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Assessment of core strength of concrete by artificial neural networks

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Research Paper

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Assessment of core strength of concrete by artificial neural networks

The proposed work deals with the use of Ultrasonic pulse velocity technique as an alternative method to identify compressive strength of the core concrete. The use of non-destructive technique without causing damages to the structure is tedious with interpretation of results influenced by various factors. Hence, an empirical relationship is developed using artificial neural network model for creating a regression between pulse velocity and compressive strength of concrete core specimens. Tests were conducted on reinforced concrete cylinders at various orientation angles (0°, 45°, 90°). The tests were conducted based on the design of experiment using the Box-Behnken model. These results were trained using the Levenberg-Marquardt back propagation model with hidden layers. Results indicate that the prediction of core compressive strength for the grade mixes is nearer for the two-level factorial design with R^2 = 0.897, and the sum of squared error is found to be 0.9968.

Key words:
non-destructive techniques, compressive strength, ultrasonic pulse velocity, artificial neural network, grade of concrete

Prethodno priopćenje

Herald Lessly Stephenson, Senthil Rajendran

Ocjena čvrstoće betonskih jezgri pomoću umjetnih neuronskih mreža

U ovom se radu koristi postupak baziran na brzini ultrazvučnih impulsa kao alternativna metoda za određivanje tlačne čvrstoće betonskih jezgri. Primjena nerazornog postupka kojim se ne oštećuje analizirana konstrukcija je dugotrajna, a na tumačenje rezultata utječu brojni faktori. Stoga je, radi definiranja regresije između brzine ultrazvučnih impulsa i tlačne čvrstoće betonskih jezgri, razvijen empirijski odnos zasnovan na primjeni modela umjetnih neuronskih mreža. Ispitivanja su provedena na armiranobetonskim valjcima pri različitim kutovima usmjerenja armature (0°, 45° i 90°). Ispitivanja su provedena eksperimentalnim planiranjem pomoću Box-Behnkenovog modela. Dobiveni rezultati analizirani su postupkom učenja pomoću Levenberg-Marquardtovog modela povratnog prostiranja sa skrivenim slojevima. Rezultati pokazuju da je predviđanje tlačne čvrstoće mješavina točnije za dvorazinski faktorski plan s R^2 = 0,897, a ustanovljeno je da suma kvadratne pogreške iznosi 0,9968.

Ključne riječi:
nerazorni postupci, tlačna čvrstoća, brzina ultrazvučnih impulsa, umjetna neuronska mreža, razred tlačne čvrstoće betona

1. Introduction

The strength and durability of concrete varies continuously throughout its life cycle due to a variety of reasons including environmental factors. Therefore, determination of concrete strength becomes essential for carrying out periodical maintenance, repair and rehabilitation of concrete structures. Usual practice for evaluating concrete structures includes testing through destructive, semi-destructive, and non-destructive methods. The quality of concrete in civil engineering structures is determined through compressive strength tests on standard concrete cylinders extracted from the existing structural members. Extracting core samples from an existing structure and testing it by compression can induce damage to the structure. The concrete core compression testing is the most direct method to assess the in-situ concrete compressive strength in an existing structure. Although this test is quite simple to conduct, the results obtained may sometimes contain considerable errors because of the influence of various parameters. The main challenge in the assessment of in-situ concrete strength is conversion of core results to an equivalent cube/cylinder strength. The various factors influencing core test results are core diameter, length-to-diameter ratio (L/d), concrete age, aggregate characteristics, direction of coring, etc [1]. Another potential factor influencing the testing of cores is the presence of reinforcing bars within the core. Generally, it is advisable to extract cores without reinforcement. Sometimes it is not possible to obtain cores without rebar. In such cases, the core strength is considerably affected by the presence of reinforcement. The concrete strength gets affected during the drilling of core over the reinforcement zones which drastically increases the stress relaxation factor of rebars thus affecting concrete strength. This creates the internal stress cracking of concrete and concrete strength is reduced [2]. In such circumstances, the core strength does not represent the compressive strength of concrete in the structure from which the core was extracted. The effects of the presence of reinforcement on the strength of cores have been investigated by few researchers only. Reinforcement bars passing through a core will increase the uncertainty of results and should be avoided wherever possible. The correction factor for such cores with reinforcing bars are given in BS EN 12504-1, British Standard BS 6089, BS 1881: part 120, and also in [3, 4]. Modifications to the existing codal provisions have been presented by [5] However, some standard codes such as ACI 214, BS EN 13791 and [6] recommend that core specimens for compression tests should preferably not contain any reinforcing bars. There is considerable contradictory evidence related to the steel bar effect: a some investigators found no effects [7] while others proposed various conflicting trends [8, 9]. The investigation by [7] found that the reduction in compressive strength due to embedded steel decreases with a decrease in L/d ratio. The concrete quality is usually assessed through empirical relationships between strength and non-destructive parameters. Ultrasonic Pulse Velocity (UPV) method is one of the well-established conventional non-destructive testing methods for evaluating the quality of concrete. Various researchers [9-11] have created a methodology for using ultrasonic waves to determine the initial setting time in concrete. Martin and Forde [12] have applied P-waves to determine the properties of concrete.

The Artificial Neural Network (ANN) model is a proven computational prototype to solve various intricate problems including prediction problems. ANN is a tool used to framework complicated interrelationships between input and output. ANN has been widely applied for civil engineering problems in recent days. Two back feed propagation algorithms aimed at determining the bar diameter and depth were proposed by [13]. The neural network model for evaluating compressive strength of concrete based on integration of various non-destructive approaches was presented by [14]. Various regression functions aimed at determining compressive strength of concrete were formulated by [15]. Maitham at al. [16] established a conversion model interrelationship between the destructive and non-destructive testing results. A reliability expression was developed by minimizing the number of uncertainties. The usefulness of neural networks (NN) tool for estimating the compressive strength and slump of high strength concrete (HSC) was studied by [17]. ANN model was developed, trained and evaluated using results of 187 distinct concrete mix-designs of high strength concrete. The Neural Network (NN) model speculates the compressive strength and slump values of HSC. Multiple Linear Regression model (MLR), Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS) and statistical techniques, were also used by several researchers to predict the quality of concrete [11, 16, 18-21]. Mucteba and Harun [22] developed ANN as an alternative approach for determining the core compressive strength of self-compacting concrete using the high correlation coefficient. ANN models developed by [23] predicted compressive strength of concrete with different mix ratios. Rahmat at al. [24] proposed the Group Method of Data Handling type neural network (GMDH) using experimental results available in reported literatures considering concrete strength, L/d ratio, core diameter, aggregate size, and concrete age. The multilayer feed forward propagation neural network using UPV values and experimental data sets, developed by [25] has shown good validation with experimental results.

In this paper, experimental investigations were carried out towards development of a tool combining non-destructive testing and statistical parameters for evaluating the compressive strength of concrete core. The advantage of the technique proposed in this paper is the assessment of concrete strength from UPV testing, thereby avoiding core extraction and the associated damage to existing

Table 1. Mix proportions of different concrete mixtures

Mix	Cement [kg/m³]	Fine aggregate [kg/m³]	Coarse aggregate [kg/m³]		Water [kg/m³]
			20 mm	**12,5** mm	
M20	350	674	593,5	593,5	158
M25	380	647	595	595	172
M30	410	625	598	598	185

structures. Experimental investigations were carried out with concrete cores specially cast with different L/d ratio, rebar orientations and concrete grade. The concrete cores were subjected to both destructive and non-destructive testing. The findings of the experimental investigations were used as input parameters for ANN development and for validating the developed technique. The details of the specimens cast, and experimental investigations carried out along with the validation studies, are fully described in the following sections.

2. Materials and methods:

2.1. Materials used

Ordinary Portland Cement (OPC) of 53 grade as per IS 8112 was utilized for this experimental work. Physical properties of cement, i.e., specific gravity and bulk density, amounting to 2.58 and 2708 kg/m³, respectively, were obtained by laboratory testing. Locally available river sand, free from impurities, was used in the present study. Provisions of IS 2386:1975 were applied. The specific gravity and fineness of fine aggregate amount to 3.09 and 1.95 %, respectively. 20 mm and 12.5 mm coarse aggregate was utilized in the present study. Physical properties of coarse aggregates, i.e., specific gravity, water absorption, and bulk density, amount to 2.73, 2.24 %,and 1512 kg/m³, respectively, for 12 mm aggregate, and to 2.68, 1.38 %& 1491 kg/m³, respectively, for 20 mm aggregate. Concrete mix ratios and relevant descriptions are given in Table 1.

2.2. Preparation of test specimens for experimental investigation

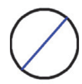
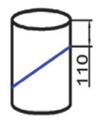
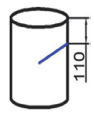
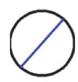
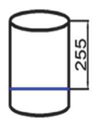
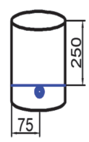
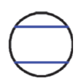
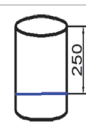
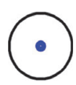
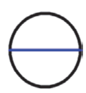
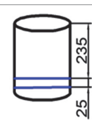
Various length to diameter (L/d) ratios of 2, 1.5, and 1, with and without reinforcement, were used. 12 mm diameter bars were used in the present study to evaluate compressive strength of concrete. Core samples were moist cured until the testing time. Six samples were tested for each (L/d) ratio. 138 core specimens were tested in this experimental investigation, with three repetitions of each combination of test parameters.

As proposed by [26], the (L/d) ratio of specimens varies from 1 to 2. Test results are considered to be erratic if this ratio is lower than one. The correction factor as per [6] is used for several (L/d) ratio given in Table 2. The rebar orientations with different grades of concrete are listed in Table 3.

Table 2.Correction factor for various L/d ratios

Sl. No.	L/d ratio	ASTM C 42-90
1	1.0	0.87
2	1.5	0.86
3	2.0	1.0

Table 3. Rebar orientations with various grades of concrete mix

	The orientation of the R/F		Grade of concrete	L/d ratio
	Plan	Section		
R1			M20	1
			M25	1.5
			M30	2
R2			M20	1
			M25	1.5
			M30	2
R4			M20	1
			M25	1.5
			M30	2
R5			M20	1
			M25	1.5
			M30	2
R6			M20	1
			M25	1.5
			M30	2
R3			M20	1
			M25	1.5
			M30	2
R7			M20	1
			M25	1.5
			M30	2

R1: 45°/ fully protruded / Ø 12 mm	R2: 45°/ fully protruded / Ø 12 mm
R3: 90°/ fully protruded / Ø 12 mm	R4: 0°/ fully protruded / Ø 12 mm
R5: 0°& 90°/ fully protruded / Ø 12 mm	R6: 0°/ fully protruded / Ø 12 mm
R7: 0°/ fully protruded / Ø 12 mm	

2.3. Test procedure

The core compression tests of concrete cylinders (M20, M25 and M30) with varying rebar orientation of (R1-R7) and L/d ratios (1, 1.5 & 2) were conducted as per [5]. The compression load was applied at a rate of 0.22 MPa/s according to TS EN12390-3 (2012). The photographic view of the compression testing machine is given in Figure 1. Figure 2.a shows a photographic view of crack patterns of specimens after failure.

Figure 1. a) Specimen fails after application of load; b)Cracks after specimen failure

The ultrasonic method based on the theory of elastic wave propagation is applied for evaluating mechanical and dynamic characteristics of the in situ concrete structures. By transmitting high-frequency elastic waves through concrete specimens, we can estimate compressive wave velocities knowing sample length and using guidelines given in ASTM C597. The UPV transducer calibration for Zero error correction is achieved by inverting the incoming pulse to the ultrasonic pulse using the transducer, and the process should be executed separately for Primary (P) and Secondary (S) waves. Smoothness and uniformity are the most essential parameters influencing the response. After transmitting a wave from one end of the concrete sample, the arrival time of wave on the other end is noted, and the velocity is calculated from the ratio of the distance between the transmitter and receiver probes to the time T. The transducers utilized were 50 mm in diameter and had maximum resonant frequencies that canbe fine-tuned based on the length of the specimen. The transducers were initially calibrated by placing them on either side of a calibration bar. The direct through transmission method, shown in Figure 2, is used in this paper.

The probes were placed in the middle of opposite faces, perpendicular to the direction of concrete. Grease was applied between the surfaces of the specimen and the transducers to ensure that any air voids due to surface irregularities are filled. Then the ultrasonic device noted the transmission time during the passage of ultrasonic waves through concrete specimens, as shown in Figure3.

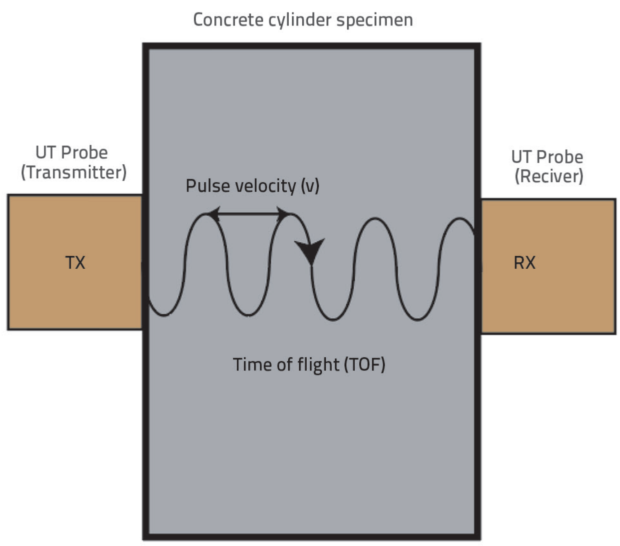


Figure 2. Direct mode of UPV transmission

Figure 3. UPV test on concrete specimen

A digital readout is given in a 4-digit LCD, as shown in Figure4. The pulse velocity can be obtained as V = L/T where V is the pulse velocity (km/s), L is the path length (cm), and T is the transit time (µs). According to this equation, the ultrasonic instrument records the travelling time of waves in the concrete specimen. Then, the pulse velocity is obtained using the dimensions of the specimen.

Figure 4. Data logger with LCD display

2.4. Design of experiments

The design of experiments is proposed based on the Box-Behnken model with 46 trials based on 5 factors, namely the grade mix, rebar angle orientation (degree), Time of flight (ns), set frequency (kHz), and L/d ratio, with the response of uniaxial compressive strength (MPa), as shown in Table 4. This design is categorised under the class of rotatable second-order designs based on three-level incomplete factorial designs. The total number of trials to be conducted was evaluated using N = 2k (k-1) +C0, (where k is number of factors, and Co is the number of central points). The Box-Benkhen design (BBD) involves combinations of all factors that are important without neglecting any data points under extreme conditions for insignificant conditions.

Because of block orthogonality, the second-order model can be augmented to include block effects without affecting parameter estimates, i.e., the effects themselves are orthogonal to the block effects. This orthogonal blocking is a desirable property when the experiments have to be arranged in blocks and the block effects are likely to be large.

2.5. ANN model for predicting core compressive strength using UPV technique

Neural network was selected to acquire the prediction visibility of the proposed Box-Behnken model, which could be used as state wide rather than as a model specific for each location or a set of locations. The proposed neural network architecture includes 1 input layer, 1 hidden layer and 1 output layer, as shown in Figure 5. The input layer consists of 5 neurons, output layer consists of 1 neuron, and hidden layer consists of 3 neurons with synapses (numerical weights) that connect hidden layer neurons with input and output layer neurons. The weighted values of each factor of the input layer are summated at the hidden layer. The threshold value was tuned to reduce the cumulative input to relate the activation function with the output layer [27-29]. The sum of the weighted values estimated through the neuron that links the neighbouring neurons is transferred to a nonlinear function, called a transfer function. The neural network model implements the feed forward back propagation model algorithm with the linear transfer functions for hidden and output layers based on the Purelin function. The training function uses

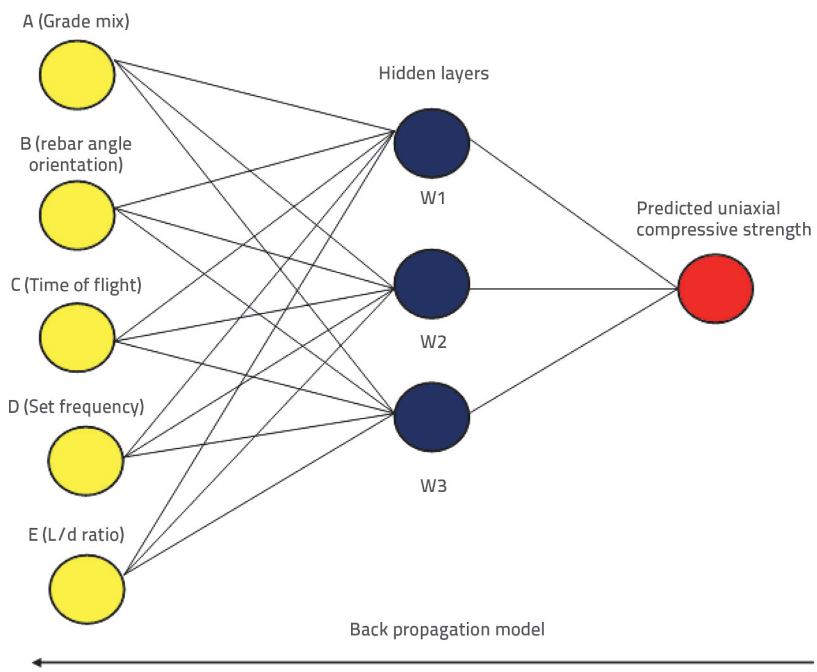


Figure 5. Schematic of ANN Back propagation model

Table 4. Design of experiments based on Box-Behnken model

Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Response 1
A: Grade Mix	B: Rebar angle orientation [°]	C: Time of fligh [ns]	D: Frequency [kHz]	E: L/d ratio	Uniaxial compressive strength [MPa]
25	45 (R1)	-70	4	1	27.63
30	0 (R4)	-50	4	1.5	28.34
30	90 (R3)	-50	4	1.5	29.52
30	45 (R1)	-30	4	1.5	29.62
25	45 (R2)	-50	5	1	22.6
30	45 (R1)	-50	4	1	29.62
25	90 (R5)	-50	4	1	26.41
25	45 (R1)	-50	3	1	27.63
25	45 (R2)	-50	4	1.5	28.02
25	0 (R6)	-30	4	1.5	26.28
20	0 (R7)	-50	4	1.5	24.63
25	0 (R6)	-50	4	2	26.28
20	45 (R1)	-50	5	1.5	23.02
20	45 (R2)	-50	3	1.5	24.11
25	90 (R3)	-50	4	2	26.41
25	45 (R1)	-30	5	1.5	27.63
25	90 (R4)	-70	4	1.5	26.41
25	45 (R2)	-30	4	2	27.63
20	45 (R1)	-50	4	1	24.53
25	45 (R1)	-70	4	2	27.63
25	90 (R3)	-50	3	1.5	26.41
25	45 (R2)	-50	4	1.5	26.14
25	45 (R1)	-30	3	1.5	25.91
25	45 (R1)	-70	3	1.5	26.27
25	45 (R2)	-50	5	2	26.34
25	45 (R1)	-70	5	1.5	26.43
30	45 (R1)	-50	4	2	29.62
25	45 (R2)	-50	4	1.5	26.06
25	45 (R2)	-50	4	1.5	25.86
25	45 (R1)	-50	3	2	26.16
30	45 (R2)	-50	5	1.5	28.13
25	90 (R4)	-50	5	1.5	26.41
25	0 (R7)	-50	4	1	26.28
25	45 (R1)	-50	4	1.5	25.86
30	45 (R2)	-50	3	1.5	30.21
25	90 (R3)	-30	4	1.5	26.53
25	0 (R6)	-50	3	1.5	26.31
20	45 (R1)	-70	4	1.5	24.53
20	90 (R3)	-50	4	1.5	23.36
25	0 (R7)	-70	4	1.5	26.28
25	45 (R1)	-50	4	1.5	27.63
20	45 (R1)	-30	4	1.5	24.53
30	45 (R2)	-70	4	1.5	29.62
25	0 (R4)	-50	5	1.5	26.28
25	45 (R1)	-30	4	1	27.63
20	45 (R2)	-50	4	2	23.02

the Levenberg Marquardt model to minimize the linear combination of squared errors and weights in minimizing the overall prediction error to approach second-order training speed without computing the Hessian matrix [30]. The weights are adjusted by gradient error values obtained in the reverse direction from the output layer toward the input layer of the network passing through hidden layers. The training mechanism evolves the initiation of weights to be small random values derived from the input data in the forward direction. The first trained results deviate from the expected range with a high error rate. The model is adjusted to reduce the weights with minimum error with the experimental data through the backward iteration [31, 32]. The learning function includes the stochastic gradient descent (GDM) for optimizing the transfer function with suitable differentiable properties based approximation.

Table 5. Parameters of artificial neural network process for RMS

Name	Model BBD
Network type	Model FFBP
Transfer function	PURELIN
Training function	TRAINLM
Learning function	LEARNGDM
Performance function	Mean square error
Number of neurons	3
Sum of squared error	0.9968
Number of epochs	17
Validation checks	6
Performance	0.878

Table 5 shows results of the data predicted by the ANN compared with real data. The methodology presented below has been used to obtain the effectiveness of ANN in evaluating differentiations in concrete mixes and their compressive strength, based on relationship between the mix parameters for different grades of concrete. A neural network can track the relationship between the compressive strength, UPV value, and mix parameters, based on the number of neurons in the hidden layer.

3. Results and discussion

This section deals with interpretation of the compressive strength of cores using UPV test parameters. Whitehurst [33] stated that reinforcement bars that are present in the extracted core of in-situ concrete influences the core compressive strength.
Zacob and Ishibashi [34] found that the process of rebar cutting while drilling may cause a reduction in compressive strength because of the formation of cracks between the concrete and rebar. The strength reduction is approximately 3.5 % when the angle of orientation is 45°, while it is approximately 5.2 % when the angle of reinforcement is 90° to the loading plane. Parameters like (L/d) ratio of the core specimen and grade of concrete have greater influence on the compressive strength of core concrete.
Figures 6.a - 6.e shows regression plots of interaction between each input factor and the output response (uniaxial compressive strength). The regression equations were developed based on cubic interpolation of the curve fitting model. The plots of regression analysis involve identification of the relationship between a dependent variable and one or more independent variables. The cubic model has been hypothesized and it evaluates the input factors to generate the regression equation.

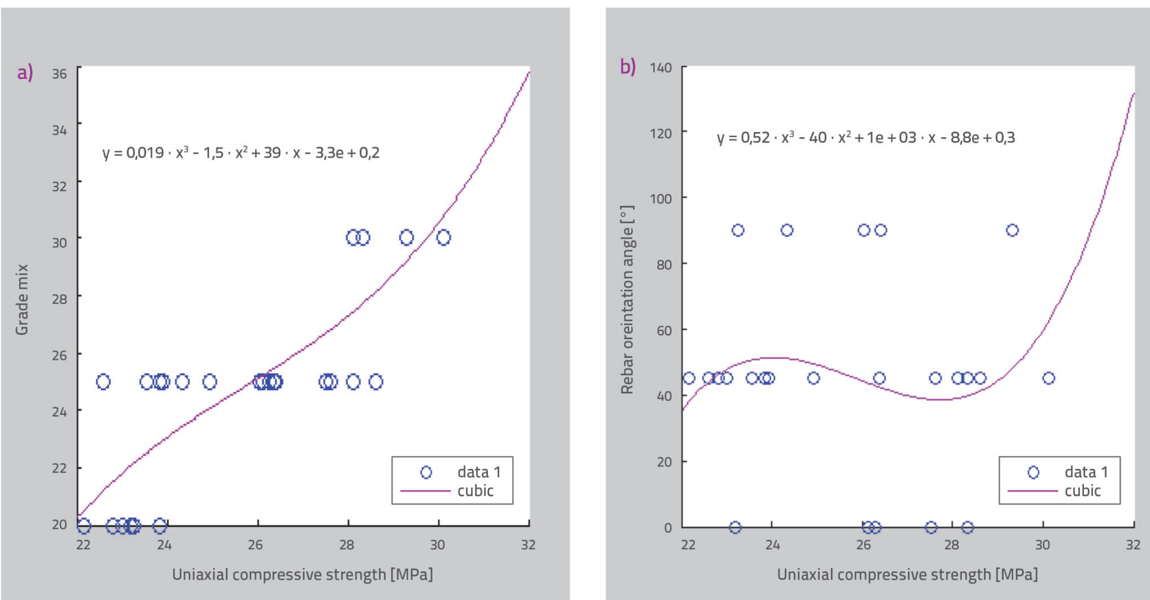


Figure 6. a) Grade Mix vs. UCS [MPa]; b) Rebar orientation angle (degree) Vs. UCS [MPa] (UCS - Uniaxial Compressive Strength)

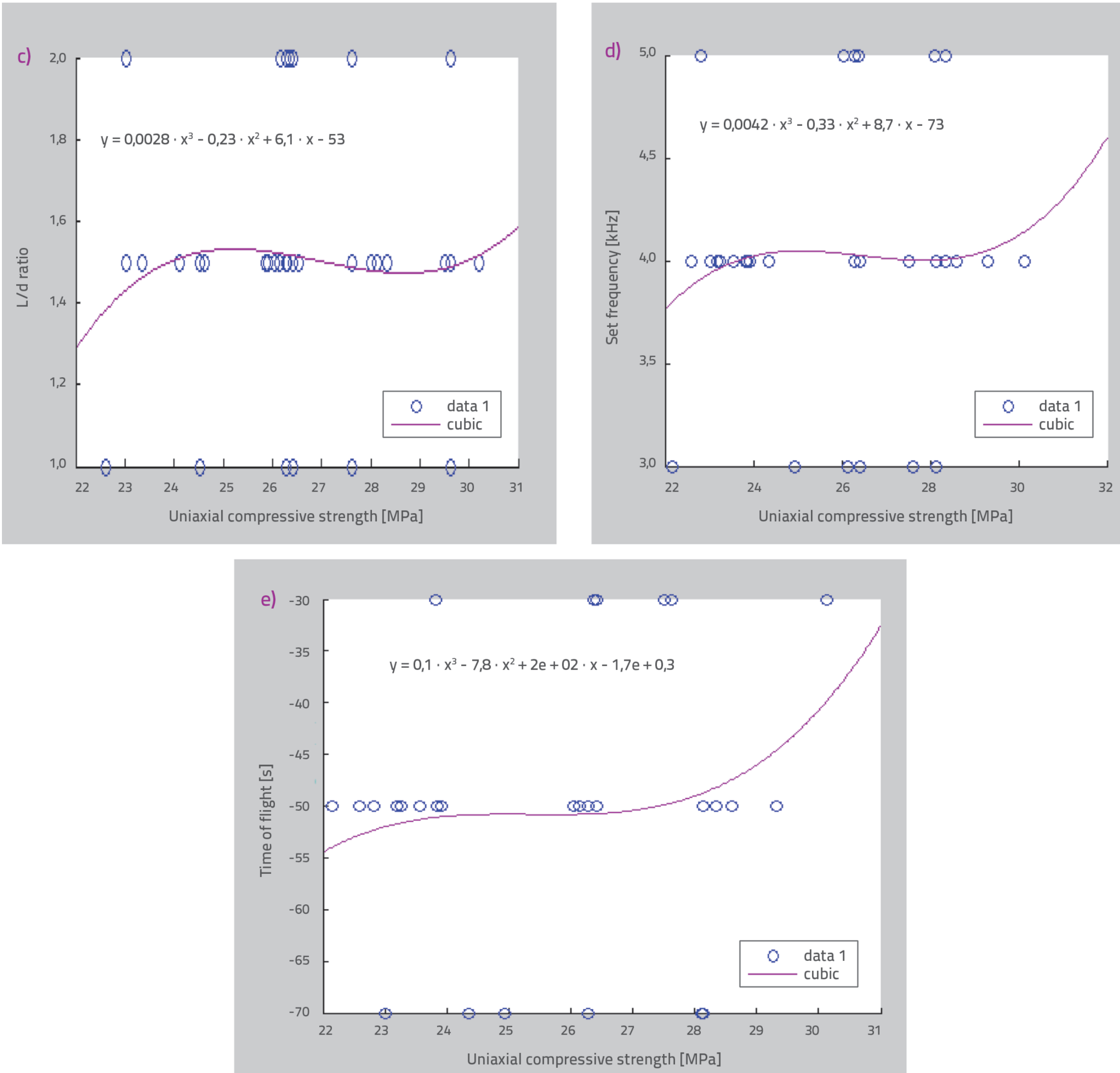


Figure 6. c) L/d ratio Vs. UCS [MPa]; d) Set Frequency (kHz) Vs. UCS [MPa]; e) Time of Flight (ns) Vs. UCS [MPa] (UCS - Uniaxial Compressive Strength)

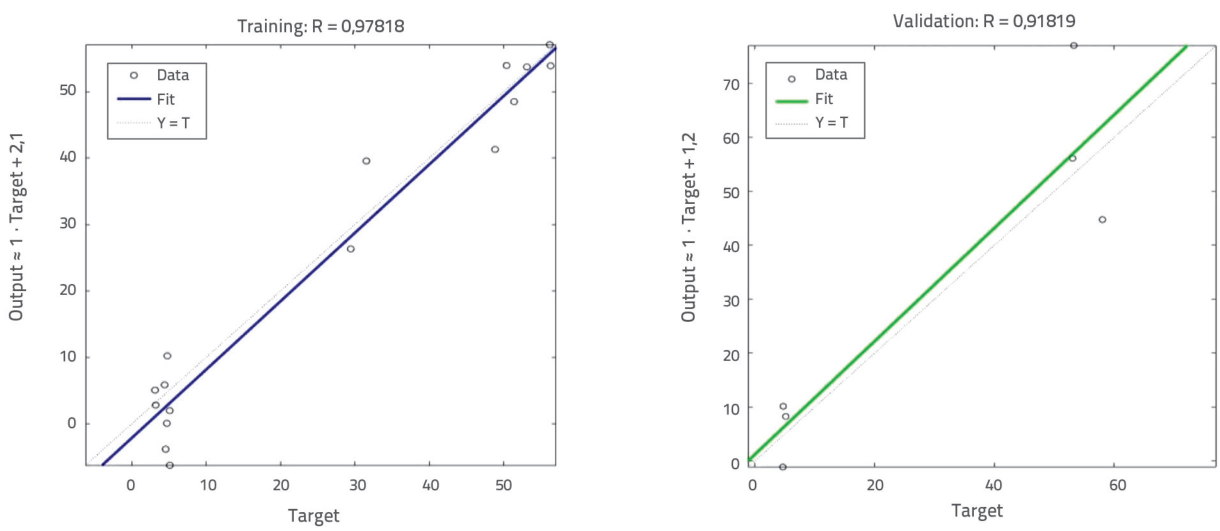


Figure 7. Box – benkhen design (BBD)

The training and testing validation performance between the five input factors and the output response are shown in Figure 7; and R^2 value of 0.9258 was obtained with the best fit curve accurate to 92 %. The value obtained is then compared to the results from destructive testing and the accuracy percentage is found.

$$\text{Error [\%]} = \frac{(\text{Predicteded value} - \text{Measured value})}{\text{Measured value}} \cdot 100\ [\%] \tag{1}$$

$$\text{Accuracy [\%]} = 100 - \text{Error [\%]}$$

The above equation is then used to calculate the average accuracy percentage, which amounts to 93.50 %. Thus, it can be noted that the compressive strength of concrete specimen, as obtained from MATLAB analysis, is very close to actual compressive strength values obtained by destructive testing. The validation performance based on the mean squared error values is shown in Figure 8.

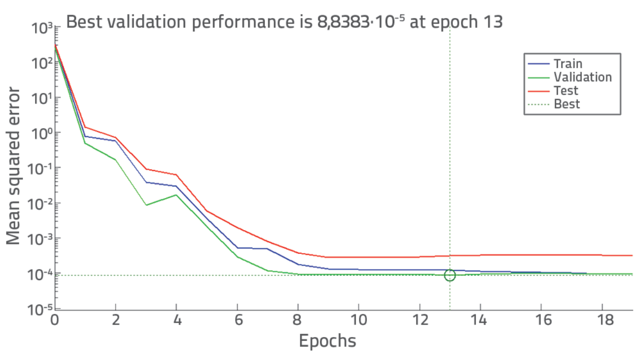


Figure 8. Validation performance based on mean squared error values

This predicts the best fit for the proposed model, which was observed at 13 epochs of iteration with 0.9968.A comparison of compressive strength values obtained from regression analysis, ANN, and destructive testing, is given in Figure 9.

Figure 9. Compressive strength values from Regression analysis, ANN, and destructive testing

4. Conclusion

Experimental studies were carried out towards developing a methodology for estimating the compressive strength of concrete from the Ultrasonic Pulse Velocity values using Artificial Neural Networks (ANN). Concrete cylinders were cast with different (L/d) ratios and seven rebar orientations. Reduction factors were obtained for different specimens and incorporated in the MATLAB code for improving accuracy of the results. The correlation coefficient obtained between corrected core strength vs. (L/d) ratio for M 20 (R^2 = 0.996), M 25 (R^2 = 0.8704) and M30(R^2 = 0.8268) denotes a good degree of linearity. In other words, it can be stated that the linear regression of the compressive strength at different (L/d) ratios of 0.5, 1, and 1.5,hasa good compliance with experimental data. The strength of concrete decreases approximately by 3.5 % when the angle of reinforcement is 45°, and by 5.2 % when the angle of reinforcement is 90° to the loading plane. This is due to the formation of cracks around reinforcement bars. The orientation of the reinforcement bar in the core sample does not have an appreciable effect on the UPV. It can be seen from the experimental investigations that the average accuracy percentage amounts to 93.50 %. Thus, compressive strengths of the concrete specimen, as obtained from regression analysis and ANN validations, are very close to the actual compressive strength value obtained by destructive testing. It can be deduced from experimental performance that the statistical model developed to predict the core concrete strength is very optimistic.

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