Analytic Formulae for Concrete Mix Design Based on Experimental Data Base and Predicting the Concrete Behavior Using ANN Technique

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Abstract

The Local Egyptian practice in producing concrete for different structural applications is based on the known properties of cement. Cement has been produced locally under the Egyptian standards ES 372, 373 and 584 for ordinary, rapid hardening and sulphate resisting types. In 2007, the Egyptian standards issued ES 4756 that adopted the European standard EN 197 for producing cement. This resulted in new types of cements to replace the types that local construction companies used to apply for decades. Many doubts appeared about whether the rules applied for concrete mix proportioning are still valid. In the current research, an experimental investigation of concrete properties is made using two of the locally most common types of cements CEM I 32.5 R & CEM I 42.5 N. Slump, compressive strength, rebound number and ultrasonic pulse velocities were investigated for 64 mixes. The main parameters were type of cement, cement content, water content, and fine/coarse aggregate ratio. Data base was established for the mix proportions and corresponding properties. Analytic formulae are proposed for utilizing the collected data base for concrete mix design. Also, using the experimental data base presented in the current study, numerical approach, using one of the artificial intelligence techniques, is adopted to simulate the concrete behavior for different mix proportions. Artificial Neural Network (ANN) technique is developed in the present work to simulate the concrete slump and concrete compressive strength for different mix proportions at different ages for the two types of cement and then predict the concrete behavior for different mix proportions at ages rather than those investigated in the experimental work.

Keywords: Cement type, Concrete mix proportion, Concrete behavior, Modeling, Artificial neural network.

1. INTRODUCTION

Cement plays a vital role in construction industry. More than 90% of structures are made from reinforced concrete [1]. Besides, wall construction and finishing of surfaces is made using cement mortar. In 2007, Egyptian standards issued a new version of cement standard ES4756 that adopts solely the European norm EN197. This version included major changes in the concept of cement industry. Mainly, cement started to have a grade and rate of hardening in addition to its type. The term "Ordinary Portland cement OPC" is no longer correlated with strength or strength development. This drastic change dictated a comprehensive investigation of the properties of new types of cement. Results of such an investigation will be of major importance for Engineers and scientists since they will help to identify the properties of cement-based products, and to deal with any ill effects resulting from using these new types for some applications. The current paper represents a part of this targeted investigation [2, 3] applied to the local Egyptian cement.

Different concrete mixes are made using local materials with different proportions. Slump, compressive strength and non-destructive strength measurements were made and analyzed in order to identify the properties of concrete mixes using the new local cements and to establish a data-base for concrete mix-design and prediction of properties of different concrete mixes.

Since the experimental work needs a lot of effort, time and money, the need for utilizing new methodologies and techniques to reduce this effort, save time and money (and at the same time preserving high accuracy) is urged. Artificial intelligence has proven its capability in simulating and predicting the behavior of the different physical phenomena in most of the engineering fields. Artificial Neural Network (ANN) is one of the artificial intelligence techniques that have been incorporated in various scientific disciplines. Minns [4] investigated the general application of ANN in modeling rainfall runoff process. Ramanitharan and Li [5] utilized ANN with back-propagation algorithm for modeling ocean curves that were presented by wave height and period. Tawfik, Ibrahim and Fahmy [6] showed the applicability of using the ANN technique for modeling rating curves with hysteresis sensitive criterion. Kheireldin [7] presented a study to model the hydraulic characteristics of severe contractions in open channels using ANN technique. The successful results of his study showed the applicability of using the ANN approach in determining relationship between different parameters with multiple input/output problems. Abdeen [8] developed neural network model for predicting flow depths and average flow velocities along the channel reach when the geometrical properties of the channel cross sections were measured or vice versa. Allam [9] used the artificial intelligence technique to predict the effect of tunnel construction on nearby buildings which is the main factor in choosing the tunnel route. Allam, in her thesis, predicted the maximum and minimum differential settlement necessary precautionary measures. Abdeen [10] presented a study for the development of ANN models to simulate flow behavior in open channel infested by submerged aquatic weeds. Mohamed [11] proposed an artificial neural network for the selection of optimal lateral load-resisting system for multi-story steel frames. Mohamed, in her master thesis, proposed the neural network to reduce the computing time consumed in the design iterations. Abdeen [12] utilized ANN technique for the development of various models to simulate the impacts of different submerged weeds' densities, different flow discharges, and different distributaries operation scheduling on the water surface profile in an experimental main open channel that supplies water to different distributaries.

2. PROBLEM DESCRIPTION

To investigate and predict the behavior of concrete made from two of the locally most common types of cements CEM I 32.5 R & CEM I 42.5 N, experimental and numerical techniques will be presented in this study. The experimental program and its results will be described in detail in the following sections. After experimental presentation, analytic formulae are proposed for concrete mix design. The numerical models presented in this study utilized Artificial Neural Network technique (ANN) using the experimental data. Numerical models, then, can predict the performance of concrete for different mix proportions at different ages.

3. EXPERIMENTAL PROGRAM

There are many parameters figured for the investigation of cement application in concrete. Namely, type of cement, aggregate type and grading, cement and water contents are the most important. In order to limit the scope of the current investigation, the most common variations (alternatives) in the actual practice were assigned to the above mentioned parameters, CEM I 32.5 R and CEM I 42,5 N are the most common in the local Egyptian market. Desert siliceous gravel and sand were considered as aggregates. Sand to gravel ratio was considered as 1:2 (most widely used) and 1:1 (common for case of fine sand). Cement content ranges usually from 250 to 400 kg/m3. Water content ranges usually from 150 - 250 kg/m3. Four cement and water contents were used to cover the above mentioned ranges. Table (1) summarizes the Mix proportions for the investigated mixes in the current study. One can see that the selected parameters yielded sixty four mixes. For each of the mixes, slump, compressive strength at 3,7,28 and 56 days were measured. Some measurements of shmidt rebound numbers and ultrasonic pulse velocity were also made on concrete cubes before testing them in compression at different ages.

<table>
<tr><th>Mix No</th><th>Type of Cement</th><th>Cement Content (kg/m³)</th><th>Water Content (kg/m³)</th><th>Sand : Gravel</th></tr>
<tr><td>1 – 4</td><td rowspan="8">CEM I 32.5 R</td><td>250</td><td rowspan="8">120-160-200-240</td><td rowspan="4">1 : 1</td></tr>
<tr><td>5 – 8</td><td>300</td></tr>
<tr><td>9 – 12</td><td>350</td></tr>
<tr><td>13 – 16</td><td>400</td></tr>
<tr><td>17 – 20</td><td>250</td><td rowspan="4">1 : 2</td></tr>
<tr><td>21 – 24</td><td>300</td></tr>
<tr><td>25 – 28</td><td>350</td></tr>
<tr><td>29 – 32</td><td>400</td></tr>
<tr><td>33 – 36</td><td rowspan="8">CEM I 42.5 N</td><td>250</td><td rowspan="8">120-160-200-240</td><td rowspan="4">1 : 1</td></tr>
<tr><td>37 – 40</td><td>300</td></tr>
<tr><td>41 – 44</td><td>350</td></tr>
<tr><td>45 – 48</td><td>400</td></tr>
<tr><td>49 – 52</td><td>250</td><td rowspan="4">1 : 2</td></tr>
<tr><td>53 – 56</td><td>300</td></tr>
<tr><td>57 – 60</td><td>350</td></tr>
<tr><td>61 – 64</td><td>400</td></tr>
</table>

TABLE 1: Mix Proportions of Investigated Concrete Mixes

3.1 Concrete Materials

3.1.1 Cement

Two types of cement CEM I were used for the current study: CEM I 32.5 R and CEM I 42.5 N. These are locally produced according to Egyptian Standards ES4756 that complies with the EN 197.

3.1.2 Fine Aggregate

Local desert sand was used. The specific gravity, bulk density and fineness were measured. The sand has a specific gravity of 2.62, a bulk density of 1740 kg/m^3 and modulus of fineness of 3.3.

3.1.3 Coarse Aggregate

Local desert gravel was used in the current study. It has a specific gravity of 2.60, a bulk density of 1540 kg/m3, and a maximum nominal aggregate size of 25 mm.

3.1.4 Water

Tap water was used for mixing and curing concrete.

3.2 Test Specimens

Standard concrete cubes (150 mm size) were cast from each of the mixes shown in Table (1). Dry constituents were mixed first for about one minute in a tilting type 140 liter mixer. Then, water was added and mixing continued till homogeneous mixture was obtained. Slump was measured for the mix within 15 minutes after mixing. Then concrete was cast in the steel cube molds and vibrated using a vibrating table. Molds were covered with plastic sheets and stored in a humid room for 24 hours. Cubes were then de-molded and cured by immersion in water at about 23º C till the day of testing.

3.3 Test Results

3.3.1 Slump

Values of slump are shown in Tables (2) (a & b) for all mixes. One can easily see that results follow the well known trend where slump increases with increase of water content. In order to identify the effect of type of cement and sand: gravel ratio, slump values are plotted versus water content in Fig. (1). Two charts are shown; one for each type of cement. Data for sand : gravel ratio of 1:1 are shown in unfilled symbols whereas data for ratio of 1:2 are shown in filled symbols. One can easily see that increasing sand content reduces slump for all cases. Also, it can be seen that slump values are higher for cement CEM I 32.5 R. This is probably due to the high fineness of CEM I 42.5 N [13] that results in early hydration and, consequently, high water consumption. However, this was not expected to exceed the consumption of 32.5R (rapid setting).

Content			**CEM-I 32.5 R**		**CEM-I 42.5 N**	
Water W (kg/m^3)	**Cement C (kg/m^3)**	**Sand (S = G) (kg/m^3)**	**Slump (mm) Exp.**	**Slump (mm) ANN**	**Slump (mm) Exp.**	**Slump (mm) ANN**
120		1000	8.0	7.995	5.0	4.848
160		950	38.0	38.000	18.0	18.194
180	250	**925**		**70.376**		**37.409**
200		900	124.0	123.991	72.0	72.012
240		850	244.0	244.018	194.0	194.003
120		981	13.0	12.989	5.0	4.840
160		931	34.0	34.017	16.0	16.123
180	300	**906**		**56.024**		**36.229**
200		881	101.0	101.014	75.0	74.972
240		831	225.0	224.985	202.0	201.998
120		961	4.0	4.013	0.0	0.25563
160		911	30.0	29.986	21.0	20.890
180	350	**886**		**52.611**		**41.946**
200		861	90.0	89.993	71.0	71.029
240		811	215.0	215.007	184.0	183.999
120		941	0.0	0.001	0.0	0.2006
160		891	38.0	38.000	16.0	16.079
180	400	**886**		**65.511**		**33.197**
200		841	101.0	101.004	60.0	59.989
240		791	240.0	239.997	196.0	196.000
120		**921**		**9.910**		**5.988**
160	**450**	**871**		**64.847**		**30.639**
200		**821**		**126.733**		**88.235**
240		**771**		**253.927**		**228.975**

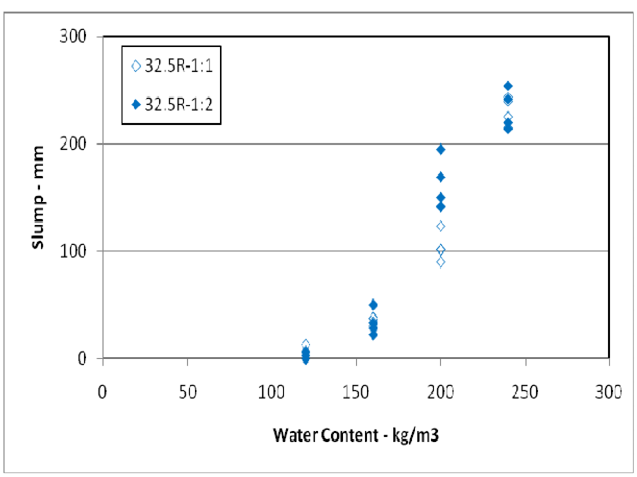
Note: data with **bold red** color represents the predicted ANN slump

TABLE 2(a): Slump results for sand: gravel ratio of 1: 1

Content			CEM-I 32.5 R		CEM-I 42.5 N	
Water W (kg/m^3)	Cement C (kg/m^3)	Sand S = G/2 (kg/m^3)	Slump (mm) Exp.	Slump (mm) ANN	Slump (mm) Exp.	Slump (mm) ANN
120	250	667	7.0	7.110	5.0	4.958
160		633	50.0	49.970	26.0	26.015
180		**616**		**134.992**		**56.661**
200		600	194.0	193.999	103.0	103.000
240		567	254.0	253.972	226.0	225.998
120	300	654	6.0	5.722	10.0	10.106
160		621	33.0	33.113	31.0	30.947
180		**604**		**102.126**		**56.367**
200		587	169.0	169.027	93.0	93.002
240		542	244.0	244.028	220.0	220.011
120	350	641	3.0	3.250	4.0	3.838
160		607	28.0	27.855	36.0	36.060
180		**590**		**72.568**		**62.272**
200		574	150.0	149.984	91.0	90.987
240		541	219.0	218.976	202.0	201.996
120	400	627	0.0	0.078	3.0	3.139
160		594	22.0	22.066	27.0	26.943
180		**577**		**55.670**		**51.313**
200		561	142.0	142.002	91.0	91.010
240		527	214.0	214.010	233.0	232.996
120	**450**	**613.0000**		**0.087**		**11.855**
160		**580.0000**		**8.779**		**47.772**
200		**547.0000**		**173.774**		**160.713**
240		**513.0000**		**247.906**		**240.125**

Note: data with **bold red** color represents the predicted ANN slump

TABLE 2(b): Slump results for sand: gravel ratio of 1: 2



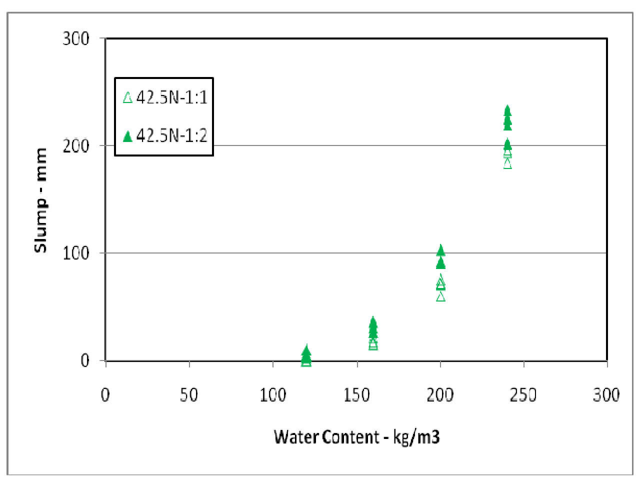


FIGURE 1: Slump versus Water Content for different types of cements and different sand: Gravel Ratios.

3.3.2 Compressive Strength

Compressive strength values for all mixes, at all ages, are presented in Figures (2-5). Each point represents the average result of three tested cubes. In the title of each chart the ratio following type of cement is the sand: gravel ratio. In the legend, data set is defined by cement content (in kg/m^3) followed by water content (kg/m^3). Lines represent artificial neural network (ANN) data presented later in this paper.

From figures, one can see that strength values increase with cement content, and with reduction of water content for the same cement content. Also, it is obvious that strength increases, slightly, with decrease of sand content. These observations comply with the known trend of strength variation for concrete mixes, and, therefore, indicate reliability of collected data. As a finding concerning the investigated new types of cements, one can see that for CEM I 42.5 N cement, strength development almost stops after 28 days and minor increase of strength occurs between 28 and 56 days. For CEM I 32.5 R cement, a significant increase of strength occurs between 28 and 56 days (almost 50%). This trend is not consistent with the designation R and N of cement type that dictates the early development of strength for R and late development for N.

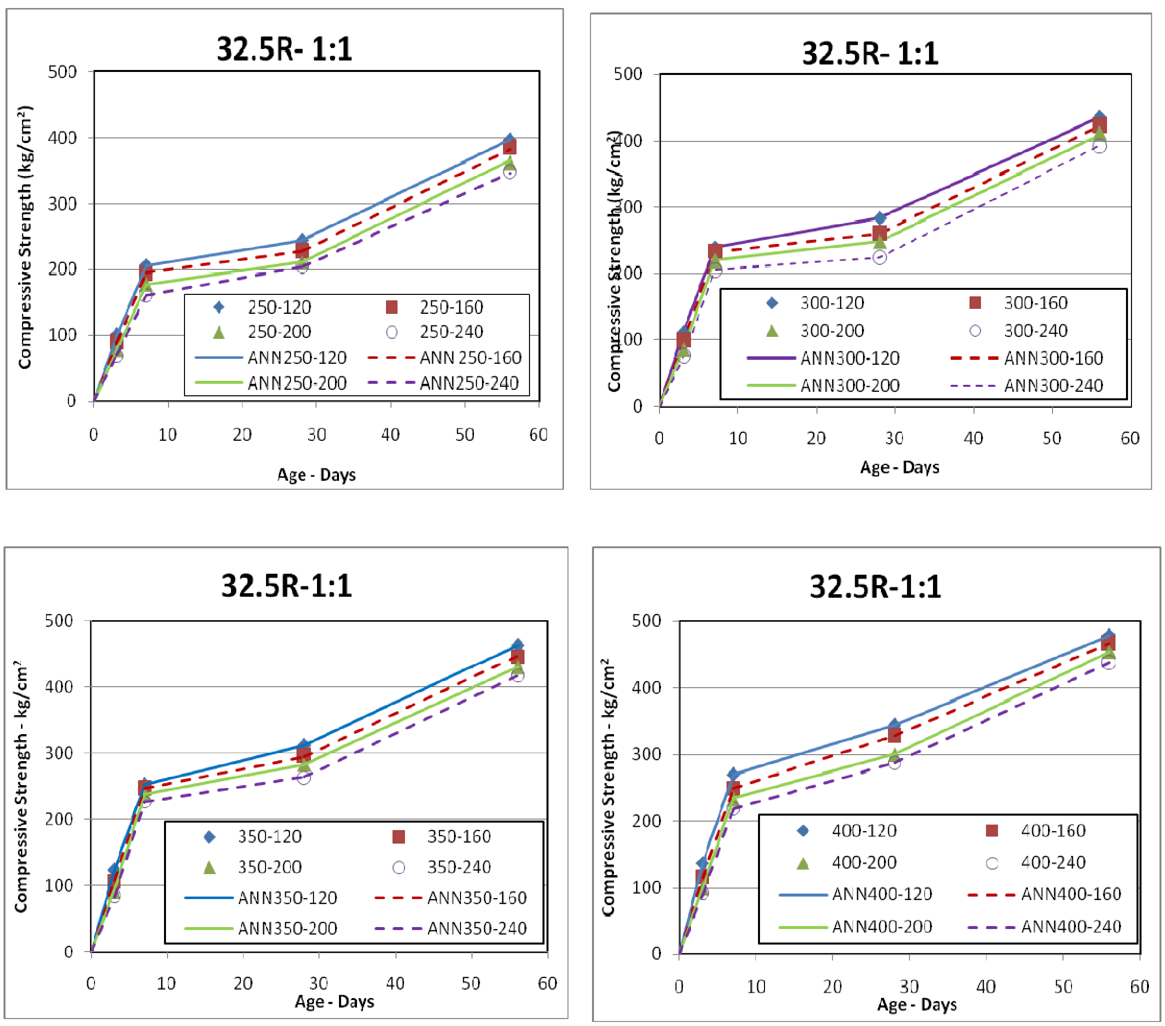


FIGURE 2: Development of Concrete Compressive Strength using CEM I 32.5 R and Sand: Gravel Ratio of 1:1 with different Cement and Water Contents.

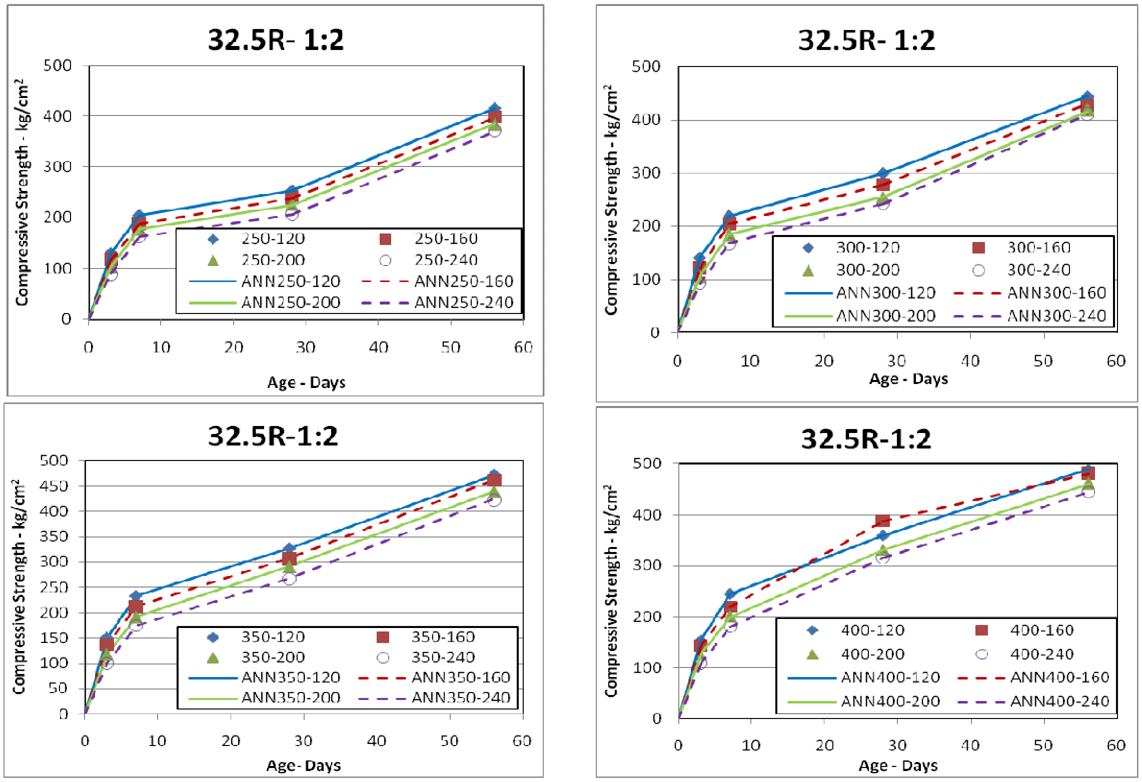


FIGURE 3: Development of Concrete Compressive Strength using CEM I 32.5 R and Sand: Gravel Ratio of 1:2 with different Cement and Water Contents.

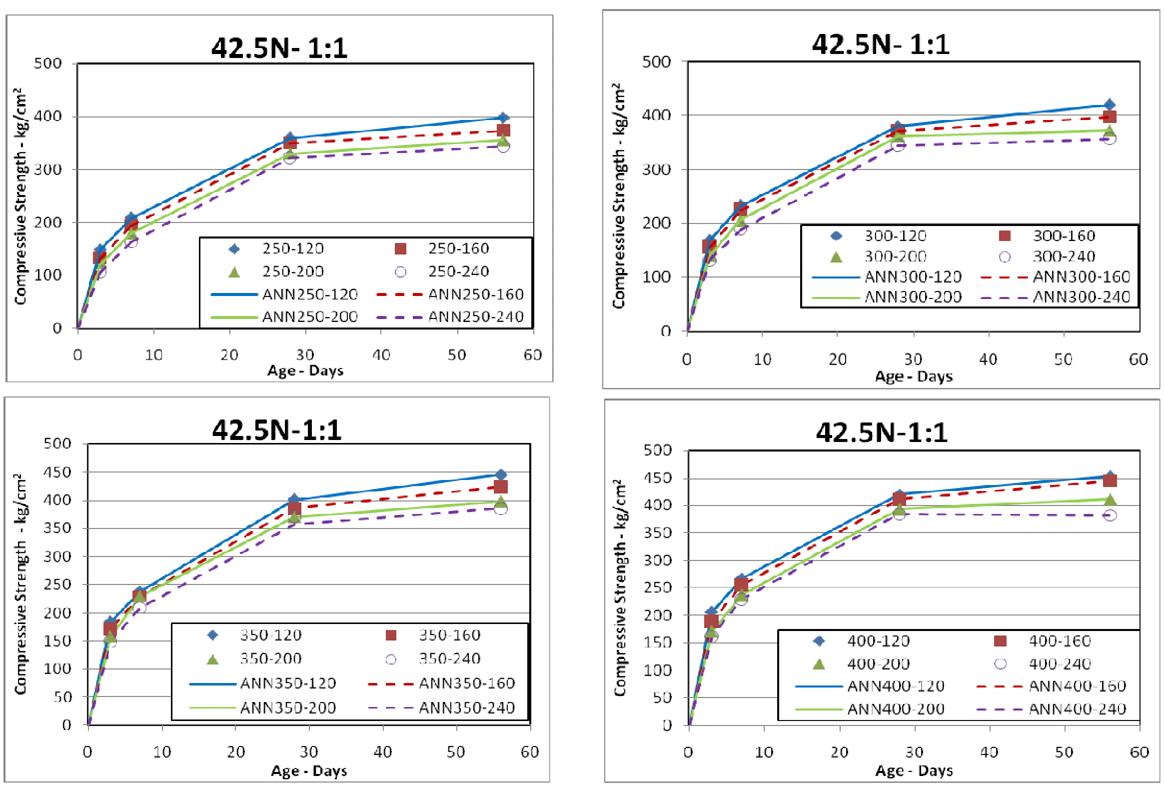


FIGURE 4: Development of Concrete Compressive Strength using CEM I 42.5 N and Sand: Gravel Ratio of 1:1 with different Cement and Water Contents.

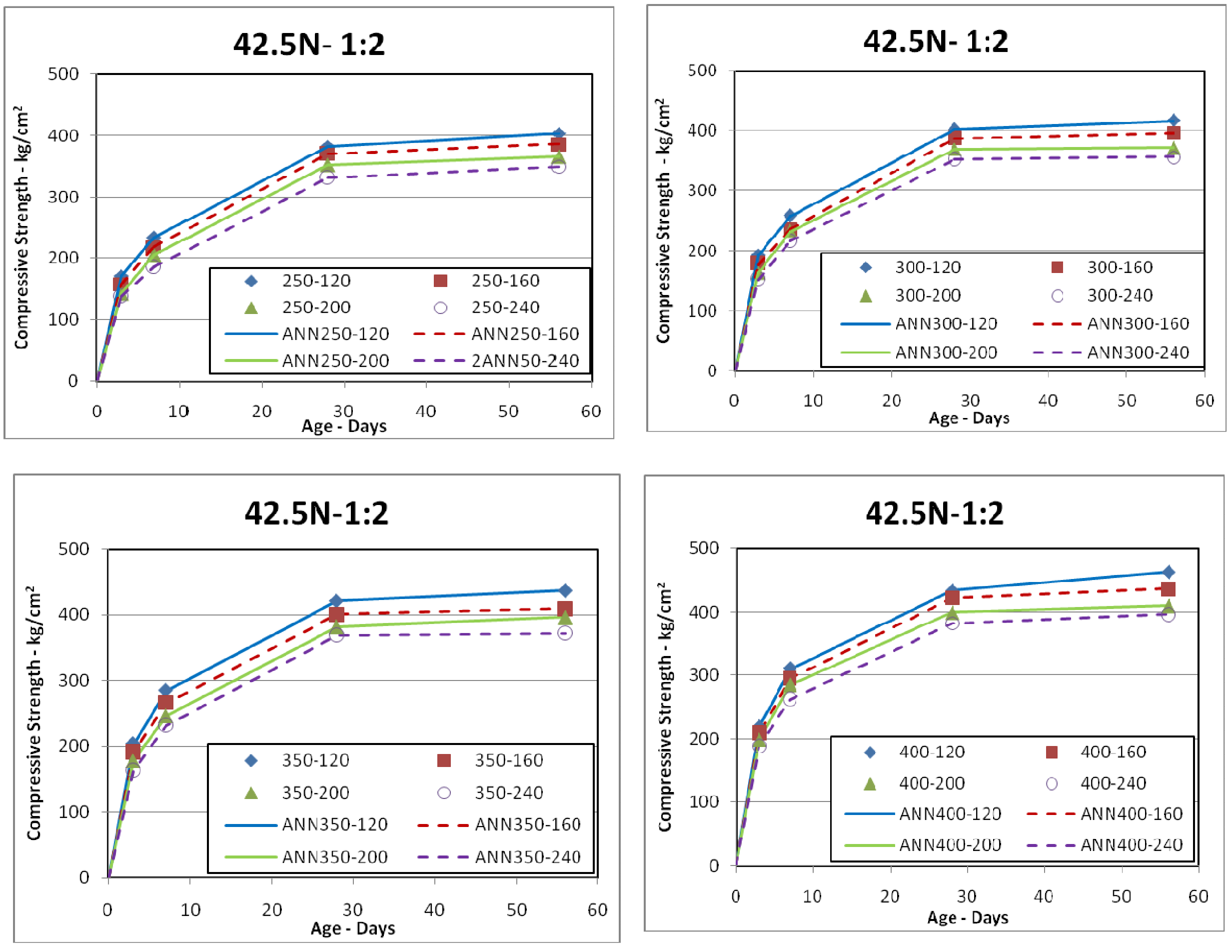


FIGURE 5: Development of Concrete Compressive Strength using CEM I 42.5 N and Sand: Gravel Ratio of 1:1 with different Cement and Water Contents.

The trend of strength development is consistent with the observed reduction of slump for CEM I 42.5 N, and the reported high fineness of this cement.

In order to evaluate the effect of cement content, data are presented in Fig. (6). Four charts are shown. In each chart, four series of data are presented: two for CEM I 32.5 R and two for CEM I 42.5 N. Filled symbols show the experimental results and unfilled ones show the ANN predictions, explained later in this paper. For each type of cement data for highest and lowest cement contents are presented together with highest and lowest water contents. One can see that, generally, for all cases, mixes with CEM I 32.5 R show lower strength than similar mixes with CEM I 42.5 N. At 56 days, however, mixes with 32.5 R cement show strength values higher than similar mixes with CEM I 42.5 N cement.

Strength values are plotted versus water/cement ratio (w/c) in Fig. (7). Two charts are shown in Fig. (7): one for each type of cement. Unfilled symbols represent mixes with sand/gravel ratio of 1:1, and filled symbols represent mixes with sand/gravel ratio of 1:2. It can be seen that the well known trend of strength reduction with increase of w/c ratio is fulfilled. There is also a slight effect of sand: gravel ratio on strength values. This is particularly true for later ages (28 days and higher).

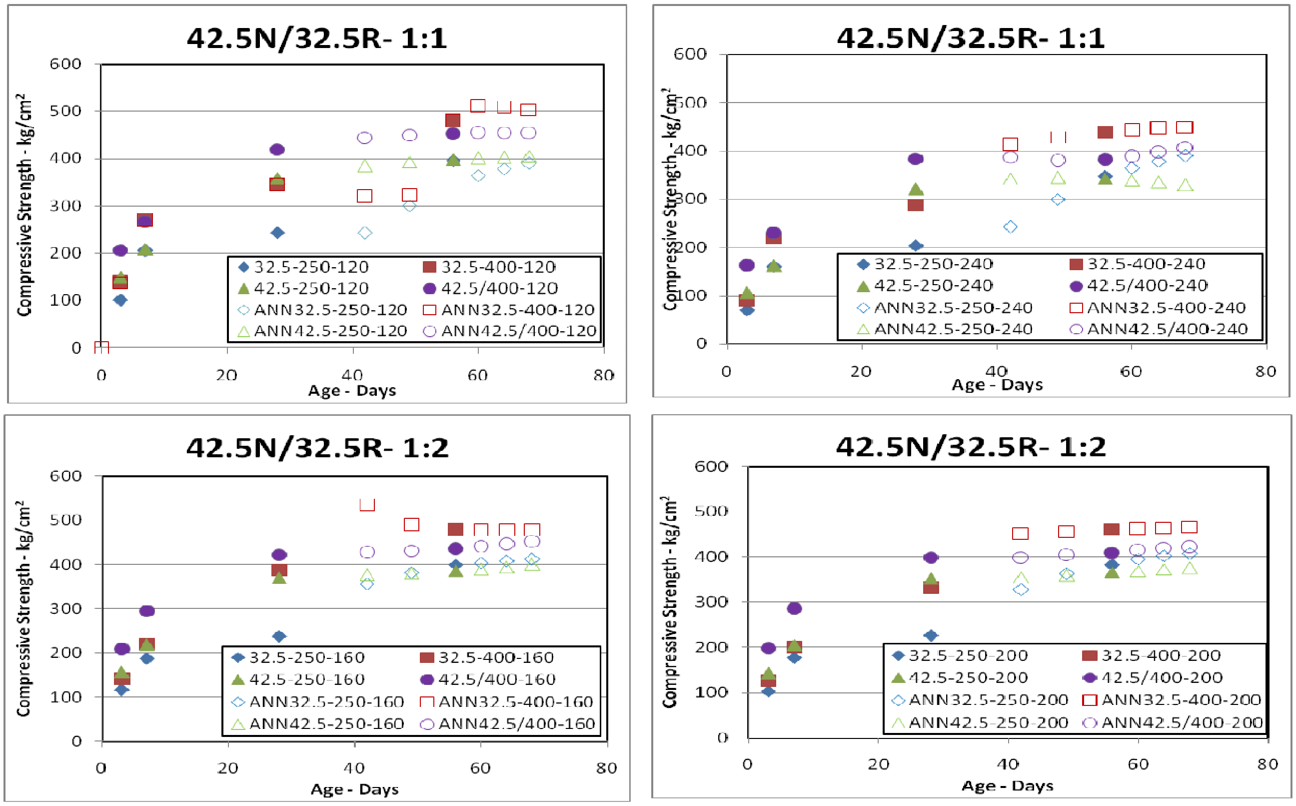


FIGURE 6: Comparison of Concrete Compressive Strength Development for CEM I 32.5 R and CEM I 42.5 N at different Cement and Water Contents.

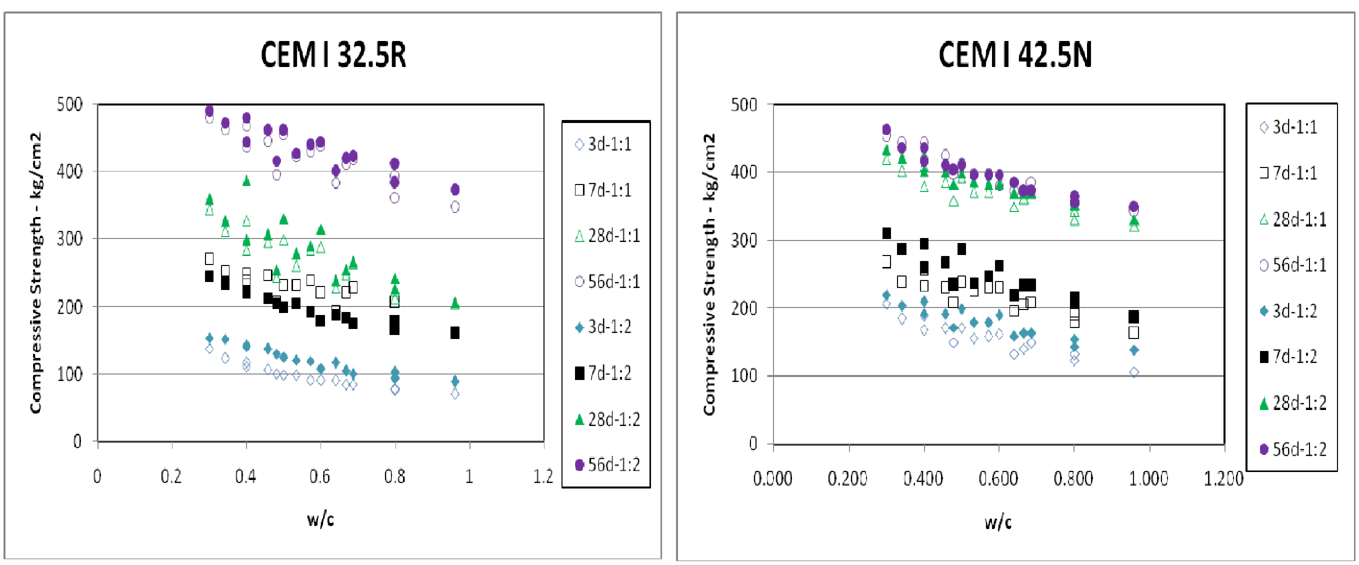


FIGURE 7: Concrete Compressive Strength versus Water/ Cement Ratio for different Mixes and Types of Cement.

3.3.3 Non-Destructive Testing (NDT)

Results of measuring Rebound number and ultrasonic pulse velocity are plotted versus measured compressive strength in Figs (8 - 11). The large filled symbols are used for measurements after 3 days; large unfilled symbols are used for 7-day measurements. Small filled and unfilled symbols are used for 28 and 56 day measurements, respectively. Some early age measurements are missing for concretes made from CEM I 32.5 R. This is due to some technical problems with measuring device at these specific ages. One can easily see that the correlation between compressive strength and rebound number or pulse velocity is an age dependent one. This is in good agreement with the known facts on NDT testing of concrete [14]. For rebound number (R_N) measurements on CEM I 32.5 R, one can see a slight increase in R_N for increased content of coarse aggregate. There is almost no effect of cement content on the correlation between compressive strength and rebound number at all ages for the two investigated types of cement. Ultrasonic pulse velocity showed similar trend to that of R_N, where it increases for increased coarse aggregate content with CEM I 32.5 R. There is no effect of cement content on correlation with compressive strength at all ages for the two investigated types of cement.

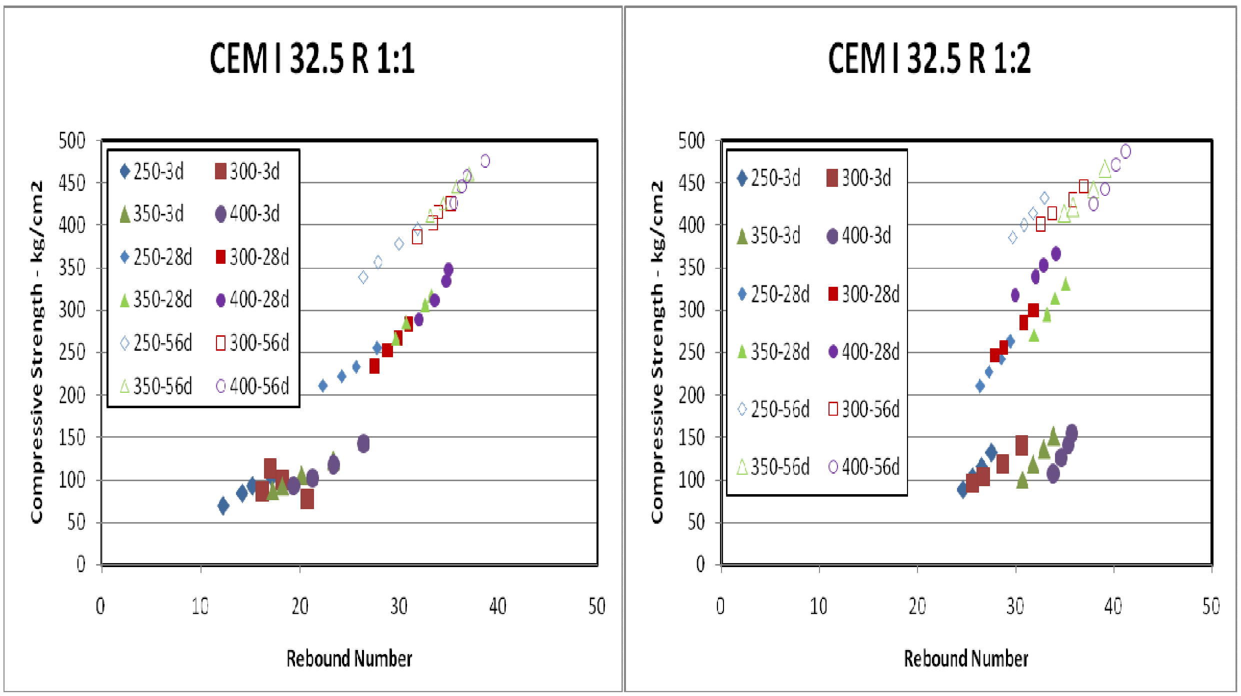


FIGURE 8: Rebound Number versus Compressive Strength at different ages and Cement Contents for CEM I 32.5 R and Sand: Gravel Ratios = 1:1 & 1:2

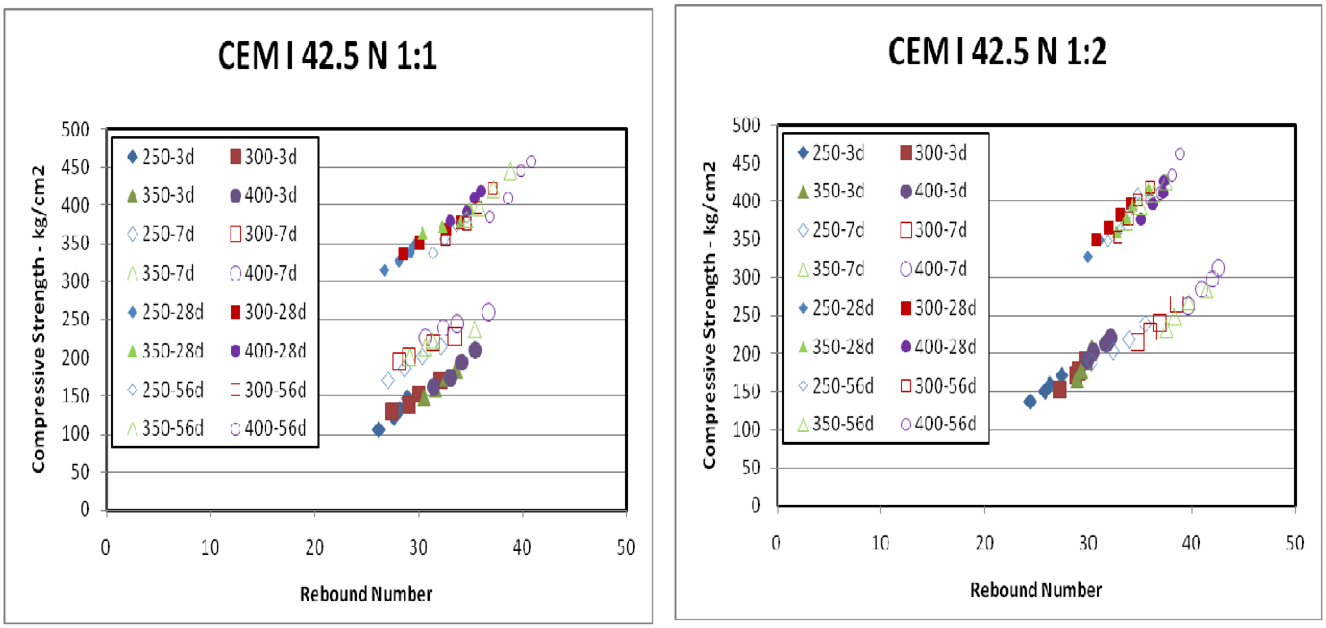


FIGURE 9: Rebound Number versus Compressive Strength at different ages and Cement Contents for CEM I 42.5 N and Sand: Gravel Ratios = 1:1 & 1:2

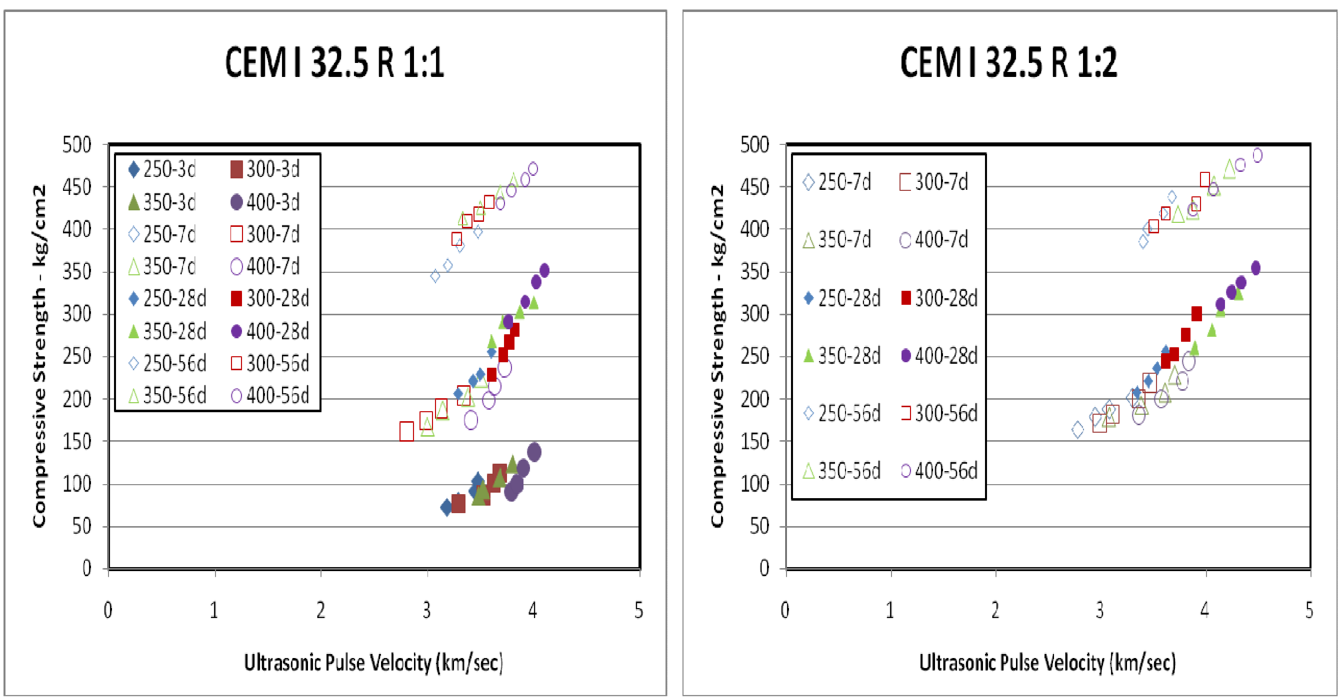


FIGURE 10: Ultrasonic Pulse Velocity versus Compressive Strength at different ages and Cement Contents for CEM I 32.5 R and Sand: Gravel Ratios = 1:1 & 1:2

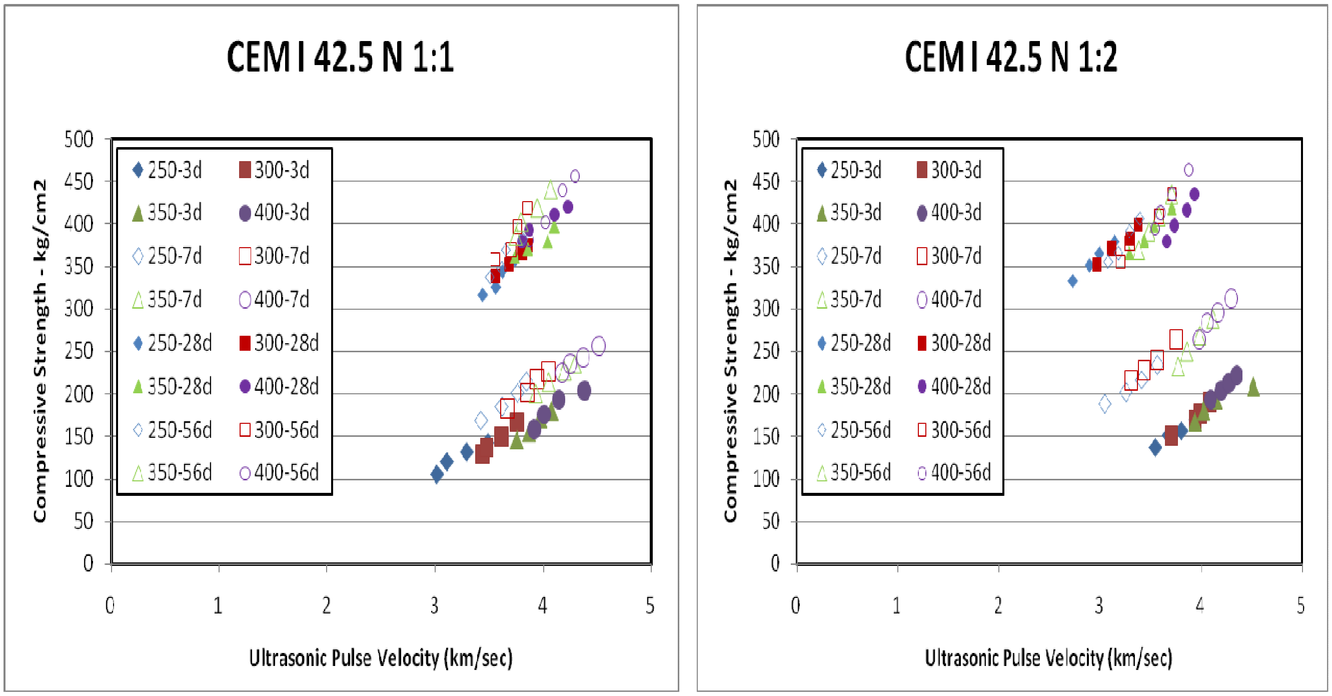


FIGURE 11: Ultrasonic Pulse Velocity versus Compressive Strength at different ages and Cement Contents for CEM I 42.5 N and Sand: Gravel Ratios = 1:1 & 1:2

4. ANALYTIC FORMULAE FOR MIX DESIGN

Usually mix design is made following the steps:

1) Given the required concrete slump (and the sand: gravel ratio), get water content (w) from the available database.
2) Given the target concrete compressive strength get the suitable water/cement (w/c) ratio from the available data base.
3) From the above two steps get cement content (c): c= w ÷ (w/c).
4) Applying the equation of absolute volume of concrete constituents, get the absolute volume of aggregate = 1000 – w – c/3.15.
5) Given aggregate specific gravity and sand: gravel ratio, get the sand and gravel contents.

Search in data base for steps 1 and 2 above is usually made through curves and tables. Although this graphical presentation of database can still be applied for the current database, formulae for such presentations are sought. The curves in Figs (1) and (7) were fitted to equations using the least mean square method. For the case of slump (S), the following equations were obtained:

$$S = 294\ln(w) - 1432$$ (R^2 = 0.834) for CEM I 32.5 R, Sand: Gravel = 1:2 (1)

$$S = 259\ln(w) - 1265$$ (R^2 = 0.787) for CEM I 32.5 R, Sand: Gravel = 1:1 (2)

$$S = 346\ln(w) - 1677$$ (R^2 = 0.896) for CEM I 42.5 N, Sand: Gravel = 1:2 (3)

$$S = 310\ln(w) - 1507$$ (R^2 = 0.847) for CEM I 42.5 N, Sand: Gravel = 1:1 (4)

Where: S = Slump in mm, w = water content (kg/m^3)
For the case of compressive strength, the following form was obtained

$$fc = A.e^{(-B*w/c)} \qquad w/c = [\ln(A) - \ln(fc)]/B \tag{5}$$

Where fc = Compressive Strength (kg/cm^2), w/c = water/cement ratio.

A & B are constants depending on age of concrete (in days) and can be obtained from the following equations:

$A = 116.7\ln(age) + 60.62$ (R^2 = 0.99) for CEM I 32.5 R (6)

$A = 82.17\ln(age) + 188.3$ (R^2 = 0.971) for CEM I 42.5 N (7)

$B = 0.94, 0.64, 0.78, 0.41$ for CEM I 32.5 R at 3, 7, 28, 56 days, respectively. (8)

$B = 0.80, 0.68, 0.38, 0.43$ for CEM I 42.5 N at 3, 7, 28, 56 days, respectively. (9)

4.1 Analytic Example

Find the mix proportions for a concrete mix having 150 mm slump, and 28-day compressive strength of 300 kg/cm^2, given that sand: gravel ratio is 1 : 2, and cement type is CEM I 32.5 R.

From Eqn. (1),

150 = 294 ln (w) -1432 w = 217 kg/m3

From Eqn. (6),

A = 450

From Eqn. (8),

B = 0.78

From Eqn. (5),

w/c = 0.52 c = 217 / 0.52 = 417 kg/m^3

Absolute volume of aggregate = 1000-217-417/3.15 = 650 liter / m^3 of concrete

Weight of aggregate = 1690 kg (using specific gravity of 2.6 as measured early in this paper)

Mix Proportions = water: cement: sand: gravel = 217 : 417 : 560 : 1130 kg

Comparing this result with Table 2(b) and Fig. (3), one can see that the mix proportions are in good agreement with the experimental database.

5. NUMERICAL MODEL STRUCTURE

Neural networks are models of biological neural structures. Abdeen [8] described in a very detailed fashion the structure of any neural network. Briefly, the starting point for most networks is a model neuron as shown in Fig. (12). this neuron is connected to multiple inputs and produces a single output. Each input is modified by a weighting value (w). The neuron will combine these weighted inputs with reference to a threshold value and an activation function, will determine its output. This behavior follows closely the real neurons work of the human's brain. In the network structure, the input layer is considered a distributor of the signals from the external world while hidden layers are considered to be feature detectors of such signals. On the other hand, the output layer is considered as a collector of the features detected and the producer of the response.

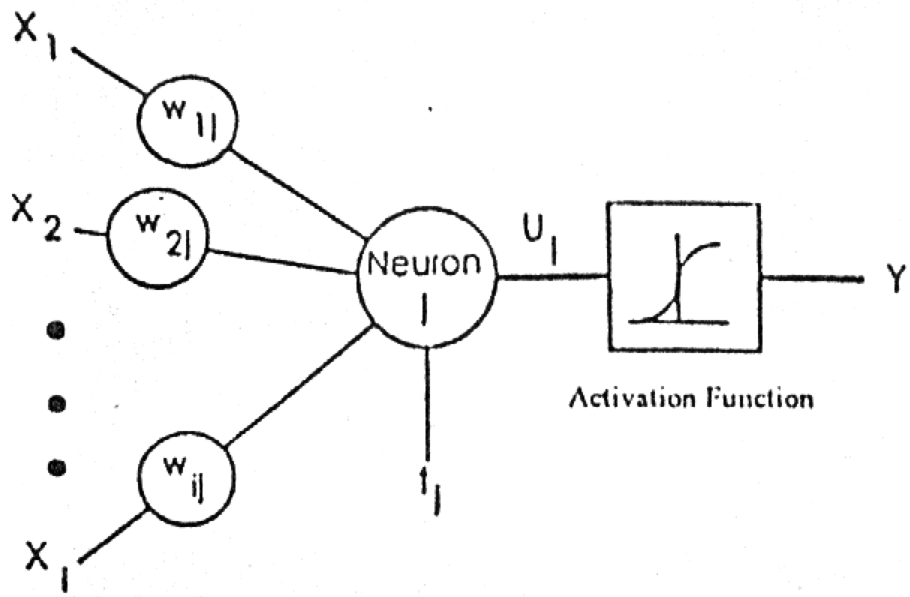


FIGURE 12: Typical picture of a model neuron that exists in every neural network

5.1 Neural Network Operation

It is quite important for the reader to understand how the neural network operates to simulate different physical problems. The output of each neuron is a function of its inputs (X_i). In more details, the output (Y_j) of the j^{th} neuron in any layer is described by two sets of equations as follows:

$$U_j = \sum\left(X_i . w_{ij}\right) \tag{10}$$

And

$$Y_j = F_{th}\left(U_j + t_j\right) \tag{11}$$

For every neuron, j, in a layer, each of the i inputs, X_i, to that layer is multiplied by a previously established weight, w_{ij}. These are all summed together, resulting in the internal value of this operation, U_j. This value is then biased by a previously established threshold value, t_j, and sent through an activation function, F_{th}. This activation function can take several forms such as Step, Linear, Sigmoid, Hyperbolic, and Gaussian functions. The Hyperbolic function, used in this study, is shaped exactly as the Sigmoid one with the same mathematical representation, as in equation 12, but it ranges from – 1 to + 1 rather than from 0 to 1 as in the Sigmoid one (Fig. (13))

$$f(x) = \frac{1}{1+e^{-x}} \tag{12}$$

The resulting output, Y_j, is an input to the next layer or it is a response of the neural network if it is the last layer. In applying the Neural Network technique, in this study, Neuralyst Software, Shin [15], was used.

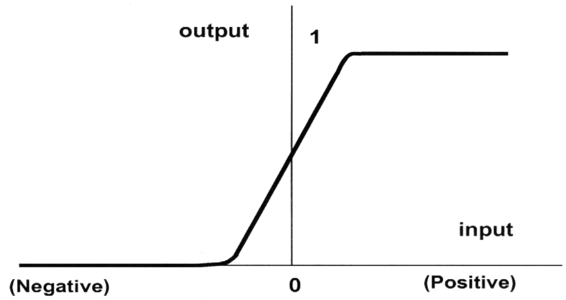


FIGURE 13: The Sigmoid Activation Function

5.2 Neural Network Training

The next step in neural network procedure is the training operation. The main purpose of this operation is to tune up the network to what it should produce as a response. From the difference between the desired response and the actual response, the error is determined and a portion of it is back propagated through the network. At each neuron in the network, the error is used to adjust the weights and the threshold value of this neuron. Consequently, the error in the network will be less for the same inputs at the next iteration. This corrective procedure is applied continuously and repetitively for each set of inputs and corresponding set of outputs. This procedure will decrease the individual or total error in the responses to reach a desired tolerance. Once the network reduces the total error to the satisfactory limit, the training process may stop. The error propagation in the network starts at the output layer with the following equations:

$$w_{ij} = w_{ij}^{'} + LR\left(e_j X_i\right) \quad (13)$$

And,

$$e_j = Y_j\left(1 - Y_j\right)\left(d_j - Y_j\right) \quad (14)$$

Where, w_{ij} is the corrected weight, $w_{ij}^{'}$ is the previous weight value, LR is the learning rate, e_j is the error term, X_i is the i^{th} input value, Y_j is the ouput, and d_j is the desired output.

6. SIMULATION MODELS

To fully investigate numerically the effect of concrete mix proportions at different ages on the performance of concrete, four numerical models are considered in this study, two for each type of cement (CEM-I 32.5 R and CEM-I 42.5 N). The models of each type of cement simulate the concrete slump and concrete compressive strength for different mix proportions at different ages.

6.1 Neural Network Design

To develop a neural network model to simulate the effect of concrete mix proportion on the performance of concrete, first input and output variables have to be determined. Input variables are chosen according to the nature of the problem and the type of data that would be collected in the field or from experiment. To clearly specify the key input variables for each neural network simulation model and its associated outputs, Table (3) is designed to summarize all neural network key input variables and output for the simulation models.

Model	Input Variables					Output
	Water	Cement	Sand	Gravel	Days	
Slump CEM-I 32.5 R	☑	☑	☑	☑		Slump
Compressive Strength CEM-I 32.5 R	☑	☑	☑	☑	☑	Comp. Strength
Slump CEM-I 42.5 N	☑	☑	☑	☑		Slump
Compressive Strength CEM-I 42.5 N	☑	☑	☑	☑	☑	Comp. Strength

TABLE 3: Key input and output variables for all ANN models

Several neural network architectures are designed and tested for all simulation models investigated in this study to finally determine the best network models to simulate, very accurately, the effect of mix proportions on the performance of concrete based on minimizing the Root Mean Square Error (RMS-Error).

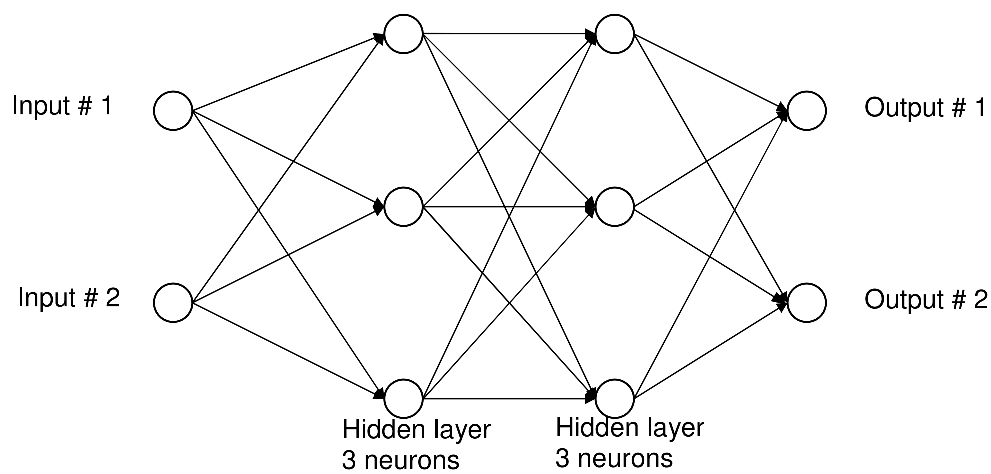


FIGURE 14: General schematic diagram of a simple generic neural network

Fig. (14) Shows a schematic diagram for a generic neural network. The training procedure for the developed ANN models, in the current study, uses the data for all the concrete mix proportions available from the experiments and then different mix proportions at different ages are used to test the power of prediction of the neural network models.

Simulation Model	No. of Layers	No. of Neurons in each Layer					
		Input Layer	First Hidden	Second Hidden	Third Hidden	Fourth Hidden	Output Layer
Slump CEM-I 32.5 R	4	4	8	6	-	-	1
Compressive Strength CEM-I 32.5 R	6	5	7	6	5	4	1
Slump CEM-I 42.5 N	5	4	8	6	4	-	1
Compressive Strength CEM-I 42.5 N	6	5	9	7	5	3	1

TABLE 4: The developed neural network models

Table (4) shows the final neural network models and their associate number of neurons. The input and output layers represent the key input and output variables described previously for each simulation model.

The parameters of the various network models developed in the current study are presented in Table (5), where these parameters can be described with their tasks as follows:

Learning Rate (LR): determines the magnitude of the correction term applied to adjust each neuron's weights during training process = 1 in the current study.
Momentum (M): determines the "life time" of a correction term as the training process takes place = 0.9 in the current study.
Training Tolerance (TRT): defines the percentage error allowed in comparing the neural network output to the target value to be scored as "Right" during the training process = 0.001 in the current study.
Testing Tolerance (TST): it is similar to Training Tolerance, but it is applied to the neural network outputs and the target values only for the test data = 0.003 in the current study.
Input Noise (IN): provides a slight random variation to each input value for every training epoch = 0 in the current study.
Function Gain (FG): allows a change in the scaling or width of the selected function = 1 in the current study.
Scaling Margin (SM): adds additional headroom, as a percentage of range, to the rescaling computations used by Neuralyst Software, Shin (1994), in preparing data for the neural network or interpreting data from the neural network = 0.1 in the current study.
Training Epochs: number of trails to achieve the present accuracy.
Percentage Relative Error (PRR): percentage relative error between the numerical results and actual measured value for and is computed according to equation (6) as follows:

PRE = (Absolute Value (ANN_PR - AMV)/AMV)*100 (15)

Where :
ANN_PR : Predicted results using the developed ANN model
AMV : Actual Measured Value
MPRE : Maximum percentage relative error during the model results for the training step.

Simulation Parameter	Slump (CEM-I 32.5 R)	Comp. Strength (CEM-I 32.5 R)	Slump (CEM-I 42.5 N)	Comp. Strength (CEM-I 42.5 N)
Training Epochs	489275	670443	323209	648395
MPRE	8.33	3.73	4.66	0.9
RMS-Error	0.0003	0.0016	0.0003	0.001

TABLE 5: Parameters used in the developed neural network models

6.2 Numerical Results

Numerical results using ANN technique are indicated with experimental data to simulate the concrete slump and concrete compressive strength for different mix proportions at different ages for the two types of cement.

6.2.1 Slump

Values of slump (experimental and numerical) are shown in Tables (2) (a & b) for all mixes for the two types of cement (CEM I 32.5 R & CEM I 42.5 N). The black color values are the ANN results during the training process. It is clear that ANN models presented in the current paper are very efficient for describing the slump property. The bold red color values are the predicted ANN results using the present model without the need to make any experiment. These predicted values are logic and in the range of the expected slump values. The ANN slump results shown in these Tables prove that the presented ANN models are very capable in simulating and predicting the slump property.

6.2.2 Compressive Strength

Compressive strength values (experimental and numerical) for all mixes, at all ages, are presented in Figures (2-6). Figures (2-5) show the numerical and experimental results during the training process of the present ANN models. One can see from these figures that the presented ANN models can accurately simulate the compressive strength property for all mixes at all ages for the two types of the cement. To check the power of the presented ANN models in predicting the compressive strength for all mixes at ages different than those used in the experiments, Figure (6) is drawn. In this Figure unfilled symbols represent the ANN predictions. It is clear that the presented numerical models using ANN technique are efficiently capable of predicting the compressive strength without the need to make a lot of experiments which will save time, effort and money.

7. CONCLUSIONS

Based on the results obtained from testing 64 concrete mixes with different types of cement, cement content, water content and sand/ gravel ratio, the following can be concluded:

- Concrete mixes with CEM I 42.5 N showed less slump than similar mixes with CEM I 32.5 R, and this was attributed to the high fineness of the former type as reported elsewhere.
- Concrete made from CEM I 32.5 R show early strength less than similar concrete with CEM I 42.5 N. However, after 28 days concrete with CEM I 32.5 R continue developing strength that exceed the strength of concrete with CEM I 42.5 N after 56 days.
- Non destructive testing techniques applied to concrete made from the two types of cement showed the known trend of measurements and showed almost no effect of Type of cements on the measured values.
- Some analytic formulae were proposed to correlate concrete properties and mix proportions of the collected database. These formulae were investigated as a basis for mix design and gave good results.
- The results of implementing the ANN technique in this study showed that this approach was capable of identifying relationship between different uncertain parameters with multiple input/output criterions. The presented designed ANN models in this study were very successful in simulating and predicting the concrete slump and concrete compressive strength for different mix proportions at different ages for the two types of cement (CEM I 32.5 R & CEM I 42.5 N).

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