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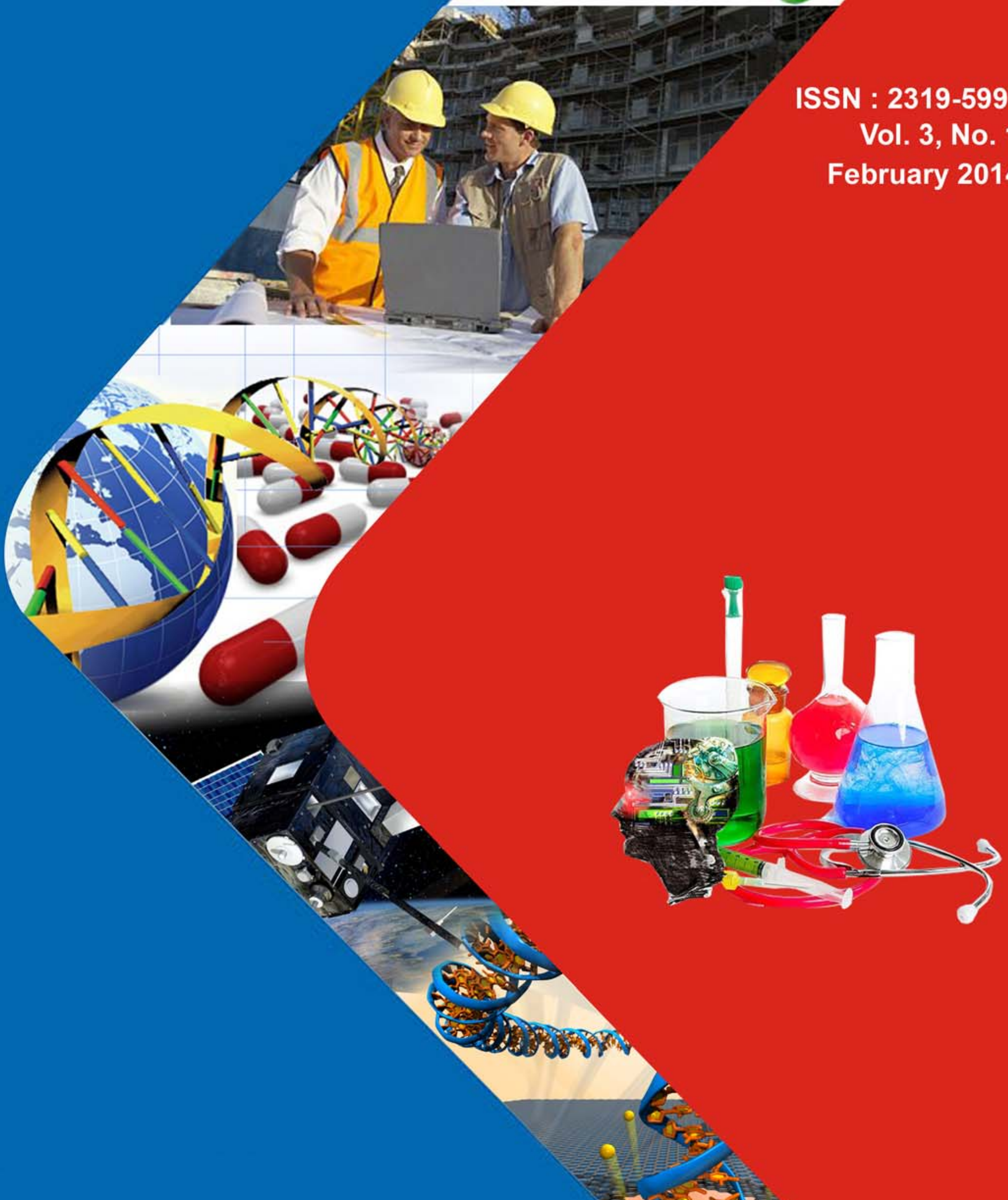

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Research Paper

NEURO-FUZZY MODEL TO EVALUATE READY-MIX CONCRETE PROPERTIES

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This study, implementation of an artificial Neural Network and Neuro-Fuzzy system has been developed for prediction of compressive strength of Ready Mix Concrete (RMC). Factors affecting strength of RMC in general were studied. Focus was made on mix constituents in particular as they found to be of significant importance and can have great role in strength development of concrete. As a result; mix constituents considered as input variables, and neural networks besides Neuro-Fuzzy system were constructed. These models have been validated and tested to predict the 28-days compressive strength of RMC. Analyzing the results indicate that Neuro-Fuzzy model was more feasible in predicting the 28-days RMC compressive strength. The resulting model reflect high correlation factor of (r_T = 1, r_t = 0.99994, r_V = 0.99999, r_{all} = 0.99999) for the train, test, validation and full data set respectively.

Keywords: Artificial intelligent, Concrete, Ready mix, Neural

INTRODUCTION

The compliance of any produced concrete with standard specifications considers as significant evidence for good concrete. These specifications, generally, include a statement of physical and chemical requirements. Among all, strength tests are prescribed by all specifications, because compressive strength of concrete in the hardened condition is very important, and perhaps it is the most obviously required for structural use.

Specifications usually specify test method as well as age of test. Strength of concrete, as specified by all the standards, is very important (from 1 to 28 days), because after all, it is this property which is relied upon in structural design of concrete as a construction material (Kheder *et al*., 2003).

Neural Networks and Neuro-Fuzzy have been proposed in this work because strength of concrete is a complex non-linear process dependent on many variables. It is a problem well suited to the artificial intelligence concept known as Artificial Neural Networks (ANNs) and Fuzzy logic. Artificial neural networks and fuzzy logic have been widely used in many areas in civil engineering applications. Most of the interested

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researchers ensure that the ANN can be used to predict some properties of concrete as core compressive strength of SCC using the ingredients of concrete (Mucteba Uysal and Harun Tanyildizi, 2011), compressive strength of recycled aggregate concrete (Duan *et al*., 2013), and compressive strength of expanded polystyrene light weight concrete (Sadrmomtazi *et al*., 2013), cement compressive strength at the age of 7 and 28 days within 24 h (Kheder *et al*., 2003) and many others.

One of the complex problems in the civil engineering works; is the problem of the concrete properties. The main purpose of mix design is to obtain a product that will perform according to predetermined requirements. These principal requirements include but not limited to: concrete properties, quality (strength and durability), workability, and economy.

ARTIFICIAL NEURAL NETWORK

An ANN is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well. Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback and several eras (Abbas *et al*., 2008).

Input Variables to Predict Concrete Strength

Strength of concrete is commonly considered its most valuable property, although, in many practical cases, other characteristics, such as durability and permeability, may in fact be more important. Nevertheless, strength usually gives an overall picture of the quality of concrete because strength is directly related to the structure of the hydrated cement paste. Moreover, the strength of concrete is almost invariably a vital element of structural design and is specified for compliance purposes. Factors that affect concrete strength may be divided into four categories: (1) constitute materials, (2) methods of preparation, (3) curing procedures, and (4) test conditions. Therefore, we will be concerned with the effects of constitute materials (water, cement, and aggregate) on concrete strength.

The influence of the water/cement ratio (*w/c*) on strength does not truly constitute a law because the water/cement ratio rule does not include many qualifications necessary for its validity. In particular, strength at any water/cement ratio depends on; degree of hydration of cement, chemical and physical properties of cement, temperature at which hydration takes place, air content of the concrete, change in the effective water/cement ratio, formation of cracks due to bleeding. The cement content of the mix and the properties of the aggregate-cement paste interface are also relevant. It is more correct, therefore to relate strength to the concentration of the solid products of hydration of cement in the space available for these products. In addition, the rate of strength gain depends on the *w/c* ratio, low *w/c* ratio mixes gain strength faster than high *w/c* ratio mixes.

Concrete is a mixture of cementious material, aggregate, and water. Aggregate is commonly considered inert filler, which accounts for 60 to 80% of the volume and 70 to 85% of the weight of concrete. When determining the strength of normal concrete, most concrete aggregates are several times stronger than the other components in concrete and therefore not a factor in the strength of normal strength concrete. Lightweight aggregate concrete may be more influenced by the compressive strength of the aggregates.

MATERIALS AND METHODS

The data were imported from previous research, the reasons behind choosing this set of data "Table 1" due to the large number of concrete mixes samples, and these mixes were from different plants of ready mix concrete, and this is to prove that the proposed model valid for ready mix concrete. Another reason that these data were from Korea, so, this is also a good prove that the model could work for any type and any place in spite of variation of data. The variation in test results for ready mix concrete are much more that of ordinary concrete and this is very important to how the technique deal and analyze the data and how close the prediction will be to the real data.

Variation in concrete strength of the test specimens depends on how well the materials, concrete manufacture and testing is controlled. Especially construction practices may cause variation in strength of in-situ concrete due to inadequate mixing, poor compaction, delay and improper curing. The variables available in data are mix proportions, i.e., the percent of materials used in the mix and slump test results with the percent of the admixture material (Jee Namyong *et al*., 2004).

RESULTS AND DISCUSSION

It is very important to analyze the effect of mix constituents on strength of concrete. Mix design is a specific combination of raw materials that are used in a particular concrete to reach a given target strength. So the significant factor in 28 days compressive strength is the concrete composition. Concrete theory suggested that water to cement ratio (w/c) of concrete is a primary factor influencing the strengthening process, both the final strength and the rate of hardening are affected. Also, it is well known that decreasing water content increases strength for the concrete. Furthermore, strength of concrete is highly affected by cement content and amount of fine and coarse aggregate used in the mix as well as any other additional material added to the mix in order to improve specific property for the concrete like fly ash, silica fume and slag or admixture like superplasticizer.

Test the Original Data Set: First test with traditional Neural Network was constructed for the prediction of compressive strength of concrete as a unique output, compared with compressive strength of concrete that obtained through practical test by researchers as output. Figure 1 shows a comparison between the compressive strength of original data set (blue line) and predicted compressive strength (red line). The

Table 1: Ready Mix Proportions with Compressive Strength

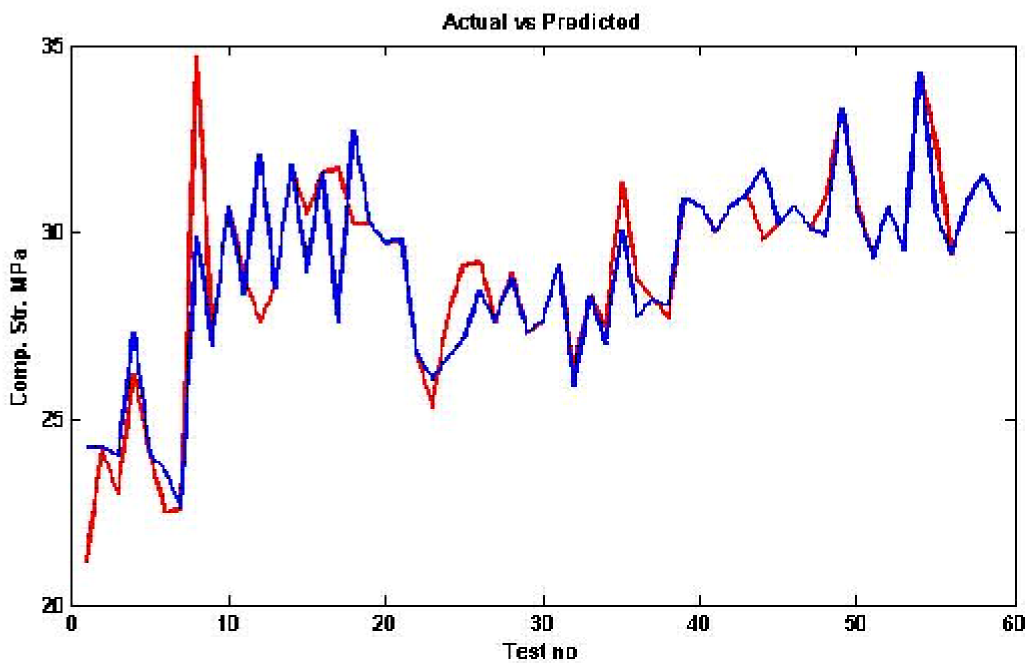
S. No.	w/c%	S/a%	Weight of Unit Volume (kg/m^3)					Compressive Strength (MPa)	
			W	C	S	g	Agent	7 Days	28 Days
1	60.21	51.19	174	289	933	900	0.86	15.5	21.2
2	59.74	52.07	184	308	927	860	0.91	16.3	24.2
3	60.6	52.04	183	302	926	860	0.91	16.3	23
4	57.48	52.7	173	301	961	863	0.9	21.5	26.2
5	60.32	50.9	190	315	904	862	0.47	18.6	24
6	61.49	51.2	190	309	911	859	0.46	17.4	22.5
7	59.55	46.09	184	309	821	975	0.92	15.8	22.6
8	50	48.47	164	328	886	942	1.64	23.2	34.7
9	47.83	45.1	176	368	805	988	0.77	19.1	26.9
10	49.44	48.8	178	360	858	914	1.08	23.3	30.7
11	52.35	47.88	178	340	839	931	0.51	22.6	28.8
12	44.47	44.9	165	371	810	1000	1.85	20.7	27.6
13	44.69	47.6	164	367	847	940	1.84	18.9	28.5
14	48.56	49.63	169	348	882	902	1.74	24.1	31.8
15	48.92	49.4	181	370	866	887	1.11	23	30.5
16	50	49.51	171	342	885	913	1.71	23	31.6
17	49.73	49.93	181	364	865	874	1.09	21.6	31.7
18	44.75	48.77	179	400	835	894	2.8	22	30.2
19	45.34	46.14	180	397	790	939	2.78	22.4	30.2
20	46.56	43.9	183	393	759	981	1.18	20.4	29.7
21	50	45.99	175	350	804	955	1.05	16	29.8
22	47.04	44.71	183	389	778	962	1.17	19.8	26.7
23	47.3	44.71	184	389	778	962	1.17	18.1	25.3
24	48.04	47.09	184	383	810	924	1.15	20.1	27.8
25	48.41	47.41	183	378	807	902	1.13	22	29.1
26	48.41	47.41	183	378	818	924	1.13	22.8	29.2
27	47.79	47.59	184	385	812	922	1.16	21.2	27.6
28	45.69	48.32	175	383	846	905	0.77	22.8	28.9
29	46.76	50.31	173	370	889	878	1.11	21.3	27.3

Table 1 (Cont.)

S. No.	w/c%	S/a%	Weight of Unit Volume (kg/m³)					Compressive Strength (MPa)	
			W	C	S	g	Agent	7 Days	28 Days
30	46.74	50.49	179	383	879	862	1.15	21.2	27.6
31	44.21	49.01	168	380	868	903	1.9	21.1	29.1
32	47.77	46.1	182	381	812	956	0.8	20	26.2
33	45.14	47.2	172	381	815	940	1.91	21.5	28.3
34	48.41	47.41	183	378	807	923	1.13	20.7	27.5
35	45.89	43.5	184	401	754	978	2.01	23.7	31.3
36	48.56	45.8	185	381	800	946	1.91	21.9	28.7
37	45.69	48.3	175	383	863	888	1.92	20.6	28.2
38	47.78	45.14	172	360	794	965	1.08	21	27.7
39	45.87	44	189	412	730	947	1.65	25	30.9
40	45.99	43.96	189	411	732	951	1.44	20.7	30.7
41	42.76	46.29	180	421	784	927	0.85	22.7	30
42	40.89	42.47	184	450	713	977	1.35	22.6	30.7
43	40.62	42.01	184	453	704	983	1.59	23.6	31
44	41.97	47.49	183	436	804	889	0.87	22.8	29.8
45	44.1	48.32	187	424	812	882	1.27	22.4	30.2
46	43.57	46.8	183	420	785	920	1.26	22.8	30.7
47	44.31	46.61	183	413	780	921	1.24	23.9	30.1
48	44.31	46.61	183	413	791	923	1.24	23.6	30.9
49	40.98	46.42	168	410	811	936	2.05	22.6	33.3
50	42.45	47.71	180	424	813	891	1.27	22.9	30.8
51	44.31	46.61	183	413	783	956	0.87	20.8	29.3
52	48.4	47.6	196	405	786	879	0.61	22.4	30.7
53	45.17	48.5	187	414	818	883	1.24	22.8	29.5
54	44.31	46.61	183	413	780	900	1.24	25.9	34.3
55	44.31	46.6	183	413	783	914	1.24	24.5	32.4
56	39.37	45.2	176	447	760	970	1.34	24.7	29.4
57	43.75	44.7	182	416	771	954	2.08	23.4	30.8
58	41.47	45.5	175	422	782	937	0.84	23.7	31.5
59	43.85	44.59	171	390	768	969	1.17	24.9	30.6

Note: Were w/c = water to cement ratio, S/a= strength of aggregate , W=water, C=cement, S=sand, g=gravel, agent=superplasticizer.

Figure 1: Compressive Strength Vs. Test No. of the Original Data Set



model constructed with one layer for the output and three layer for the inputs. The number of neurons was (15, 15, 25) respectively for each layer and the type of function was tansig for all layers. The epoch number was 8 but the actual need was 8 iterations only to reach the represented model. The time for analysis and model development was 1 s only.

The coefficient of correlation for the train, test, validation and all data set were (R_{train} = 1, R_{test}=0.58123 , R_{val}=0.90674, R_{all}=0.88472) respectively (Figure 2)

The best performance was at epoch number 5 with performance equal to 2.1468. There were some convergences between the results of the train, validation and test data set with the best solution. The comparison between the observed and predicted outputs (compressive strength at age of 28 days) shows that the behavior of predicted data was close to the actual results except six points was diverge from the line of equality.

Test with Neuro-Fuzzy Technique

Neuro_Fuzzy technique used to analyze the set of data and construct the model with one layer for the output and three layer for the inputs. The number of neurons were (15, 15, 15, 25) respectively for each layer and the type of function was tansig for all layers. The epoch number was 500, but the actual need was 59 iterations only to reach the represented model. The time for analysis and model development was few seconds only. This model reflect very excellent prediction (Figure 3).

The coefficient of correlation for the train, test, validation and all data set were ($r_{T=}$ 1 , $r_{t=}$0.99994, $r_{V=}$ 0.99999 , $r_{all=}$ 0.99999) respectively (Figure 4). The best performance was at epoch number

Figure 2: Correlation of Predicted Compressive Strength for the Original Date Set

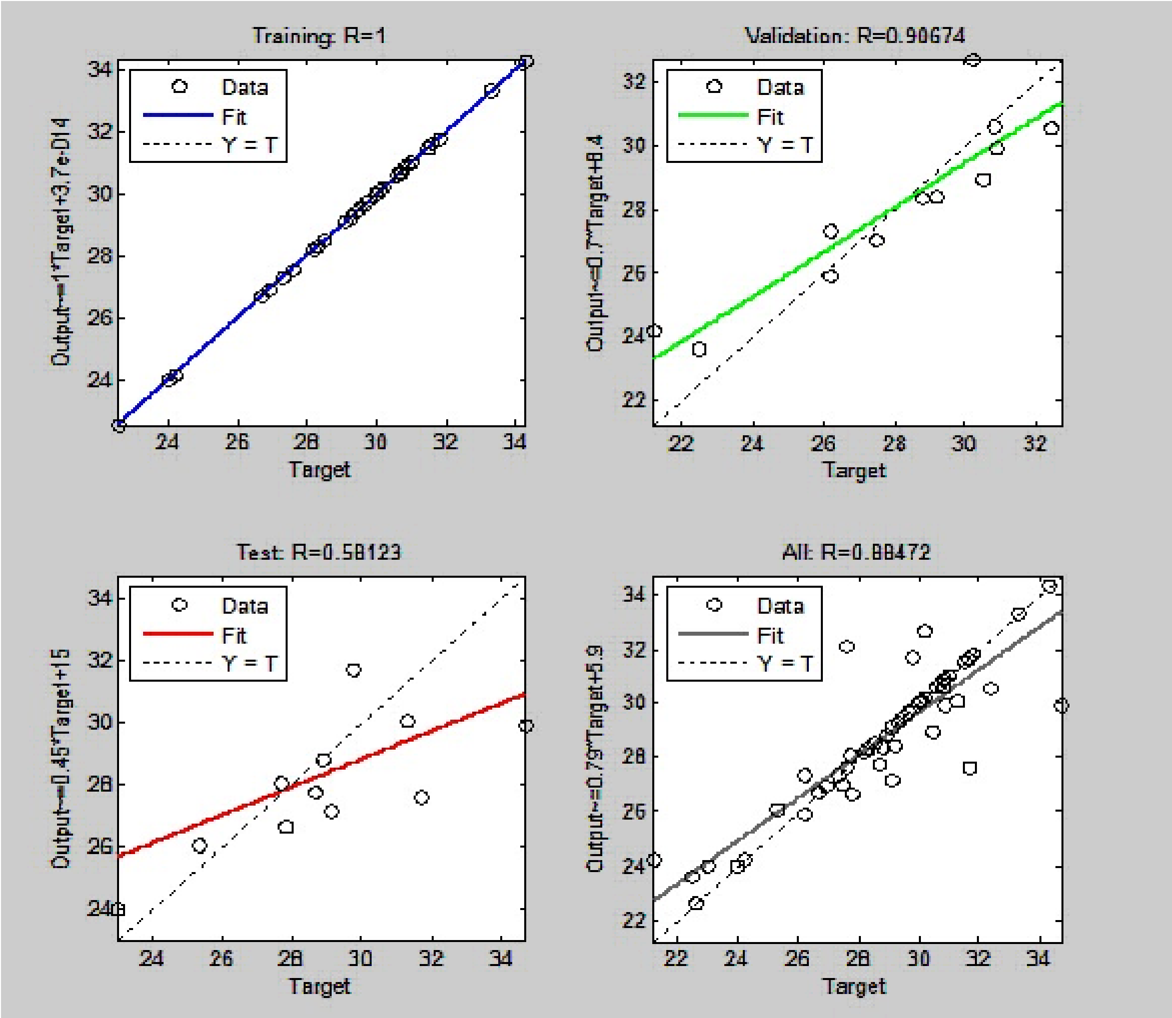


Figure 3: Test with Neuro-Fuzzy technique

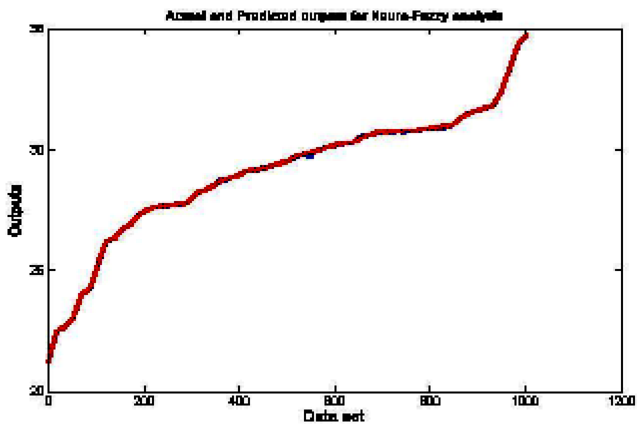


Figure 4: Correlation for all Parameters with Training, Validation and Test Data

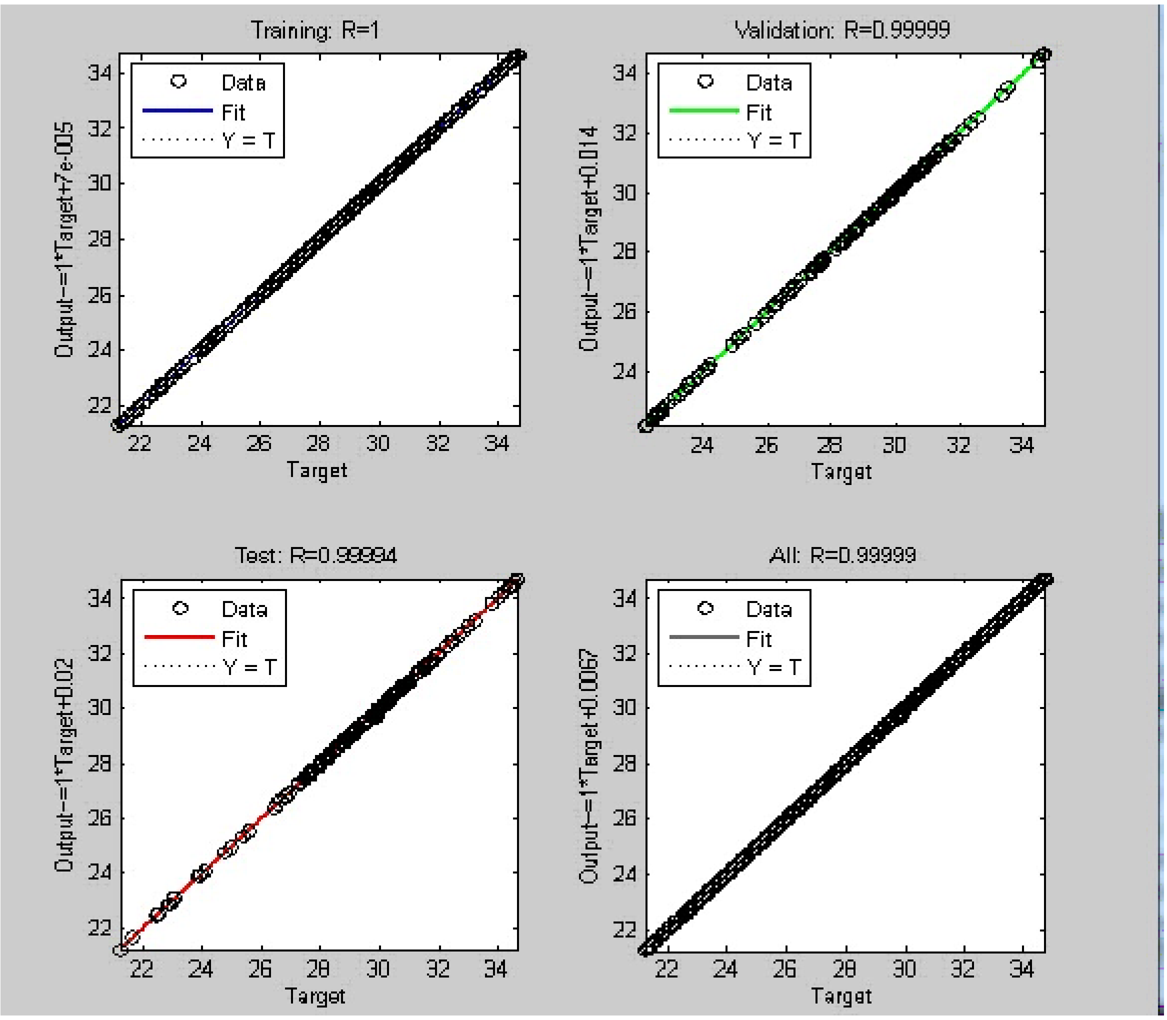
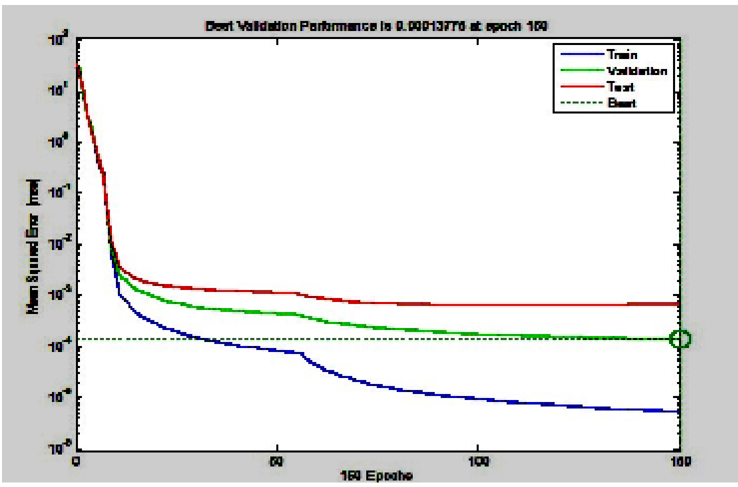


Figure 5: Main Square Error Diagram for all Parameter of Concrete



150 with performance equal to 0.00013775. Figure 5 explain the convergences between the results of the train, validation and test data set with the best solution.

The comparison between the observed and predicted outputs (compressive strength at age of 28 days) was shown in Figure, the behavior of predicted data was very close to the actual results except six point was diverge from the line of equality.

This final model has been proved to be used for ready mix concrete to predict the 28-day compressive strength depending on the properties of mix proportion.

CONCLUSION

In this study, analysis was made for Neuro-Fuzzy technique that was used to predict the 28 days compressive strength of concrete. The proposed technique can be used as a very useful tool for reducing the duration of the project execution in huge civil projects. Using the proposed tools we can have a precise prediction of the 28-day compressive strength of the concrete on the first day (or 7 days if this value was included in the models).

The models in this study for strength prediction were made using the traditional Neural Network and the Neuro-Fuzzy network. The following results could be drawn from this study:

For traditional Neural Network model, the coefficient of correlation for the train, test, validation and all data set were (R_{train} = 1, R_{test}=0.58123 , Rval=0.90674, Rall=0.88472) respectively.

Meanwhile for the Neuro-Fuzzy technique, The coefficient of correlation for the train, test, validation and all data set were (Rtrain = 1 , Rtest = 0.99994, Rval = 0.99999 , Rall = 0.99999) respectively.

This ensures that Neuro-Fuzzy model could predict the 28 days compressive strength of concrete with significant performance owing to their modern and smart computing technique. This model could predict the 28 days compressive strength of concrete in a best manner and accurate results.

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