Prediction of Flexural strength of concrete reinforced with hybrid steel fibers Using ultrasonic velocity and artificial neural networks

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Abstract:

This paper discusses how artificial neural networks and ultrasonic pulse velocity (UPV) can be used to predict the flexural strength of concrete reinforced with hybrid steel fibers. Artificial neural networks (ANNs) are introduced to train and test data sets. The purpose of this research is to investigate the flexural strength of concrete reinforced with two types of fibers using an experimental program that includes non-destructive (UPV) and flexural testing on various specimens made of conventional concrete (CC) reinforced with steel fibers at varying contents. The multilayer back propagation network is the most appropriate model. It was created to realize the nonlinear relationship between the input data network and the target. It is established by incorporating an experimental database and selecting an appropriate architecture and learning process. The findings show that artificial neural network models accurately predicted the flexural strength of steel fiber-reinforced concrete, demonstrating that the combination of non-destructive testing (ultrasonic pulse velocity) and neural networks is extremely effective for estimating the flexural strength of concrete and fiber-reinforced concrete at any age.

***Keywords**: flexural strength, ultrasonic pulse velocity, steel fibers, artificial neural network, concrete.*

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1. Introduction

Concrete is the world's most widely used heterogeneous and complex building material. Concrete was traditionally made by combining a few well-defined ingredients: cement, fine aggregates, coarse aggregates, water, and so on. The flexural strength of concrete is a critical property that determines its ability to withstand bending loads, which is essential for structural applications. This strength can be significantly enhanced by using high strength concrete in combination with high strength reinforcement, allowing for increased flexural capacity without compromising the maximum reinforcement ratio [1]. Additionally, the flexural strength is influenced by various factors, including the water-cement ratio, type of aggregates, and curing conditions, which engineers must consider when optimizing concrete mix designs [2]. Testing methods such as the three-point and four-point bending tests are standardized procedures used to accurately assess the flexural strength of concrete [3]. As reported in previous works of literature [4–11], the incorporation of steel fibers in concrete improves the mechanical characteristics (compressive strength, flexural strength, and tensile strength), making the concrete more strong and resistible to cracks, The flexural strength of fiber-reinforced concrete is considerably increased compared to ordinary concrete [12]. The use of hybrid steel fibers not only enhances the structural integrity of concrete but also contributes to sustainability by reducing maintenance costs and extending the lifespan of construction materials [3]. Thus, hybrid steel fibers represent a significant advancement in concrete technology, offering versatile solutions for modern construction challenges.

Concrete quality control involves a series of tests and inspections to ensure that concrete meets the required standards and specifications. Ultrasonic Pulse Velocity (UPV) is a widely recognized non-destructive testing method used to assess the quality and condition of concrete. This technique measures the speed of ultrasonic waves traveling through concrete, which correlates with its mechanical properties, such as compressive strength. The UPV results can be classified into categories indicating the concrete's condition, ranging from excellent to problematic [12].

Artificial neural networks (ANNs) are increasingly being integrated into civil engineering, public works, and geotechnical engineering. ANNs play a crucial role in predicting material properties, enabling engineers to optimize material selection based on composition and environmental factors, leading to more sustainable construction practices [13 15]. Furthermore, ANNs can optimize construction planning by considering various factors such as resource allocation and weather conditions, thereby reducing project delays and costs [16].

However, few studies have been conducted on the use of ANNs to predict the compressive and flexural strength of fibers reinforced concrete. We particularly appreciate the work of F. Altun and al. [17], additionally, D. Zealakshmi and al [18] and Jayaranjini [19]. They have all used artificial neural networks to predict the compressive strength of fiber-reinforced concrete.

As a result, using ultrasonic pulse velocity and artificial neural networks to predict the flexural strength of fiber-steel-reinforced concrete could be a reliable and efficient method.

2. Materials

2.1 Cement

The cement used is CEM II/B42.5 N Portland cement (also known as MATINE), with an additional 18% limestone from Algerian Cement Company (ACC). The physical, chemical, and mechanical properties are summarized in table 1 and table 2.

Table 1: Physical characteristics of cement

Start of setting minute	160 – 180 min
End of setting (hours)	4 h 00 ~ 4 h 30
Specific mass (g/cm3)	3.1
Heat of hydration (J/g)	456.60
Normal consistency (%)	25 81
28 days concrete removel (µm/m)	< 100

Table 2: Mechanical characteristics of Cement

Days	Compression stress	Flexural stress
2	36.74	1.9
7	41.09	4.76
28	45.07	5.71

2.2 Sand

The crushed sand class 0/3 used comes from the quarry of AZROU KEDDARA, with the physical properties summarized in the table 3:

Table 3: Physical properties of sand

Absolute density (ρ)	2.64
Apparent density (ρ0):	1.47
Compactness	0.53
Porosity (n)%	0.47
Visual sand equivalent (VSE)%	84.3
Sand equivalent with piston (SPS)%	80.7
Methylene blue test (MB) [g/kg]	0.25

2.3 Aggregates

The aggregates used come from the AZROU KEDDARA Quarry, whose characteristics and properties are summarized in table 4:

Table 4: characteristics of aggregates

Tests / aggregates	3/8	8/15	Standards
Apparent density ρ(g/cm3)	1.36	1.42	1.30 -1.60
Absolute density .ρ(g/cm3)	2.64	2.64	2.60 - 2.80
Compactness	0.51	0.56	< 3
Porosity: %	0.49	0.44	< 3
Water absorption (%)	0.35	0.35	≤ 0.5
Surface cleanliness	1.7	1.55	
Flattening coefficient	/	11.2	//

2.4 Steel Fibers

We used two types of Dramix fibers, each with a different effect on the behaviour of concrete after cracking. They are made from steel wire designed for drawing and cold rolling according to standards NF EN 10016-1 and NF EN 10016-2. (Figure 1).

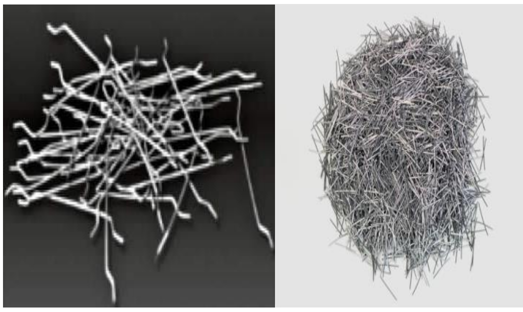

Figure1: Smooth and Hook-End (Dramix Steel Fiber)

Table 5 summarizes the mechanical and dimensional properties of the fibers used in this study.

Table 5: Characteristics of used fiber

Steel Fiber type	*F* Smooth	*F* Hook-end
Length (*lf*), mm	15 ± 3	30 ± 3
Diameter (*df*), mm	0.12 ± 0.01	0.375 ± 0.02
Hooked length (*l*), mm	Smooth	$1 \leq l \leq 3$
Hooked amplitude, mm	/	$h \geq 0.75$
Hooked angle	/	$\alpha \geq 20°$
Tensile strength, MPa	>1,000	>1,050
Conditioned	Free	Glued in plate
Slenderness factor *lf*/*df*	125	80

As part of the database preparation procedure, we formulated a standard concrete with the volumetric composition listed below (Table 6).

Table 6: Characteristics of formulated concrete

Materials	**Cement**	**Fine** aggregats **3/8**	**Coarse** aggregats **8/15**	**Sand 0/3**	**Water (l)**
Weight kg	400	243	881 kg	623	160

Three-point destructive bending tests and non-destructive testing (UPV) were carried out during the experimental study. The deduced experimental results serve as training and testing datasets for validating the ANN model developed in this study. 42 specimens measuring 70 x 70 x 280 mm are prepared and used in this study to determine propagation time, velocity, and bending strength. The specimens are exposed to the natural outdoor environment throughout the curing process.

3. Methods

3.1 Ultrasonic pulse velocity

Ultrasonic Pulse Velocity (UPV) testing is a non-destructive technique widely employed in the field of civil engineering to assess the integrity and quality of concrete structures. This method utilizes ultrasonic pulses to measure the speed of sound waves as they travel through a concrete specimen, providing valuable information about the material's uniformity, homogeneity, and potential presence of defects such as cracks in concrete. UPV testing is a crucial tool for evaluating the concrete quality and homogeneity, detecting poor patches, internal flaws, cracks, and honeycombing. Its non-invasive nature and ability to provide quick and reliable results make it an essential component of quality control of concrete. This test is conducted in accordance with IS: 13311 (Part 1) – 1992. We used a PROCEQ Pundit 200 ultrasound device in this study. (Figure 2).

We also recorded the P-wave pulse velocity and propagation time for each specimen.

Figure 2: UPV device

3.2 Three-point bending

A three-point bending test was carried out for all made specimens in accordance with standard NF EN 12390-5 at the educational laboratory of the University of Bouira (Algeria). The following figure 3 shows the specimen before and after a three-point bending test.

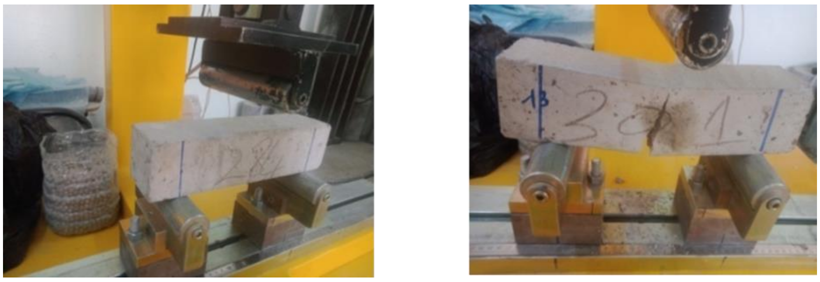

Figure 3: Specimen before and after test

All of the results obtained in this experimental work on all crushed specimens will be used as a database for the proposed neural network. The following table 5 summarizes the variation of the various parameters measured that will be used as input and output to the artificial neural network.

Table 5. Data variation.

Data	Limit variation
Velocity (m/s)	1642-3642
Time (µs)	79.9-174
Apparent density	3.24-2.54
Flexural strength (Mpa)	5-11.6

4. ANN models for prediction of concrete flexural strength

Choosing an artificial neural network (ANN) architecture and propagation algorithm requires careful consideration of the particular needs of the application. Propagation algorithms and ANN architectures differ in their advantages and disadvantages; for example, supervised learning in multi-layer feed-forward networks is frequently accomplished using the Back Propagation (BP) algorithm [20]. Based on the particular needs of the task, an ANN architecture and propagation algorithm should be chosen, taking efficiency, accuracy, and convergence speed into consideration[21 22].

The literature proposes a variety of techniques and methods for determining the optimal number of neurons in a neural network's hidden layer. In our study, the optimal structure of hidden layers was determined by comparing different structures based on error calculation to find the most efficient architecture [13].

The final architecture of the network used in this study is composed of three layers, an input layer with three parameters, a hidden layer with six neurons and a tangent hyperbolic sigmoid activation function; one output layer parameter and linear activation function were used.
The performance of the model is measured by the mean square error function (MSE), done on equation (1), and correlation values “R”, done on equation (2). The model's performance is ensured by its higher R value and lower MSE value.

$$MSE = \frac{1}{N}\sum_{k=1}^{n}(Y_k - \bar{Y}_k)^2 \qquad (1)$$

$$R = \frac{\sum_{k=1}^{n}(Y_k - \bar{Y}_k)\left(Y_k^* - \bar{Y}_k^*\right)^2}{\sqrt{\sum_{k=1}^{n}(Y_k - \bar{Y}_k)^2 \sum_{k=1}^{n}\left(Y_k^* - \bar{Y}_k^*\right)^2}} \qquad (2)$$

Where Y_k is the desired value;
Y_k^* is the estimated value;
N is the number of neurons in the output layer;
n is the number of vectors presented to the network;
$\bar{Y}_k = \frac{1}{n}\sum_{k=1}^{n} Y_k$
$\bar{Y}_k^* = \frac{1}{n}\sum_{k=1}^{n} Y_k^*$

Among the 42 databases carried out, we retained four data to later examine the selected ANN. The 38 data points were used in the ANN's three phases of development and were randomly divided into three sections: training (70%), testing (15%), and validation (15%). The artificial neural network model was trained using a training dataset. The validation dataset was used to stop the training process, and the test dataset was used to evaluate the performance of the ANN model once the training process was completed.

Each dataset consists of input vectors and their corresponding targets. First, the data will be normalized to range from 0 to +1. Before submitting to the ANN, they must agree on the limits of the activation transfer function used in the hidden and output layers. In this paper, a sample function, as expressed in Equation (3), was adopted to normalize the data.

$$X_{i,norm} = (X_i - X_{min})/(X_{max} - X_{min}) \qquad (3)$$

Where $X_{i,norm}$ is normalized data and Xmax and X_{min} are the maximum and minimum value of data, respectively. An inverse normalized process is applied to the output layer to get the test data.

The backpropagation algorithm was used to train, test, and validate the proposed model. The implementation and simulation were done with MATLAB software.

5. RESULTS AND DISCUTIONS

The main objective of this research is to predict the flexural strength of steel fiber-reinforced concrete using ultrasonic pulse velocity and artificial neural networks (ANN). A successfully trained ANN model should give an accurate output prediction, not only for input data used during the training process but also for new testing data unfamiliar to the model within the range of the training database. Figure 4; shows the correlation between predicted flexural strength values and experimentally measured values.

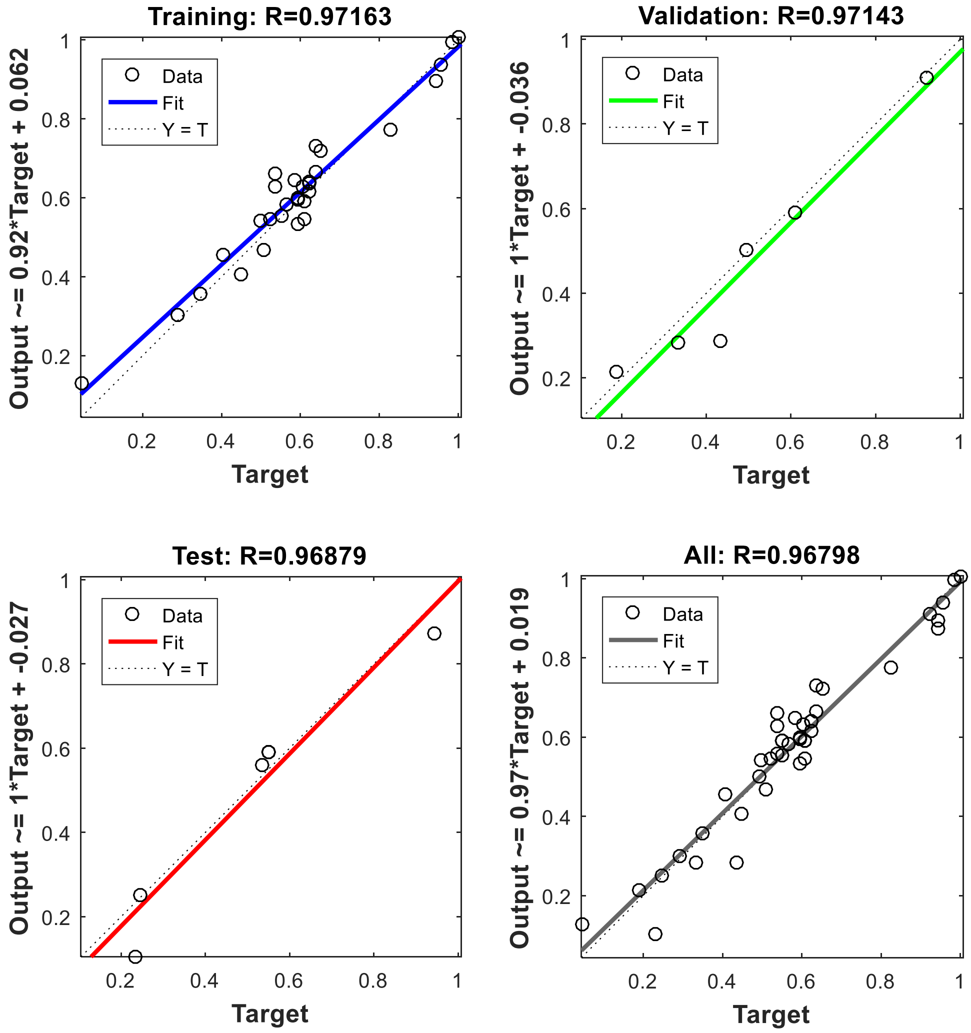

Figure 4. Relationship between the Real and ANN predicted values for training, validation testing data, and all data.

Comparisons between the predicted and the target (experimental) values for the training, validation and testing data of the flexural strength ANN model were shown in Figure 4. It was clear that the predicted values from the training, validation and testing data, calculated by the ANN model, were close to the target values. This phenomenon demonstrated the ANN model's ability to successfully learn the nonlinear relationship between input and output variables. As a result, the ANN model has the potential to estimate the flexural strength.

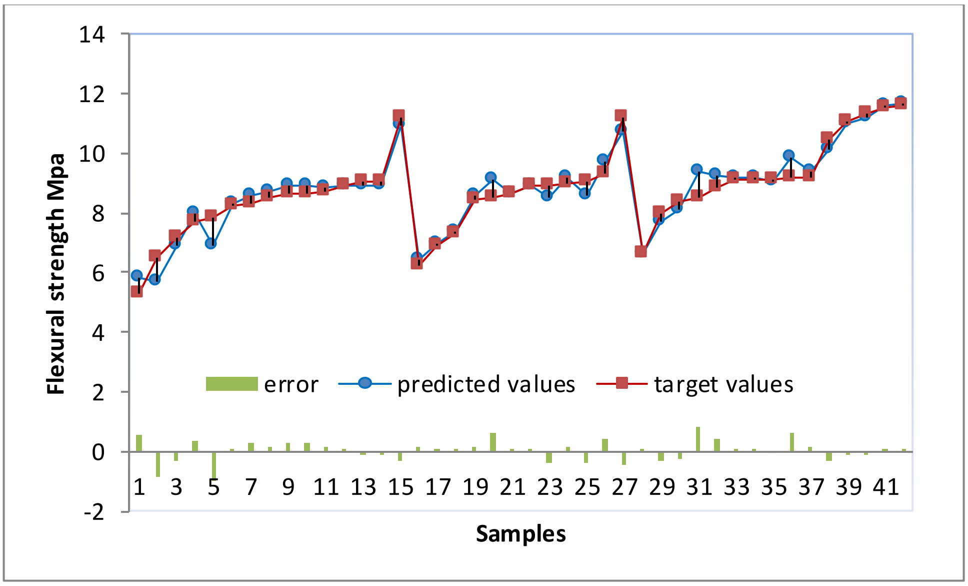

Figure 5. Comparison of predicted values from flexural strength ANN model with experimental results: all data

The figure 5, show that the comparison between the target values and predicted values of all data from experiments and flexural strength ANN model, the horizontal axis denotes number of samples, and the vertical axis denotes the flexural strength. It was obvious that the predicted values accord with the target values.

The neural network was applied to predict the flexural strength of fourth samples which were previously retained. Figure 6; shows the correlation between the predicted and measured values of flexural strength.

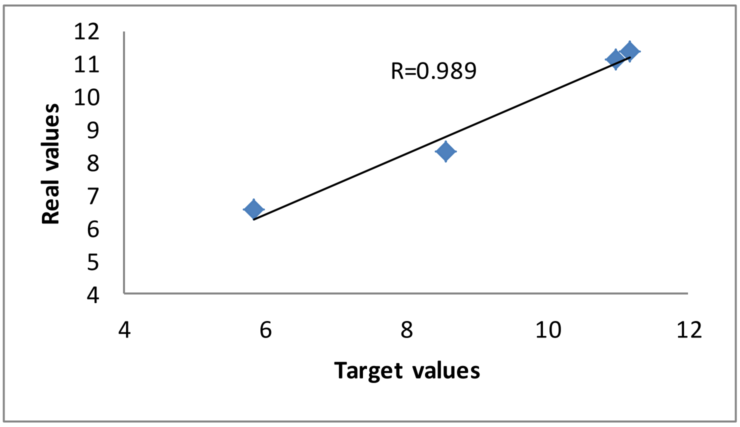

Figure 6. Correlation between predicted and measured flexural strength of retained samples

We can see that the predicted flexural strength have an excellent correlation with measured flexural strength coefficient correlation R equal to 0.989.

6. CONCLUSION

In this paper, the ANN method was applied to evaluate the flexural strength of steel fiber-reinforced concrete. A reliable database consisting of 42 flexural strength data sets from previous experimental works was established, and 38 samples were randomly chosen for training and the remainder for testing to establish the flexural strength ANN model.
The conclusions were as follows:

(1) The flexural strength ANN model was trained using the LM algorithm with six neurons in hidden layer, revealing great prediction performance. The predicted values were fairly close to the experimental results for both the training and testing data sets in the proposed model.

(2) The correlation coefficient R is greater than 0.96 in the three steps of constructing the ANN, indicating that the proposed ANN model has a better ability to predict flexural strength using ultrasonic pulse velocity and time propagation in relation to apparent density in input vectors.

(3) The combination of non-destructive testing (ultrasonic pulse velocity) and neural networks is extremely effective for estimating the flexural strength of concrete and fiber-reinforced concrete at any age.

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