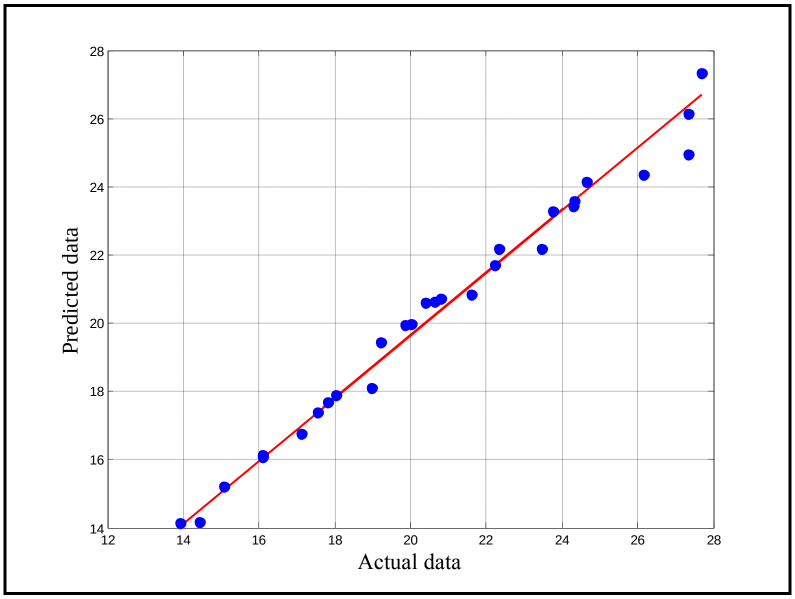


Fig.4 Difference between Actual data & Predicted data for 14 days strength.

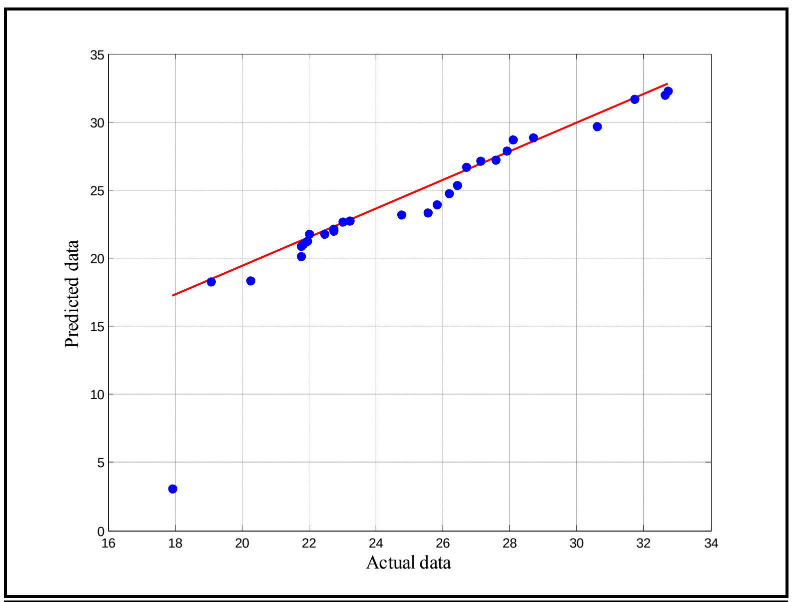
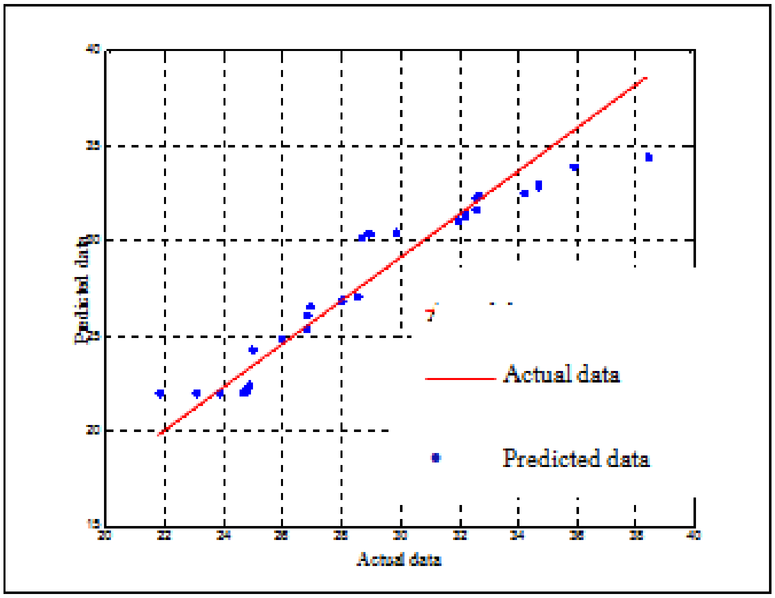


Fig.5 Difference between Actual data & Predicted data for 28 days strength



As a result, voids are likely to be greater in high-strength concrete, perhaps resulting in lower strength. Concrete is a highly complicated material, and accurately predicting and estimating its compressive strength is a challenging task.

The proposed ANN Artificial Intelligence models will save time, material waste, and design costs. An artificial intelligence controller was proposed in the study for determining compressive strengths at different ages of 7, 14, and 28 days. It allows the mix design expert to choose the suitable value for parameters such as compressive strength 7, 14, and 28.

All of the techniques successfully predicted the outputs. For engineers and research scientists working in the cement and concrete industry, ANN could be a helpful modelling tool for the purpose of compressive strength prediction. The ANN model aids in the acquisition and application of experimental data during the construction of new batches of trial mixes.

The study shows that neural networks can be used to capture non-linear interactions between numerous factors in complicated civil engineering systems. As a result, it can be stated that the usage of ANN is more user-friendly and that a more explicit model can be developed to assist the concrete industry in avoiding the danger of faulty or weak concrete, which often leads to durability and safety issues.

References

Aggarwal, Y. and P. Aggarwal, (2011), Prediction of Compressive Strength of SCC Containing Bottom Ash using Artificial Neural Networks, World Academy of Science, Engineering and Technology, 5, 662-667.

Akhmad Suryadi, Trimilan Pujo Aji. Artificial neural networks for evaluating the compressive strength of self compacting concrete. J Basic Appl Sci Res. 2011;1(3):236–241.

Alilou, V.K. and M. Teshnehlab, (2010), Prediction of 28-days compressive strength of concrete on the 3-day using Artificial Neural Network, International Journal of Engineering (IJE), 3(6), 565-576.

Diab, M., H. E. Elyamany, A. E. M. AbdElmoaty, and A. H. Shalan, “Prediction of concrete compressive strength due to long term sulfate attack using neural network,” Alexandria Engineering Journal, vol. 53, no. 3, pp. 627–642, 2014.

Faruqui, M A, R Agarwala, J Sai A. Application of artificial intelligence to predict compressive strength of concrete from mix design parameters: A structural engineering application. Journal of Civil Engineering Research. 2010;5(6):158–161.

Flood, I. and N. Kartam, (1994), Neural Networks in Civil Engineering–II: Systems and Application, Journal of Computing in Civil Engineering, 8(2), 149–162.

Gupta, S. (2013), Using artificial neural network to predict the compressive strength of concrete containing Nano-Silica, Civil Engineering and Architecture, 1(3), 96-102.

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

Kamalloo, Y. Ganjkhanlou, S. H. Aboutalebi, and H. Nouranian, "Modeling of compressive strength of Metakaolin based geopolymers by the use of artificial neural network," International Journal of Engineering, vol. 23, no. 2, pp. 145–152, 2010.

Khashman, A, P Akpinar. Non destructive prediction of compressive strength using neural networks. Procedia Computer Science. 2017;108C:2358–2362.

Mannan M A, Ganapathy C. Mix Design for Oil Palm Shell Concrete. Cement and Concrete Research. 2001;31(9):1323–1325.

Mukherjee and J. M. Despande, (1995), Modeling Initial Design Process using Artificial Neural Networks, Journal of Computing in Civil Engineering, 9 (3), 194–200.

Muthupriya, P., K. Subramanian and B. G Vishnuram, (2011), Prediction of compressive strength and durability of high performance concrete by artificial neural network, International Journal of Optimization in Civil Engineering, 1, 189-209.

Namyong, J., Y. Sangchun, and C. Hongbum, "Prediction of compressive strength of In-situ concrete based on mixture proportions," Journal of Asian Architecture and Building Engineering, vol. 3, no. 1, pp. 9–16, 2004.

Oreta, A. W. C. and K. Kawashima, (2003), Neural Network Modeling of Circular Confined Compressive Strength and Strain of Circular Concrete Columns, Journal of Structural Engineering, 129 (4), 554-561.

Palika Chopra, Rajendra Kumar Sharma, Maneek Kumar, Prediction of Compressive Strength of Concrete Using Artificial Neural Network and Genetic Programming, Advances in Materials Science and Engineering, vol. 2016, Article ID 7648467, 10 pages, 2016.

Suryadi, Triwulan and P. Aji, (2011), Artificial Neural Network for Evaluating the Compressive Strength of Self Compacting Concrete, Journal of Basic and Applied Scientific Research, 1(3), 236-241.

Yeh, I. C. Modeling of Strength of High Performance Concrete using Artificial Neural Networks, (1998), Cement and Concrete Research, 28(12), 1797-1808.

How to cite this article:

Anaa Pathak and Raana Pathak. 2022. Modelling of Concrete Strength Properties using the Artificial Intelligence tool of MATLAB. *Int.J.Curr.Res.Aca.Rev.* 10(07), 70-80. doi: https://doi.org/10.20546/ijcrar.2022.1007.004