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Prediction of Compressive Strength of Cement Mortar in Normal and Aggressive Environment Using Artificial Neural Network

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Abstract:

The influence of acidic aggressive chemicals on the behavior of building materials such as cement mortar and cement concrete are a topic of significance interest, as it affects durability of structures. Development of predictive models for the assessment of various properties and characteristics of a construction material is important for deciding its future use in appropriate applications. Various approaches have been used to model the conditions of decay and degradation of cement-based materials in aggressive environments. In this paper, Artificial Neural Networks (ANNs) have been used to predict the compressive strength of a cement mortar exposed to normal and aggressive environments. The results have been found to be encouraging.

Keywords: Cement mortar, Artificial neural network, Aggressive Environment

INTRODUCTION

Cement based materials such as cement mortar and cement concrete have been regarded as the most prominent and promising material of construction in modern times. Durability related issues for such materials become very important in aggressive environments. The influence of such environments may affect various durability related properties of such materials (Al- Amoudi 2002; Tamimi et al 2003; Brown et al 2004; Barbara 2008; Abdelmseeh 2008; Irassar et al. 2009; Aye et al 2012; Zeng et al 2018,). Apart from such issues various properties in the hardening stage are to be assessed so that appropriate decisions about the quality of mixes, to be used, might be taken. In such situations also, some predicting system is of a great importance.

Lakhdari (2017) has considered the durability aspects of 1:3 cement mortar samples in water and aggressive environments of Na2SO4 and MgSO4. The samples were water cured for 28 days and then these were put to aggressive environments. The study lasted for a duration of 3 months. In the environments of Na2SO4, a degradation of compressive strength from 38.5 MPa to 29 MPa has been reported. In the case of other environments, the degradation has been reported to be from 38.5 MPa to 27 MPa. In the initial curing in water for a duration of 28 days, strength increased as usual. In a separate study of 360 days by Huang Ji Zhuanga et al., (2017), the effect of 5% NaCl has been monitored for a duration of one year. In the case of water curing of mortar samples, compressive strength improved but in the aggressive environment of NaCl there was a conflicting pattern of increase and decrease of compressive strength. The reason for the increase of compressive strength at a particular time seems to be filling up of internal pores by ettringite. In a study by Demir et al., (2018), the cement mortar samples were put to aggressive environment of Na2SO4 from the start of the study. Water binder ratio was varied from 0.5 to 0.625. The study lasted for a period of 365 days. Values of compressive strength were reported for different ages from 7 days to 365 days for different mixes as per water binder ratio. Compressive strength in water curing condition increased from 44.6 MPa to 54.85 MPa within a time span of one year for 0.5 % water binder ratio. Kallel et.al., (2016) has reported a study conducted in Na2SO4 and HCl for a period of one year. Decrease of compressive strength has been seen to be more in the case of HCl. In the study reported by Lee (2009) a comparative study of development of compressive strength in water and MgSO4 has been made. Water cement ration of 0.45 was taken for the cement mortar samples. Compressive strength improved from 46.8 MPa to 59.1 MPa in a time span of 360 days. In the environment of MgSO4 it changed from 40.9 MPa to 38.2 MPa. In a study conducted by Sarıdemir (2009) the amount of superplasticizer was changed from 0.5 to 1.3%. It was found that compressive strength increased in the case of use of superplasticizer in cement mortar mixes. In another study by Tamiz (2017) it has been found that compressive strength deterioration occurred faster in the case of MgSO4 in comparison to Na_2SO_4 environment in a time span of 450 days.

The above discussion underlines the importance of prediction of compressive strength of cement mortar mixes in various environmental conditions, seeing to a long span of time which is needed to appreciate the effect of a particular environment on it. Normally a finite time span is needed to appreciate strength development in cement mortar mixes in a particular environment. It would be important to have sound modelling systems to predict properties of cement mortar in such cases to reduce the time requirement to assess the effect of a particular aggressive environment on cement mortar.

EXPERIMENTAL PROGRAMME

Durability performances of cement mortar mixes, with or without superplasticizers, were determined in 1N and 2N H_2SO_4 environment. Properties of cement and superplasticizer used in this sample preparation are given in Table-1 and Table-2 respectively. The fine aggregate used was Yamuna sand.

Mortar cubes samples of size 70.7 mm were prepared as per Indian standard procedure. Three dosage of superplasticizer 0.5%, 1%, 1.5% by weight of cement were taken.

Table 1. Properties of Cement

Properties	values
Cement Type	OPC 43 Grade
Specific gravity	3.15
Autoclave expansion (%)	0.10
Fineness (m^2/kg)	293
Initial Setting time (minute)	140
Final setting time	265
Consistency	31.5

Two mixes of cement: sand proportions (1:4 and 1:6) were prepared. The specimens were placed inside the curing tank in normal water for 28 days. After 28 days, some specimens were put in normal water and some cubes were stored in acidic water made by H_2SO_4 addition (1Normal & 2 Normal concentration). In both aggressive environments, the H_2SO_4 solution was replaced from time to time. Visual examination of the samples was performed at regular intervals and all significant moderation such as color change, efflorescence, change in texture, cracking, expansion, etc, were recorded. The compressive strength of the mortar specimens was measured after 28 days, 90 days, 180 days and 360 days of exposure in water and in both aggressive environments to investigate the effect of the sulfate attack on the strength loss of the samples.

Table 2. Properties of Superplasticizer

Type /chemical origin	Polycarboxylates
Specific gravity	1.03
Color	Light yellow
Form	Liquid
Chloride content	Nil
Alkali content	Typically, less than 1.5g Na_2O equivalent /liter of admixture
P^H	Minimum 6

In this paper, an effort has been made to predict compressive strength of cement mortar in various environmental conditions. The requirement of the development of cement-based mixes having more strength has resulted into the increased use of superplasticizers in concrete mixes. That is why prediction of compressive strength of cement mortar mixes, in which superplasticizer was used, has also been made.

Use of Artificial Neural Network (ANN) for prediction of compressive strength

Use of ANN has been made by various researchers to predict various properties of cement-based materials (Roca et al 2013; Eskandari 2016). Artificial neural network (ANN) is a computational or mathematical non-linear statistical data modeling tool that is inspired by structural and functional neuron aspects of the human brain [Behnood et al., 2018]. It consists of many artificial neurons interconnected where each of them gives a single output induced from all inputs (Deng 2018; Topcu 2008). The neural network is a massively parallel distributed processor that has a tendency for storing experience knowledge and making it available for use. ANN collects the data by input layer of neurons, sometimes referred to as nodes or processing units. After a neural network has been created, it needs to be configured and then trained. Layers between the input and output layers are called hidden layers and may contain a large number of hidden processing units. The input layer neurons receive information from the outside environment and transmit them to the neurons of the hidden layer without performing any calculation. Finally, the output layer neurons produce the network predictions to the outside world (Naderpour et al 2018; Zhou et al 2016; Wang et al 2018; Yadollahi et al 2016; Deshpande et al 2014).

Feed-forward networks are the most popular models and widely used in many practical applications. Feed-forward neural networks are also known by many other names, such as multilayer perceptrons (MLP) which is a modification of standard linear perceptron. Feedforward networks can be used for any kind of input to output mapping. The artificial neurons consist of a series of layers and all the neurons in each layer have connections to all the neurons in the next layer. The first layer has a connection from the network input. Each subsequent layer has a connection from the previous layer. The final layer produces the network's output. It can distinguish data that is not linearly separable. A feedforward network with one hidden layer and enough neurons in the hidden layers, can fit any finite input-output mapping problem. Generally, network consists of one input layer, hidden layers (one or two) and one output layer of neurons. Each neuron in the network behaves in the same way.

RESULTS AND DISCUSSION

In the present study, feed-forward back propagation artificial neural network model is used. ANN has been adopted in mortar mix design due to complex relation between mortar behavior due to addition of superplasticizers and mix design proportion for determining the compressive strength in normal and aggressive environment condition. The modelling has been carried out with the data available from the literature. Table 3 provides experimental and predicted values of compressive strength (F_c) for various types of cement mortar mixes in water and aggressive environmental conditions. Table 4 compares the differences between these values in percentage terms.

Table 3: Experimental and predicted values of compressive strengths

Mix. No.	Independent variables			F_C, MPa in water		F_C, MPa in H_2SO_4 (1N)		F_C, MPa in H_2SO_4 (2N)	
	Cement: sand	SP, %	Age (days)	Experimental	Predicted	Experimental	Predicted	Experimental	Predicted
1.	1:4	0	28	22.47	21.99	22.47	22.36	22.47	22.15
2.	1:4	0.5	28	27.88	26.51	27.88	27.50	27.88	28.66
3.	1:4	1	28	30.66	29.37	30.66	29.60	30.66	30.79
4.	1:4	1.5	28	29.6	30.48	29.60	29.17	29.6	30.48
5.	1:4	0	90	26.61	26.87	26.30	26.48	26.1	23.14
6.	1:4	0.5	90	33.33	31.85	32.90	33.42	32.6	30.91
7.	1:4	1	90	36.7	34.7	36.30	36.60	36.2	33.77
8.	1:4	1.5	90	35.2	35.54	34.90	36.41	34.8	33.53
9.	1:4	0	180	29.06	31.46	17.30	17.57	17.1	17.85
10.	1:4	0.5	180	36.2	36.58	21.70	21.14	21.5	23.09
11.	1:4	1	180	39.9	39.32	24.20	23.19	24.1	23.73
12.	1:4	1.5	180	37.9	39.87	22.90	23.52	22.9	21.63
13.	1:4	0	360	30.22	25.73	11.90	13.52	11.7	10.83
14.	1:4	0.5	360	37.8	32.39	15.10	14.76	14.6	14.98
15.	1:4	1	360	41.7	36.91	17.20	14.75	17	17.36
16.	1:4	1.5	360	39.7	38.78	16.00	13.68	15.7	16.25
17.	1:6	0	28	18.16	17.5	18.16	18.01	18.16	19.05
18.	1:6	0.5	28	18.52	17.94	18.52	18.37	18.52	20.19
19.	1:6	1	28	20.48	19.33	20.48	19.17	20.48	20.75
20.	1:6	1.5	28	21.77	22.74	21.77	20.77	21.77	21.91
21.	1:6	0	90	21.2	20.51	21	21.45	20.7	19.00
22.	1:6	0.5	90	21.7	20.8	21.5	22.34	21.3	21.75
23.	1:6	1	90	24.2	22.18	24	23.59	23.7	23.48
24.	1:6	1.5	90	25.6	25.85	25.5	25.65	25.2	25.50
25.	1:6	0	180	23.1	23.94	13.2	13.86	13.4	12.17
26.	1:6	0.5	180	23.7	23.97	14.3	14.72	13.9	13.50
27.	1:6	1	180	26.3	25.16	16	16.13	15.6	14.37
28.	1:6	1.5	180	27.9	28.87	17.2	18.47	16.6	15.50
29.	1:6	0	360	23.9	24.01	9.1	10.37	8.4	9.40
30.	1:6	0.5	360	24.4	24.64	9.4	10.29	8.6	10.05
31.	1:6	1	360	27.4	25.96	11.1	10.25	10	10.55
32.	1:6	1.5	360	28.8	29.61	11.8	10.33	10.8	10.82

Table 4: Comparison between Experimental and Predicted values

Mix No.	Independent variables			Variation between predicted and Experimental strength in water, %	Variation between predicted and Experimental strength in H_2SO_4 (1N), %	Variation between predicted and Experimental strength in H_2SO_4 (2N), %
	Mix	SP, %	Age (days)			
1.	1:4	0	28	-2.15	-0.50	-1.41
2.	1:4	0.5	28	-4.92	-1.36	2.78
3.	1:4	1	28	-4.22	-3.46	0.43
4.	1:4	1.5	28	2.98	-1.46	2.96
5.	1:4	0	90	1.00	0.68	-11.35
6.	1:4	0.5	90	-4.43	1.58	-5.20
7.	1:4	1	90	-5.44	0.81	-6.71
8.	1:4	1.5	90	0.96	4.33	-3.64
9.	1:4	0	180	8.26	1.55	4.39
10.	1:4	0.5	180	1.06	-2.59	7.39
11.	1:4	1	180	-1.46	-4.17	-1.54
12.	1:4	1.5	180	5.21	2.71	-5.56
13.	1:4	0	360	-14.86	13.62	-7.43
14.	1:4	0.5	360	-14.32	-2.25	2.62
15.	1:4	1	360	-11.48	-14.22	2.11
16.	1:4	1.5	360	-2.32	-14.47	3.49
17.	1:6	0	28	-3.66	-0.84	4.90
18.	1:6	0.5	28	-3.11	-0.83	9.03
19.	1:6	1	28	-5.60	-6.41	1.30
20.	1:6	1.5	28	4.45	-4.59	0.64
21.	1:6	0	90	-3.27	2.12	-8.23
22.	1:6	0.5	90	-4.16	3.93	2.12
23.	1:6	1	90	-8.36	-1.71	-0.91
24.	1:6	1.5	90	0.99	0.58	1.18
25.	1:6	0	180	3.62	5.00	-9.18
26.	1:6	0.5	180	1.12	2.97	-2.86
27.	1:6	1	180	-4.33	0.80	-7.87
28.	1:6	1.5	180	3.49	7.40	-6.63
29.	1:6	0	360	0.47	13.93	11.90
30.	1:6	0.5	360	1.00	9.45	16.83
31.	1:6	1	360	-5.25	-7.64	5.51
32.	1:6	1.5	360	2.81	-12.43	0.21

It is appreciated that the use of ANN for prediction of compressive strength values of cement mortar samples works in a satisfactory manner in different environments. In the case of water curing the minimum and maximum differences of experimental and predicted values are found to be 0.4% and 14.86% respectively. On an average scale the difference is about 4.4% which seems to be within acceptable limits. A greater value of difference in this study may be lack of knowledge of all the parameters in the past studies made by researchers. Standard deviation of 3.61% was found in this case. For the 1N aggressive environment of H2SO4, these values are 0.5%, 14.47%, 4.7% and 4.54% respectively. These values seem to be in line with those obtained in the case of water curing. It implies that the use of ANN can be effectively made in the case of samples put in aggressive environments. In the case of 2N aggressive environment of H2SO4, these values are found to be 0.21%, 16.83%, 4.95% and 3.9% respectively. Compared to the 1N aggressive environment, the minimum value of this case is found to be appreciably lower. This seems to give the impression that it may be more accurate to predict the effect of an aggressive environment it the severity of the environment is more.

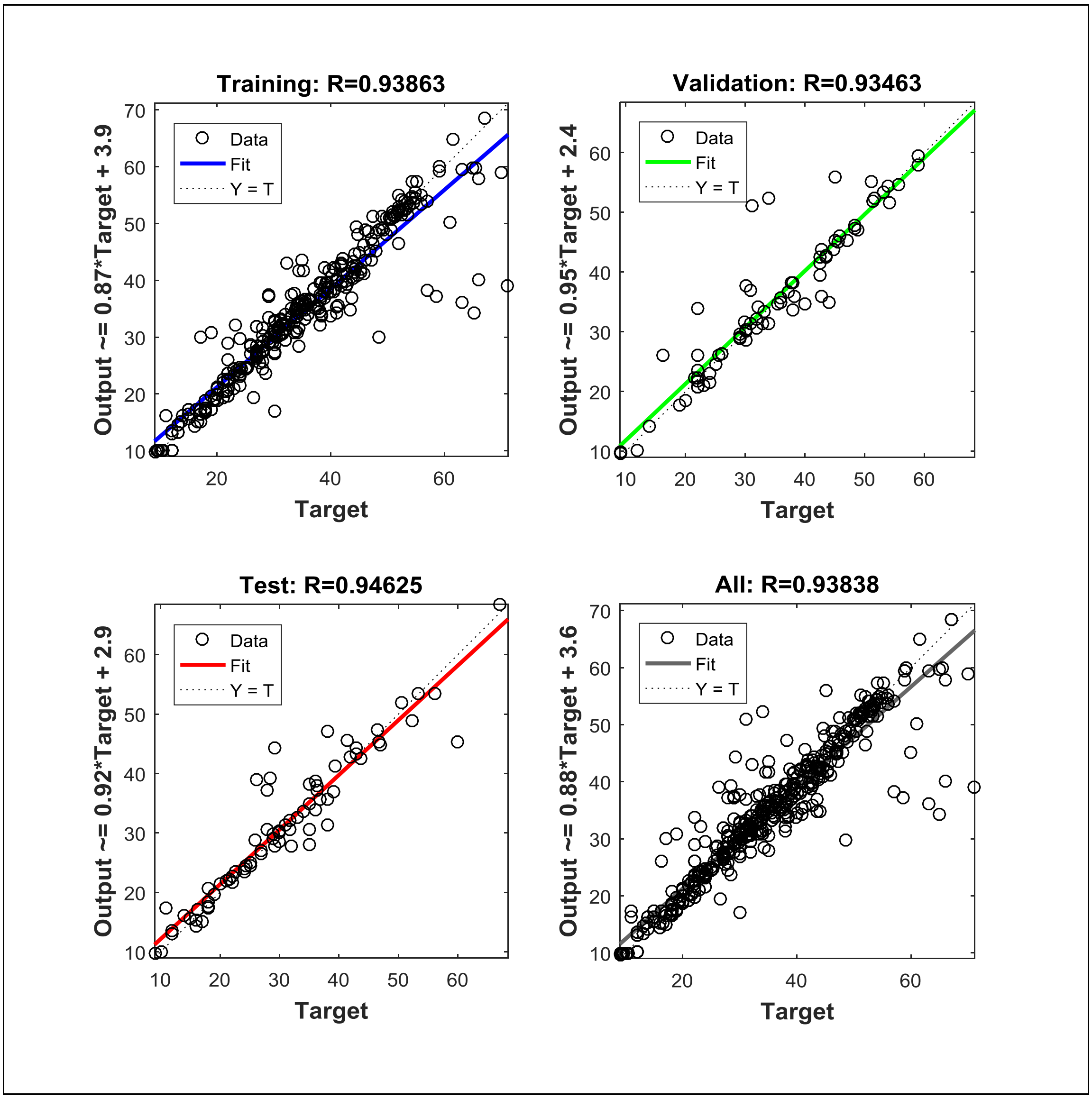

Fig. 1: Regression data for the input and predicted values

The prediction of compressive strength in aggressive environments may be more effective if sufficient parameters of past studies, undertaken by researchers, are known. This study has given sufficiently accurate results even when many parameters of past studies were not exactly known and those could not be verified. The results of regression analysis shown in Fig. 1 gives good results and it validates the use of ANN for the prediction of compressive strength values.

CONCLUSION

Based on the findings of this study it can be concluded that

1. The use of ANN technique for the prediction of compressive strength of cement mortar can be effectively made. The technique has worked well within acceptable limits for two types of aggressive environments also.
2. The prediction of compressive strength in aggressive environments may be more effective if sufficient parameters of past studies, undertaken by researchers, are known.
3. In this study a variation of superplasticizer content was considered. It is seen that variation of predicted values from experimental results change for a corresponding change in superplasticizer content. It shows that the content of superplasticizer also is an important parameter affecting compressive strength and it affects the performance of cement mortar in aggressive environment.
4. It seems that the accuracy of prediction may be more closely aligned with the experimental values if the degree of severity of aggressive environment increases. It is obvious as the effect of more severe environment can be readily assessed. In the case of less severe environments, the effect is difficult to be diagnosed and there are many grey areas in terms of actual effects of various parameters.

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