Experimental Investigation and Numerical Modeling of the Effect of Natural and Steel Fibers on the Performance of Concrete

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Abstract

The application of fibers to concrete industry is growing due to the demanding needs of concrete with better structural performance. Environmental considerations urge this application since many of the fiber types (especially natural ones) results as by products from different industrial and agricultural processes. In this study, the application of metallic steel fibers and natural (Linen) fibers in concrete industry is investigated. Twenty one mixes are made with different mix proportions and with different types of fibers. The mixes were designed first to give strengths in the range from 150 to 450 Kg/cm2, without fiber inclusion. The two types of fibers are added to each of the basic control mixes. Standard specimens in forms of cubes and cylinders were cast from each mix. The specimens were tested in compression, tension and impact. Measurements were also made using two NDT techniques. The specimens were tested at ages of 7 and 28 days and after exposure to elevated temperatures of 400 and 450°C . The results were compared and showed the enhancement level obtained by including steel and natural fibers. Following this experimental effort, the Artificial Neural Network (ANN) technique was applied for predicting the performance of concrete with different mix proportions. The current paper introduced the (ANN) technique to investigate the effect of natural and steel fibers on the performance of concrete. The results of this study showed that the ANN method with less effort was very efficiently capable of simulating and predicting the performance of concrete with different mix proportions and different types of fibers.

Keywords: Concrete, Fibers, Ultrasonic Pulse Velocity, Modeling, Artificial Neural Network.

1. INTRODUCTION

The engineering ambition represents the main motivation for producing new materials that comply with the demands of engineers and structures. Concrete is the main structural material of the majority of structures in the world. Therefore, the enhancement of its properties represents the shortest way to get new superior construction material. Also, fibers represent the best method for enhancing concrete properties since it has the advantage of increasing tensile strength and ductility which are the main disadvantages of concrete. Fibers have mainly two types: metallic and non-metallic. Steel is the main source for the first type; whereas natural fibers (vegetal type) represent a main and cheap source of the second type, Parret and Ramachandran, [15] and [16]. A continuous research oriented towards the evaluation of material (pure and composite) properties is the direct way to identify the efficiency of local resources of material. This appears in the continuous published work concerning the potential of applying many types of natural fibers, Gorillo and Silva, [10] and [18].

In this paper, the effect of applying local natural fibers (linen) to concrete is investigated experimentally. A comparison is made with two extremes of plain concrete and steel fiber reinforced concretes. The investigation is made at 7 different concrete mixes and comprehensive evaluation is made. Evaluation includes the compressive and tensile strengths, impact strength, stiffness, readings of non-destructive techniques, and effect of elevated temperatures.

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 [14] investigated the general application of ANN in modeling rainfall runoff process. Kheireldin [11] 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 [1] developed neural network model for predicting flow characteristics in irregular open channels. The developed model proved that ANN technique was capable with small computational effort and high accuracy of 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. Tahk and Shin [19] presented a study on the fault diagnosis of Roller-Shape using frequency analysis of tension signals and Artificial Neural Network (ANN) based approach in a web transport system. ALLAM [7] 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. Park and Azmathullah et. al. [9] presented a study for estimating the scour characteristics downstream of a ski-jump bucket using Neural Networks (NN). Abdeen [2] presented a study for the development of ANN models to simulate flow behavior in open channel infested by submerged aquatic weeds. Mohamed [13] proposed an artificial neural network for the selection of optimal lateral load-resisting system for multi-story steel frames.

It is quite clear from the previously presented literature that ANN technique showed its applicability in simulating and predicting the behavior of different engineering problems. However, the utilization of ANN technique in simulating and predicting the effect of fibers on concrete properties is very limited. Therefore, one of the aims of the presented study is utilizing the ANN technique in modeling the behavior of concrete after applying fibers.

2. PROBLEM DESCRIPTION

To study the effect of fibers (linen and steel) as well as elevated temperature on the performance of concrete (compressive, tensile, impact, stiffness, rebound number, ultrasonic pulse velocity), 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. The numerical models presented in this study utilized Artificial Neural Network technique (ANN) using the data of the experiments and then can predict the performance of concrete for different mix proportions.

3. EXPERIMENTAL PROGRAM

In order to evaluate the effect of adding linen fibers to concrete, it was decided to test three sets of specimens: one including linen fibers and one without any fibers and the third with steel fibers. Concrete strength was considered as a parameter. Therefore, for each set, the strength was changed in the range of 150 to 450 kg/cm^2. Fiber content was kept constant at .0.5 % volume fraction. This value was selected based on preliminary tests to check that concrete can have a workable consistency.

Compressive, splitting tensile, impact strengths, and modulus of elasticity were selected to be the criteria for evaluating effect of adding fibers to concrete mixes. Measurements of rebound hammer and PUNDIT ultrasonic testers were also planned. These two techniques were selected as being the most easy-to-apply ones, Malhorta, ACI 228, ACI 437 and ACI 544 [12], [3], [4] and [5].

The experimental program also includes the evaluation of concrete performance after exposure to elevated temperature for one hour.

4. MATERIALS AND SPECIMENS

Concrete materials were: locally produced CEM I 32.5R conforming to ES 4756-2007, tap water, sand with fineness modulus of 3.0, and gravel with maximum nominal size of 25 mm. Steel fibers with 5400 kg/cm2 tensile strength, 0.8 mm diameter and aspect ratio of 50 were used. Linen fibers were locally produced fibers and applied in decorative elements of buildings. Their properties vary in a wide range. However, they have a mean diameter of about 0.5 mm and length of 40 mm. Linen fibers are usually delivered in spools. Fibers were cut manually to the required length.

In order to get the mix proportions for concretes with different compressive strength, the database of the British method were used. In order to eliminate the effect of compaction on results, water content was kept constant at 200 litre/m^3. The strength was varied by changing the water/ cement ratio (w/c) via changing cement content. Seven mix proportions were calculated to get concrete mixes with strengths from 150 to 450 kg/cm^2 in an increment of 50 kg/cm^2. The fibers were added to each of these mixes (0.5 % by volume) to get the two other sets of concrete mixes. Table (1) shows mix proportions of different concretes.

Constituents were mixed mechanically in a tilting type mixer with 140 liter capacity. Dry materials were mixed first for about 1 minute and then water was added gradually and mixing continued till a homogeneous mix was obtained. When fibers were used, they were spread uniformly by hand during mixing other materials, as per recommendation of ACI 544 [5]. Steel molds were used to cast set of (15*30 cm) cylinders and cubes (15 cm). Specimens were covered by plastic sheets for 24 hours. Then, specimens were demolded and immersed in water till day of testing.

5. TEST RESULTS

Unless noted otherwise, each of the data points shown below represents the average of test results of testing two concrete specimens.

5.1 Compressive Strength

Compression test was made on cube specimens at ages of 7 and 28 days. Figs. (1,2) show the compressive strength values plotted versus w/c ratio at both 7 and 28 days. One can see that the addition of fibers increases compressive strength insignificantly.

Mix No	Content – kg/m^3					
	Water	Cement	Sand	Gravel	Steel Fibers	Linen Fibers
1	200	322.5	581.3	1162.6	0	0
2	200	344.8	575.4	1150.8	0	0
3	200	377.3	566.8	1133.7	0	0
4	200	416.6	556.4	1112.9	0	0
5	200	454.5	546.4	1092.8	0	0
6	200	487.8	537.6	1075.2	0	0
7	200	526.3	527.4	1054.8	0	0
8	200	322.5	581.3	1162.6	0	0.4
9	200	344.8	575.4	1150.8	0	0.4
10	200	377.3	566.8	1133.7	0	0.4
11	200	416.6	556.4	1112.9	0	0.4
12	200	454.5	546.4	1092.8	0	0.4
13	200	487.8	537.6	1075.2	0	0.4
14	200	526.3	527.4	1054.8	0	0.4
15	200	322.5	581.3	1162.6	3.9	0
16	200	344.8	575.4	1150.8	3.9	0
17	200	377.3	566.8	1133.7	3.9	0
18	200	416.6	556.4	1112.9	3.9	0
19	200	454.5	546.4	1092.8	3.9	0
20	200	487.8	537.6	1075.2	3.9	0
21	200	526.3	527.4	1054.8	3.9	0

TABLE 1: Mix Proportions (by weight) for one cubic meter of Concrete

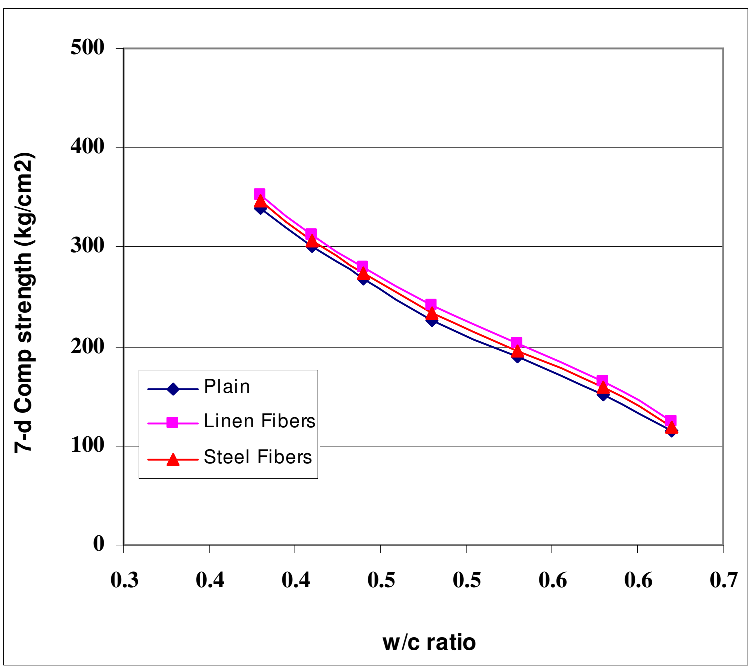

FIGURE 1: 7-day Compressive Strength

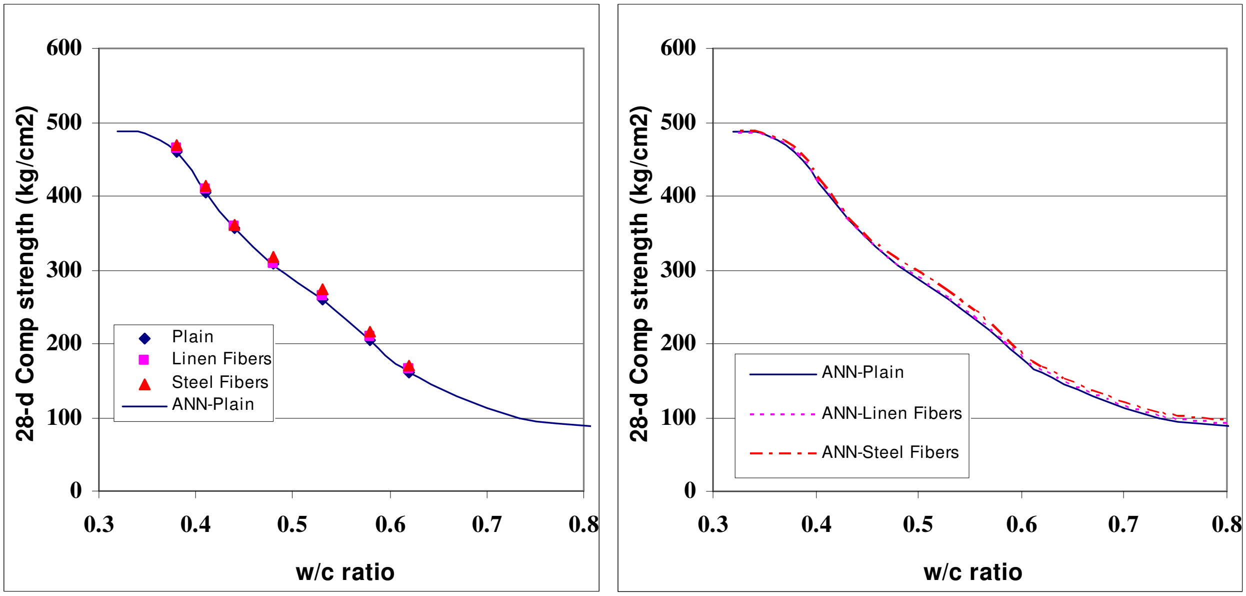

FIGURE 2: 28-day Compressive Strength

5.2 Tensile Strength

Indirect (splitting) tension test was made on cylindrical specimens at 28 days. Fig. (3) shows the Compressive strength values plotted versus the corresponding splitting tensile strengths. One can see that the addition of fibers increases tensile strength significantly. This is expected since fibers improve tensile behavior of brittle materials via crack arrest and crack bridging, Ramachandran [16]. Role of fiber tensile strength appears when observing that linen fibers improves tensile strength by about 11 %, in average, while steel fibers increases tensile strength by about 29 % in average.

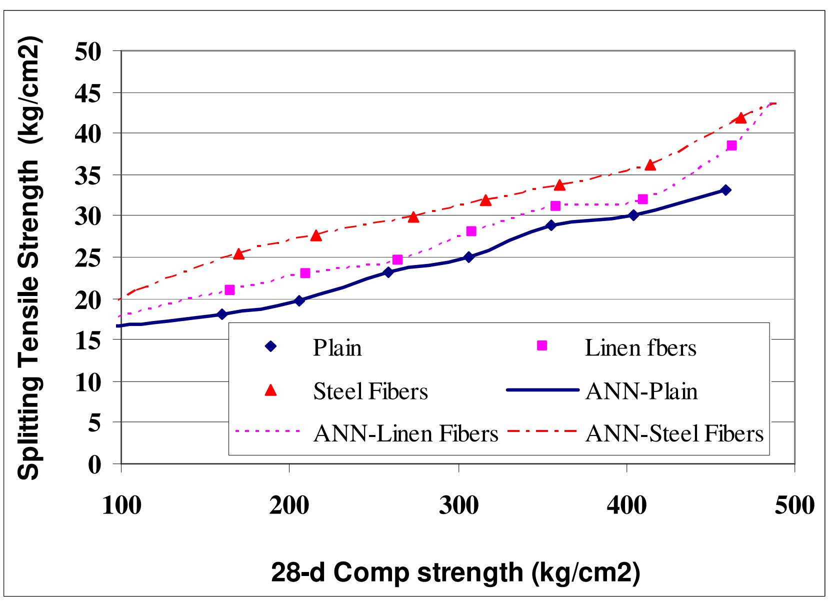

FIGURE 3: 28-day Tensile Strength

5.3 Impact Strength

Impact test was made on concrete discs (15*10 cm) cut from the standard concrete cylinders (15*30 cm). Test was made according to test method described in ACI 544 [6]. Figure (4) shows number of blows (drops of standard hammer) till the appearance of first crack. Fibers increase impact strength mainly via the fiber pull-out mechanism, Parret and Ramachandran, [15] and [16]. One can see that the improvement of impact strength due to linen fibers (34% in average) is almost half of that made by steel fibers (68% in average). There is no trend on variation of this value with concrete compressive strength.

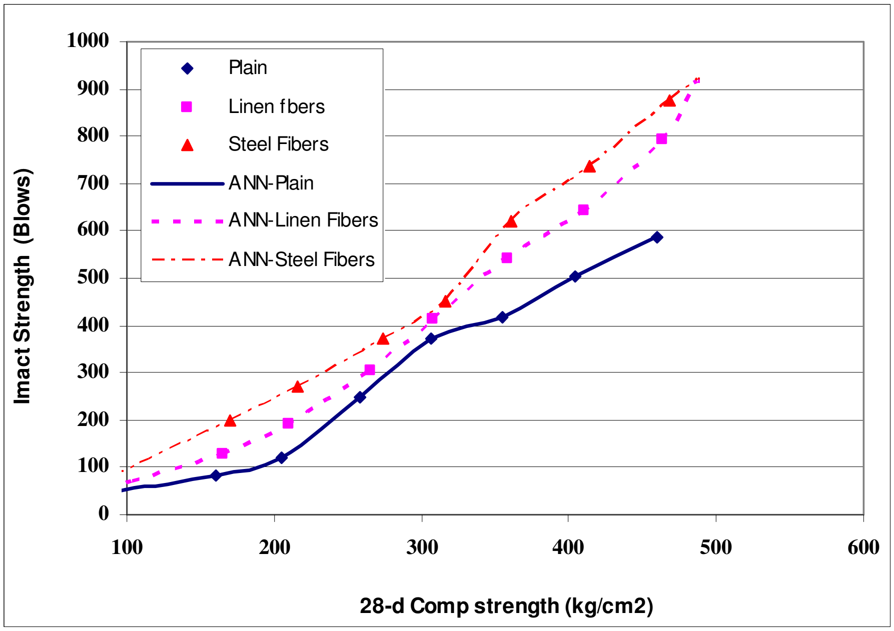

FIGURE 4: 28-day Impact Strength

5.4 Stiffness (Modulus of Elasticity)

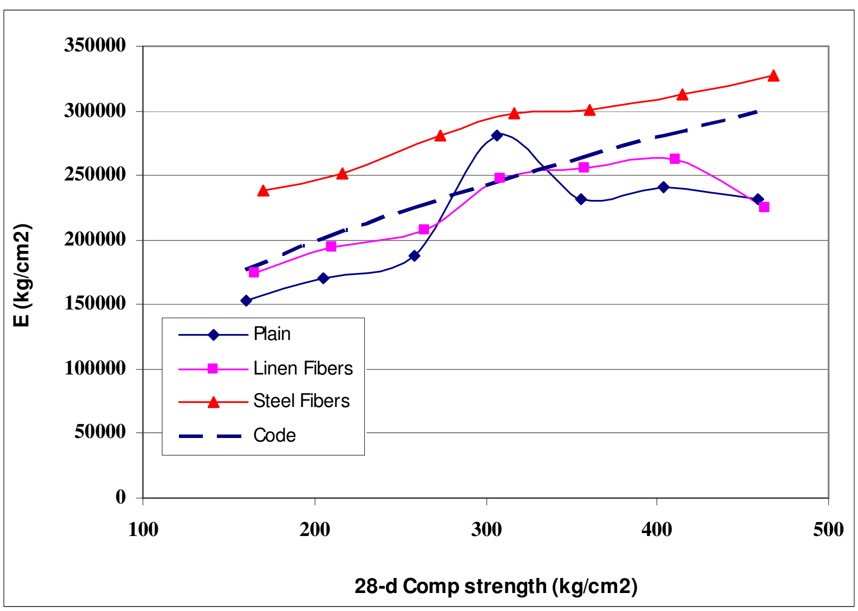

FIGURE 5: Modulus of Elasticity of Different Concretes

The stiffness of concrete was measured applying the method described by ASTM C0469-02E01 [8]. A compressometer with mechanical dial gage (accuracy of 0.001 mm) was used to measure deformations of the tested cylinders. Measurements were made on one specimen for each mix. Results are shown in Fig (5). Direct proportion can be seen in the figure. The dashed line shows the relationship given by Egyptian code of practice ECP 203/2007 $E = 14000\ (f_{cu})^{0.5}$. One can see that addition of fibers increases stiffness, since it reduces strains. Also, code equation represents an upper bound of stiffness for plain and linen fiber reinforced concrete. However, code equation represents a lower bound for steel fiber reinforced concrete.

5.5 Rebound Hammer Reading

The rebound hammer is one of the most common tools used for evaluating uniformity of concrete, and sometimes its strength. The hammer readings were taken on concrete cubes while supported in compression testing machines under 5 ton load. Angle of hammer axis was zero. Ten readings were taken on each cube (5 for each of the accessible faces). Average value of rebound number (Rn) is plotted vs. actual compressive strength measured from loading cube till failure, in Fig (6). One can see that hardness of concrete increases with inclusion of fibers. This effect is more pronounced for steel fibers, and at later ages. This is an expected effect due to the stiffening effect of fibers that is increased with stiffness of material of fiber. The range of variation of strength, at the same rebound number, reaches 25% with steel fiber reinforced concrete in the lower bound. This range, however, is identical to that known for rebound hammer readings on surfaces made from same concrete mix, Malhotra, [12].

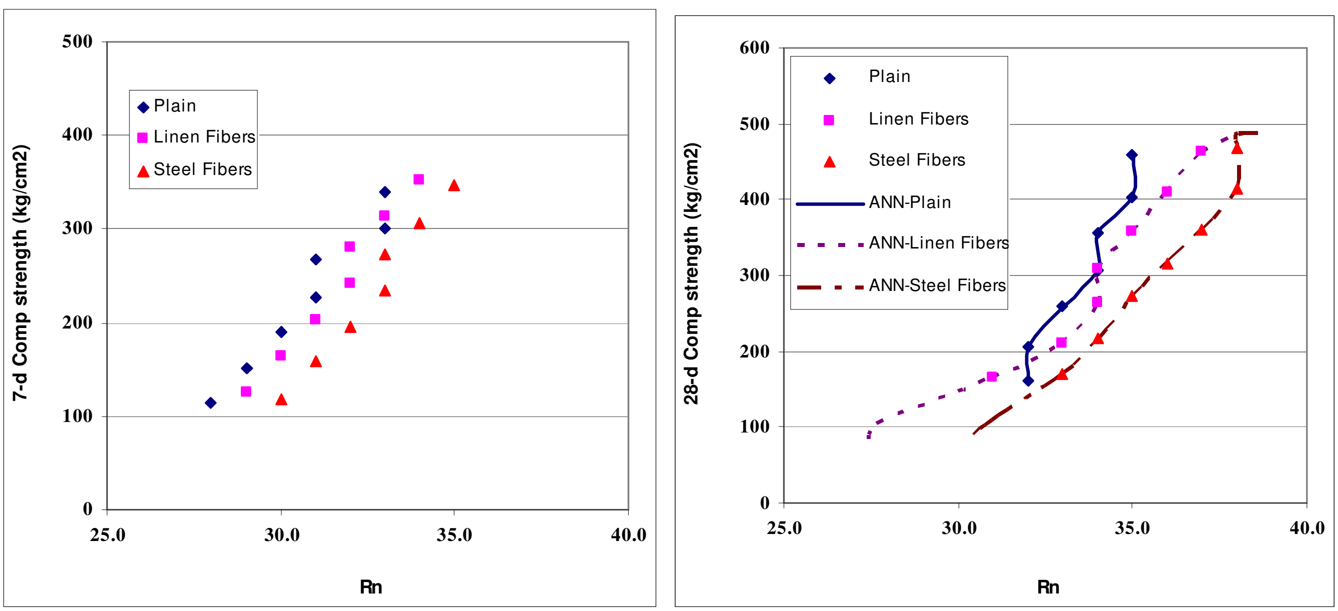

FIGURE 6: 7-d and 28-d Compressive Strength vs. Rebound Number

5.6 Ultrasonic Pulse Velocity

Another common technique applied for evaluating uniformity of concrete, and sometimes its strength. Ultrasonic pulse velocity was measured on concrete cubes using PUNDIT tester in a direct transmission. Measurements were made in two directions (using four faces of concrete cube). Average velocity (v) is plotted vs. concrete compressive strength measured from lading tested cube till failure. Data are shown in Fig (7). One can see that data is more scattered at 7-days where concrete is less mature and the effect of fibers is more pronounced.

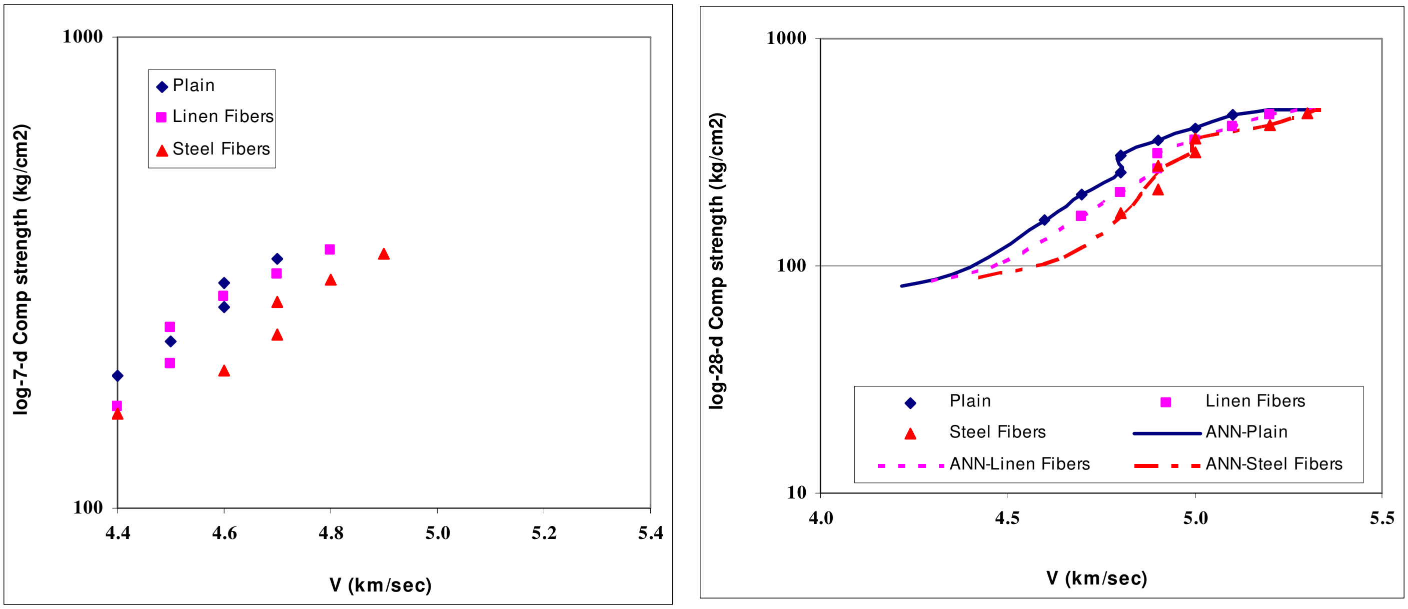

FIGURE 7: 7-d and 28-d Compressive Strength vs. Ultrasonic pulse Velocity

5.7 Effect of Elevated Temperature

The fire redundancy is one of the main requirements in structures after increasing safety precautions. In order to investigate effect of elevated temperature on mixes, concrete cubes were subjected to elevated temperature at two levels (400 and 450°C), in an electric oven, for one hour. Cubes were taken out of the furnace and cooled in ambient air. Then, measurements of rebound and ultrasonic pulse velocity were made. Later, cubes were loaded in compression till failure and residual compressive strength was measured. Results are plotted in Figs.(8-10). It shall be mentioned that tests were made at ages later than 28 days, and earlier than 56 days. One can see that the effect of elevated temperature on strength is more pronounced at 450°C. Also, inclusion of fibers improves significantly heat resistance of concrete. Steel and linen fibers have almost equal effect in the improvement of concrete heat resistance. One can also see from Fig.(8) that strength reduction is more obvious for concrete with higher rank (28-d strength). It can also be seen, from Fig.(9) that correlation between strength and Rn becomes closer for plain and fiber reinforced concretes. However, damage in surface layer for exposure at 450° C makes Rn smaller, especially for concrete with small rank. In case of exposure to 400° C, drying effect causes an increase in surface hardness as can be seen from the range of readings.

Measurements of ultrasonic pulse velocity appear to be more sensitive to heat damage. This is expected since wave propagation is more interrupted by heat induced cracks. Effect of fibers is significant since it allows transmission across cracks by bridging mechanism they offer. This is more obvious for high residual strength range; where the number of internal cracks from thermal damage is less.

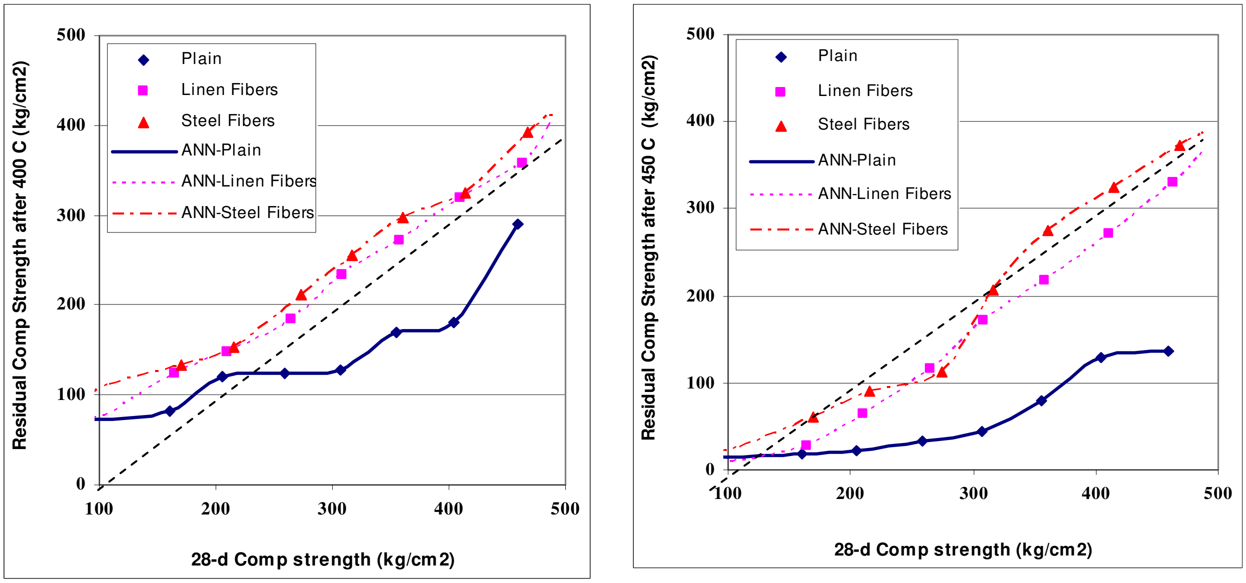

FIGURE 8: Residual Compressive Strength vs. 28-d Compressive Strength

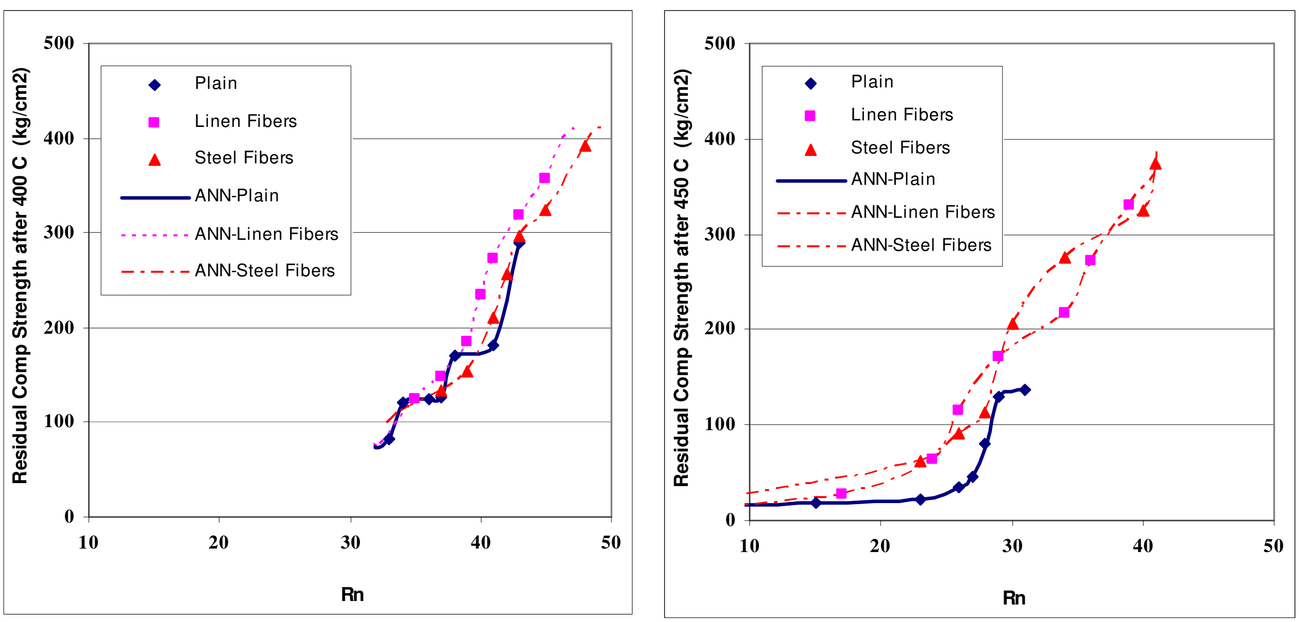

FIGURE 9: Residual Compressive Strength vs. Rebound Number

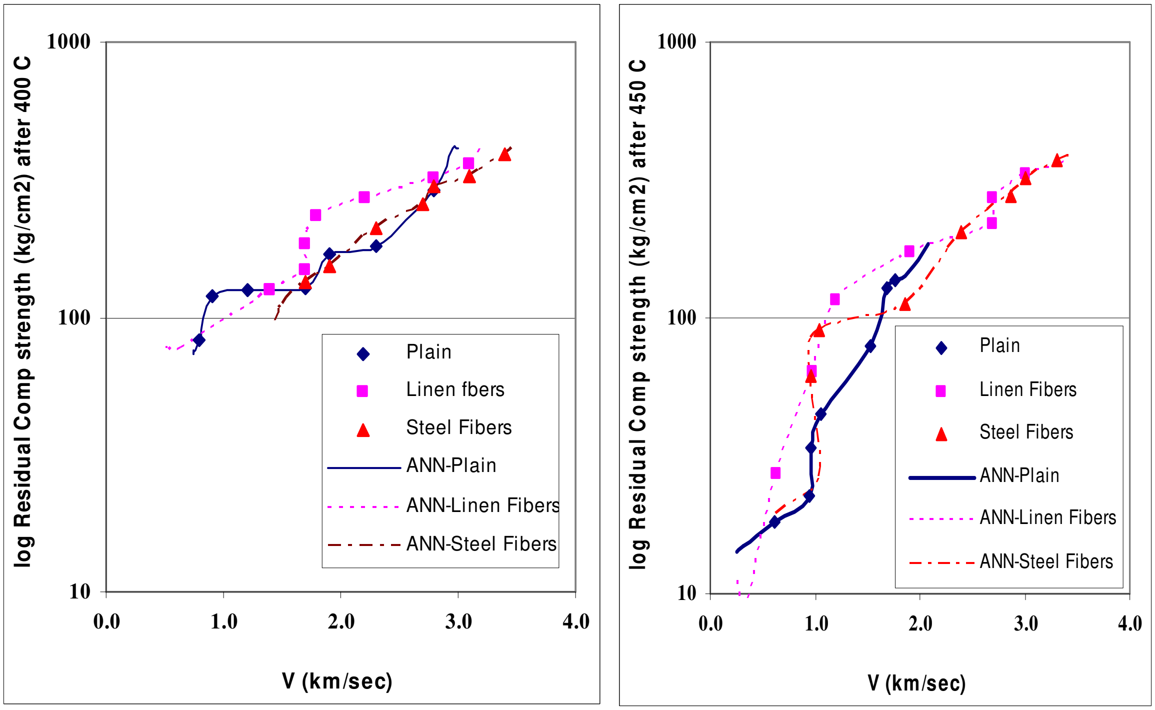

FIGURE 10: Residual Compressive Strength vs. Ultrasonic Pulse Velocity

6. NUMERICAL MODEL STRUCTURE

Neural networks are models of biological neural structures. Briefly, the starting point for most networks is a model neuron as shown in Fig. (11). 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.

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:

$$U_j = \sum \left(X_i w_{ij} \right) \tag{1}$$

And

$$Y_j = F_{th}\left(U_j + t_j\right) \tag{2}$$

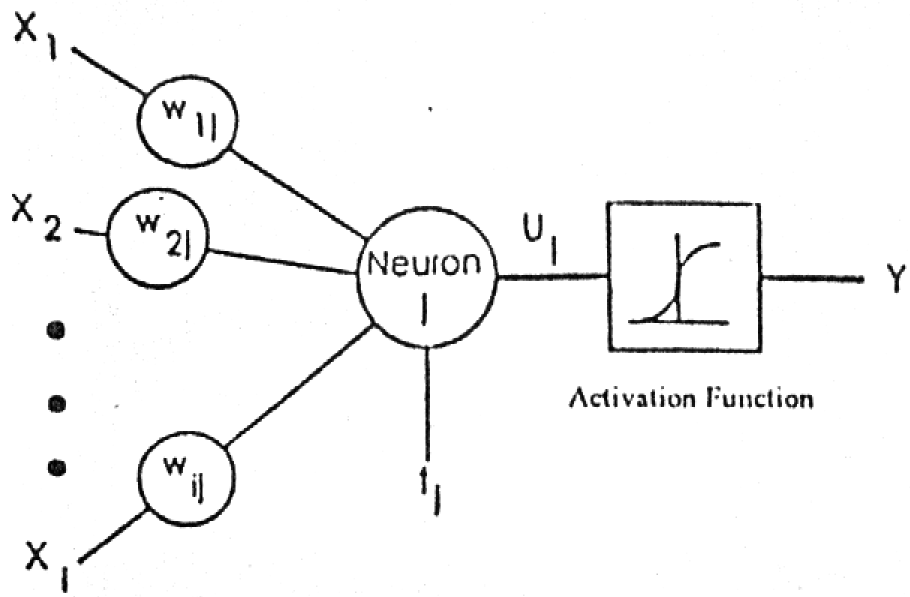

FIGURE 11: Typical picture of a model neuron that exists in every neural network

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 3, but it ranges from – 1 to + 1 rather than from 0 to 1 as in the Sigmoid one.

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

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 [17], was used.

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:

$$w_{ij} = w_{ij}^{'} + LR\left(e_j X_i\right) \tag{4}$$

And,

$$e_j = Y_j\left(1-Y_j\right)\left(d_j - Y_j\right) \tag{5}$$

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.

7. SIMULATION CASES

To fully investigate the effect of natural and steel fibers on the performance of concrete, several simulation cases are considered in this study. These simulation cases can be divided into two groups. The first group simulates the impact of fibers on the performance of concrete: compressive, tensile, impact strengths, rebound hammer reading and ultra sonic pulse velocity. The second group simulates the effect of elevated temperature on the performance of plain concrete as well as concrete with fibers: residual strength, rebound hummer reading and ultra sonic pulse velocity.

8. NEURAL NETWORK DESIGN

To develop a neural network model to simulate the effect of fibers 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. To clearly specify the key input variables for each neural network simulation groups and their associated outputs, Tables (2) and (3) are designed to summarize all neural network key input variables and outputs for these two groups respectively.

It can be noticed from Table (2) that the first simulation group consists of five simulation cases (five neural network models) to study the effect of fibers on the compressive strength, splitting tensile strength, impact strength, rebound hammer reading and ultrasonic velocity. Table (3), for the second simulation group, consists of six simulation cases (six neural network models) to study the effect of fibers on the residual compressive strength, rebound hammer reading and ultrasonic velocity in case of elevated temperature to 400^oC and 450^oC.

Several neural network architectures are designed and tested for all simulation cases investigated in this study to finally determine the best network models to simulate, very accurately, the effect of fibers as well as elevated temperature on the performance of concrete based on minimizing the Root Mean Square Error (RMS-Error). Fig. (12) shows a schematic diagram for a generic neural network.

<table>
<tr><th>Simulation Case</th><th colspan="6">Input Variables - Kg/m^3</th><th>Output</th></tr>
<tr><td>Compressive Strength</td><td rowspan="5">Water</td><td rowspan="5">Cement</td><td rowspan="5">Sand</td><td rowspan="5">Gravel</td><td rowspan="5">Steel Fibers</td><td rowspan="5">Linen Fibers</td><td>28-days Comp. Strength</td></tr>
<tr><td>Tensile Strength</td><td>Splitting Tensile Strength</td></tr>
<tr><td>Impact Strength</td><td>Impact Strength</td></tr>
<tr><td>Rebound Hammer Reading</td><td>Rebound Number 28-days</td></tr>
<tr><td>Ultrasonic Velocity</td><td>Velocity 28-days</td></tr>
</table>

TABLE 2: Key input variables and output for the first neural network simulation group

Simulation Case	Input Variables - Kg/m^3						Output
Residual Comp. Strength	Water	Cement	Sand	Gravel	Steel Fibers	Linen Fibers)	Strength at 400^{o}C
Residual Comp. Strength							Strength at 450^{o}C
Rebound Hammer Reading							Rn at 400^{o}C
Rebound Hammer Reading							Rn at 450^{o}C
Ultrasonic Velocity							Velocity at 400^{o}C
Ultrasonic Velocity							Velocity. at 450^{o}C

TABLE 3: Key input variables and output for the second neural network simulation group (elevated temperature)

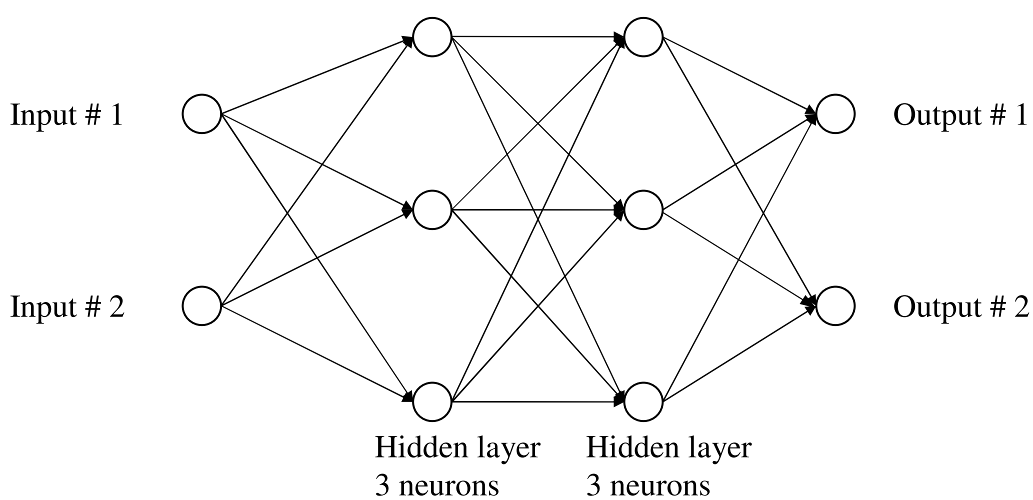

FIGURE 12: General schematic diagram of a simple generic neural network

Table (4) shows the final neural network models for all the simulated cases and their associated number of neurons. The input and output layers represent the key input and output variables described previously for each simulation case. The term PRE showed in the table referred to percentage relative error and is computed based on equation 6 as follows:

PRE = (Absolute Value (ANN_PR - AMV)/AMV)*100 (6)
Where:
ANN_PR: Predicted results using the developed ANN model
AMV : Actual Measured Value

The parameters of the various network models developed in the current study for the different simulation cases are presented in Table (5), where: (**Comp. St.**) denotes for compressive strength, (**Ten. St.**) for tensile strength and (**Rn**) for rebound number,. 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.
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.
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 [17], in preparing data for the neural network or interpreting data from the neural network = 0.1 in the current study.

Simulation Case	**No. of Layers**	**No. of Neurons in each Layer**						**Max PRE**
		Input Layer	**First Hidden**	**Second Hidden**	**Third Hidden**	**Fourth Hidden**	**Output Layer**	
Compressive Strength	6	6	6	5	4	3	1	0.122
Tensile Strength	5	6	5	5	4	-	1	0.151
Impact Strength	5	6	6	5	4	-	1	0.08
Rebound Hammer Reading	6	6	6	5	4	3	1	0.118
Ultrasonic Pulse Vel.	5	6	5	4	3	-	1	0.693
Strength at 400^{o}C	5	6	6	5	4	-	1	0.014
Strength at 450^{o}C	5	6	5	4	3	-	1	0.697
Rn at 400^{o}C	5	6	5	4	3	-	1	0.154
Rn at 450^{o}C	6	6	6	6	5	6	1	0.078
Velocity at 400^{o}C	5	6	5	4	3	-	1	0.294
Velocity at 450^{o}C	5	6	5	4	3	-	1	0.207

TABLE 4: The developed neural network models for all the simulation cases

Simulation Case	Comp. St.	Ten. St.	Impact St.	Rn	V	St. 400^{o}C	St. 450^{o}C	Rn 400^{o}C	Rn 450^{o}C	V 400^{o}C	V 450^{o}C
TRT	0.0005	0.001	0.0001	0.001	0.001	0.0001	0.0001	0.001	0.0005	0.0005	0.001
TST	0.001	0.003	0.0003	0.003	0.003	0.0001	0.001	0.003	0.001	0.001	0.003

TABLE 5: Parameters used in the developed neural network models

9. RESULTS AND DISCUSSIONS

Numerical results using ANN technique are plotted with the experimental results for the first neural network simulation group : compressive strength, tensile strength, impact strength, rebound hammer reading and ultrasonic pulse velocity as shown in Figs. (2 – 7) respectively. It can be noticed from these figures that ANN technique can accurately simulate the effect of fibers on the performance of concrete.

To study the effect of elevated temperature as well as fibers on the performance of concrete (residual strength, rebound hammer reading and ultrasonic velocity) numerically, the second neural network simulation group are prepared as shown in Table (3). The results of this group are plotted with the experimental results in Figs. (8 – 10) for both 400^{o}C and 450^{o}C. One can see from these Figs. that ANN technique can accurately simulate the effect of elevated temperature and existence of fibers on the performance of concrete.

To check the accuracy of neural network the term PRE is calculated as in equation 6 for each data point in each model. Then the Max PRE is calculated through each model and reported in Table 4. It is very clear from the column of Max PRE that this value doesn't exceed 0.7 % for all the simulation cases presented in this study.

To check the trend of the model before and after the experimental data, two mixes were chosen by reducing the cement content by 50 Kg/m^3 and 100 Kg/m^3 respectively and increasing the weights of sand and gravel content using their corresponding specific gravity. Also, in some cases, other two mixes were chosen by increasing the cement content by the same values as before and reducing the weights of sand and gravel content using their specific gravity. The numerical data resulted from neural network models for these extrapolation points are shown in Figs. (2 – 10). The trend achieved from these figures shows the power of ANN technique to simulate the behavior of concrete under the effect of fibers and elevated temperature.

10. CONCLUSIONS

Application of linen fibers to concrete yields behavior and properties close to that of plain concrete of same rank. Significant improvements were observed for tensile, stiffness, impact and fire resistance. Although an increase of surface hardness and ultrasonic pulse velocity was observed upon use of fibers, almost same calibration curves can be applied for non-destructive testing techniques of rebound hammer and ultrasonic pulse velocity. This can be done considering the range of accuracy of both techniques in evaluating compressive strength of hardened concrete.

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 ANN presented in this study was very successful in simulating and predicting the effect of fibers and elevated temperature on the performance of concrete.

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