Prediction of Strengths of Remixed Concrete

K L Bidkar, P.D. Jadhao

***Abstract*:** *This paper deals with the methodology, related to application of neural network analysis for reuse of partially set old concrete by adding fresh concrete to form usable mix by considering their time lags and blend ratios. When we relate the strength of the freshly prepared concretes the preset concrete obviously gives the reduction in strength. This problem will be overcome by adding a specific quantity of fresh mass to the partially set old concrete mass. The paper focuses on the utilization of neural network (N.N.) for predicting the 28-day strengths of concrete. The complex nonlinear relationship between the responses (factors that influence concrete strength-blend ratio, time lag, strength at initial setting time and final setting time) and the output (concrete strength) can be built by applying N.N. High degree of accuracy is achieved by the model for prediction of strengths.*

***Index Terms*:** *Neural network analysis remixed concrete, blend ratio, time lag, prediction of strength.*

I. INTRODUCTION

The strength of concrete specimen is commonly measured subsequently a curing period of 28 days. Usual methods of prediction of strength are primarily based upon statistical analysis where linear and nonlinear regression equations can be used. But, selecting an appropriate regression equation requires practice and knowledge, moreover it is rather difficult. The strength of concrete is prejudiced by various parameters. In this paper strength prediction is considered as a mapping from the influencing parameters. Instead of regression equation, by adopting N.N. a model can be formed and it can be represented The aim of the paper is to adopt a method, providing help for future experimental researches a full - scale acquaintance-based structure model by considering the most of the primary aspects of a neural network to solve the multifaceted non- linear plotting for predicting concrete strength. Concrete is prepared by carefully mixing the dry mixture of ingredients viz., cement sand and coarse aggregate with calculated amount of water. Cement is the only reactive material in the matrix responsible for developing strength, whereas sand and coarse aggregates being inert material, do not take part in chemical reaction and act only as solid filler material.

The development of strength in concrete depends on factors like, water cement ratio, aggregate shape and size, duration of vibration, etc. The gain in the strength commences immediately after addition of water. This instant of time at t=0 is known as 0- hr. And at which mix is which is fresh and retain full workability, attains usually maximum strength. It is advisable that concrete thus prepared should be cast into mold without delay in order to get maximum strength out of it, otherwise it loses the strength .The concrete if not used instantaneously, due to some reasons, and then it is necessary to add fresh concrete to it in order to enhance the strength. [2]. The deviation of strength Vs elapsed duration lag is usually fall down in nature and the reduction in this strength depends upon the mix ratio r. The mix ratio is the ratio of weights of partially set old concrete to the weights of fresh concrete. The concrete is known as simply; fresh concrete if this ratio is equal to zero. While for old concrete it is equal to infinity if the ratio is infinity .[3]

The casting delaying in concrete work in construction industry is commonly noted, Due to this the workability reduces and concrete becomes hard. Traffic jam also affects the placing of concrete at destination. The other factors causing delaying is the improper methods of handling, work scheduling, lack of site organization and the breakdown of equipment. To avoid such problem the practice of re-tempering is commonly performed to keep concrete workable. The neural network analysis was used to make inferences about concrete mix through the use of experimental design in other words experimental design as a technique was adopted and used in detail [5]. The basic purpose of the experiment is to predict the strengths .This is to bring about process Ahmed et al. [1] for predicting concrete compressive strengths, tensile strengths and modulus of elasticity for M20 concrete mix proportion.

In laboratory work the test parameters chosen were blend ratio, time lag, experimental lab strength, strength at initial setting time, and strength at final setting time of concrete, while curing condition and test conditions were kept constant. There exists intricate nonlinear relationship between the test parameters and the concrete strength.

A neural network is represented along with its layer formations as shown in table 2A, 2B; 2C illustrates network information of M20 for tensile, modulus of elasticity and compressive strength respectively. [4]. Similarly, Table 4A, 4B and 4C represents Parameter Estimates of M20 for these three strengths.

II. MODEL DEVELOPMENT

The problem pointed out the co-relation between the input parameters and the output parameter. Hence for the said N.N. , 4 factors i.e. 4 components of input vector,± 1 in the hidden layer , and ±1 in the output layer for the consideration of 28-day strength of concrete gives the model prediction . (Figure 1) .The neurons of adjoining layers are fully connected.

Retrieval Number E6974068519/19©BEIESP
Journal Website: www.ijeat.org

198

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication (BEIESP)
© Copyright: All rights reserved.

III. EXPERIMENTAL WORK

From the widespread and exhaustive laboratory work the data was collected from the first batch to build the training set and the testing set for each strength (Table 1A, 1B and 1C) The model summary is presented in table 3A, 3B and 3C. Each set consists of the influencing factors and the corresponding strength of concrete. A 53 grade Portland cement is used. Crushed coarse aggregates with maximum size of 20 mm are used in this experiment. The blends ratios (r) are 0.33,1,3 and ∞ while the time lag (t) considered are 0.75, 1.5.2.25, 3 and 3.75 hours.

IV. RELATIONSHIP BETWEEN EXPERIMENTS AND NEURAL NETWORK MODELING

The N.N. models can be utilized to pretend the possessions of some parameters on the strength, and it is found functional relations between strength and its corresponding factors, as shown in the tables 5A, 5B, 5C and figures 3A, 3B and 3C

Neural network models prove rational and realistic. The results are as shown in figures 2A,2B and 2C, representing relationship of analytical tensile strength Vs predicted strength, modulus of elasticity Vs predicted strength, compressive strength Vs. predicted strength respectively. While figures 3A, 3B and 3C gives representation of predicted tensile strength Vs residual, predicted modulus of elasticity Vs residual and predicted compressive strength Vs. residual.

Table 1A: Case Processing Summary of M20 for tensile strength

		Numbers	Percent
Sample	Training	177	71.40%
	Testing	71	28.60%
Valid		248	248
Excluded		0	0
Total		248	

Table 1B: Case Processing Summary of M20 for Modulus of Elasticity

		Numbers	Percent
Sample	Training	176	71.00%
	Testing	72	29.00%
Valid		248	100.00%
Excluded		0	
Total		248	

Table 1C: Case Processing Summary of M20 for Compressive Strength

		Numbers	Percent
Sample	Training	166	66.90%
	Testing	82	33.10%
Valid		248	100.00%
Excluded		0	
Total		248	

Table 2A: Network information of M20 for tensile strength

Input Layer	Covariates	1	XT(t)
		2	Log(r)
		3	t
	Units (Nos.)		3
	Covariates rescaling method		Normalized
Hidden Layers	Hidden layers (Nos.)		1
	Units in hidden layers (Nos.)		2
	Activate function		Hyperbolic tangent
Output Layer	Dependent Variables	1	AT(t)
	Units (Nos.)		1
	Rescaling method for scale dependents		Standardized
	Activate function		Identity
	Function for error		Sum of squares

Table 2B: N.N. information of M20 for Modulus of Elasticity

Input Layer	Covariates	1	XE(t)
		2	Log(r)
		3	t
	Units (Nos.)		3
	Covariates rescaling method		3
Hidden Layers	Hidden layers (Nos.)		Normalized
	Units in hidden layers (Nos.)		1
	Activate function		2
Output Layer	Dependent Variables	1	AE(t)
		Units (Nos.)	1
		Rescaling method for scale dependents	Standardized
		Activate function	Identity
		Function for error	Sum of squares

Table 2C: Network information of M20 for Compressive Strength

Input Layer	Covariates	1	XC(t)
		2	Log(r)
		3	t
	Units (Nos.)		3
	Covariates rescaling method		3
Hidden Layer(s)	Hidden layers (Nos.)		Normalized
	Units in hidden layers (Nos.)		1
	Activate function		2
Output Layer	Dependent Variables	1	AX(t)
		Units (Nos.)	1
		Rescaling method for scale dependents	Standardized
		Activate	Identity

		function	
		Function for error	Sum of squares

Table 3 A. Summary of M20 for Tensile Strength

Training	Error for sum of squares	0.099
	Relative error	0.001
	Stopping rule utilized	One consecutive step- no decrease in error.
	Training time	00:00.0
Testing	Error for sum of squares	0.04
	Relative Error	0.001
Dependent variable :AT(t)		

Table 3B: Summary of M20 for Modulus of Elasticity

Training	Error for sum of squares	0.099
	Relative error	0.001
	Stopping rule utilized	One consecutive step- no decrease in error.
	Training time	00:00.0
Testing	Error for sum of squares	0.04
	Relative Error	0.001
Dependent variable :AE(t)		

Table 3C: Summary of M20 for Compressive Strength

Training	Error for sum of squares	0.099
	Relative error	0.001

	Stopping rule utilized	One consecutive step- no decrease in error.
	Training time	00:00.0
Testing	Error for sum of squares	0.04
	Relative Error	0.001
Dependent variable AC (t)		

Table 4A: Parameter Estimates of M20 for Tensile Strength

Predictor		Predicted		
		Hidden layer 1		Output layer
		H(1:1)	H(1:2)	AT(t)
Input layer	Bias	0.088	-1.046	
	XT(t)	0.985	1.459	
	Log r	-0.38	0.167	
	t	-0.169	0.073	
Hidden layer 1	Bias			-0.041
	H(1:1)			1.125
	H(1:2)			2.519

Table 4B: Parameter Estimates of M20 for Modulus of Elasticity

Predict or		Predicted		
		Hidden Layer 1		Output Layer
		H(1:1)	H(1:2)	EAt
Input layer	Bias	0.088	-1.046	
	XT(t)	0.985	1.459	
	Log r	-0.38	0.167	
	t	-0.169	0.073	
Hidden Layer 1	Bias			-0.118
	H(1:1)			2.379
	H(1:2)			-1.206

Table 4C: Parameter Estimates of M20 for Compressive Strength

Predictor		Predicted		
		Hidden layer 1		Output layer
		H(1:1)	H(1:2)	AC(t)
Input	Bias	0.088	-1.046	

layer	XT(t)	0.985	1.459	
	Log r	-0.38	0.167	
	t	-0.169	0.073	
Hidden layer 1	Bias			-0.319
	H(1:1)			1.222
	H(1:2)			1.583

Table 5A: Independent Variable Importance of M20 for Tensile Strength

	Importance	Normalized importance
XT(t)	0.971	100.00%
Log(r)	0.018	1.90%
t	0.011	1.10%

Table 5B: Independent Variable Importance of M20 for Modulus of Elasticity

	Importance	Normalized importance
EX(t)	0.973	100.00%
Log(r)	0.018	1.80%
t	0.009	0.90%

Table 5C: Independent Variable Importance of M20 for Compressive Strength

	Importance	Normalized importance
XC(t)	0.953	100.00%
Log (r)	0.01	1.00%
t	0.038	3.90%

Hidden layer activation function: Hyperbolic tangent
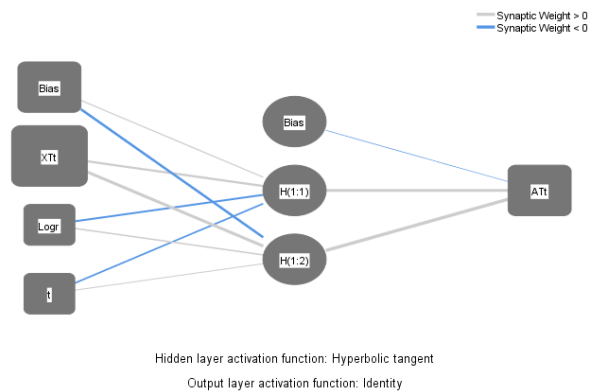Output layer activation function: Identity

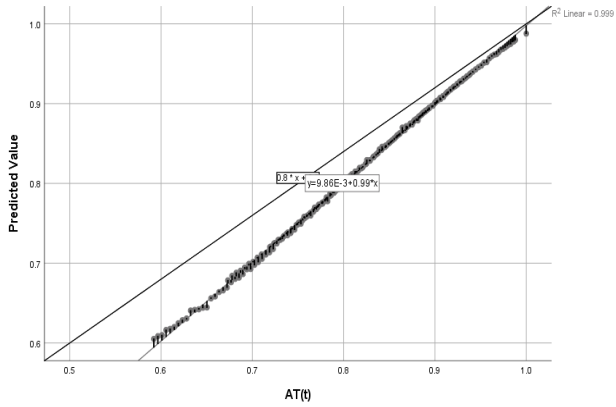**Figure 1:** Neural network diagram for strengths

Figure 2A: Representation of analytical tensile strength Vs predicted strength
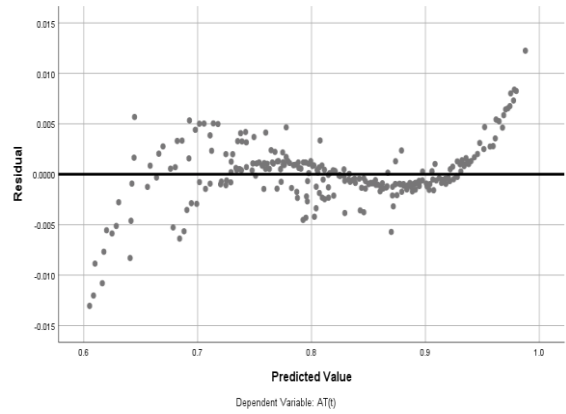

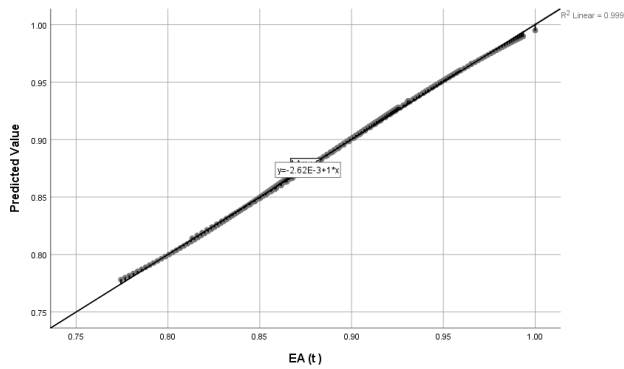**Figure 3A:** Representation of predicted tensile strength Vs residual

Figure 2B: Representation of analytical modulus of elasticity Vs predicted strength
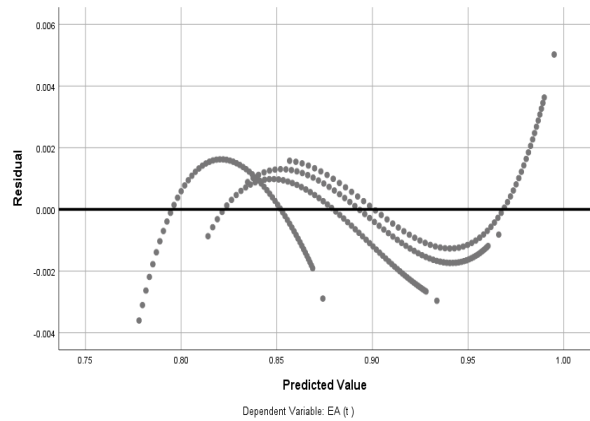

Figure 3B : Representation of predicted modulus of elasticity Vs residual
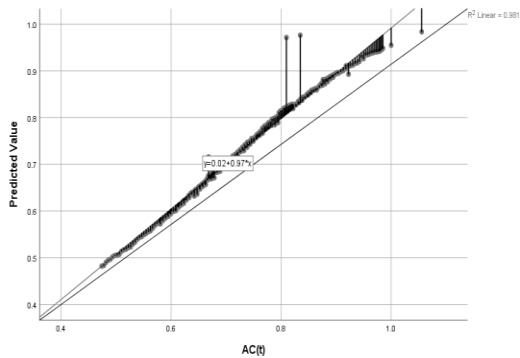

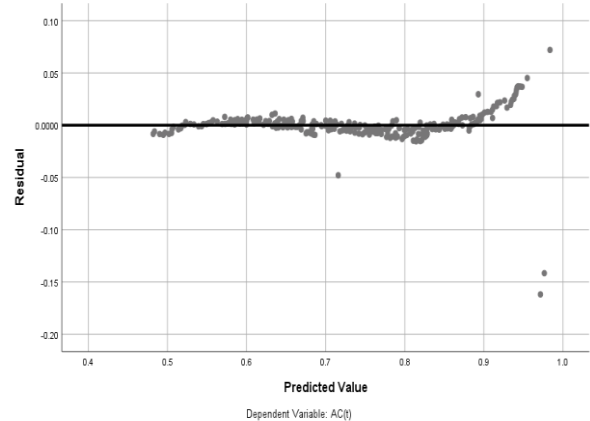**Figure 2C:** Representation of analytical compressive strength Vs predicted strength

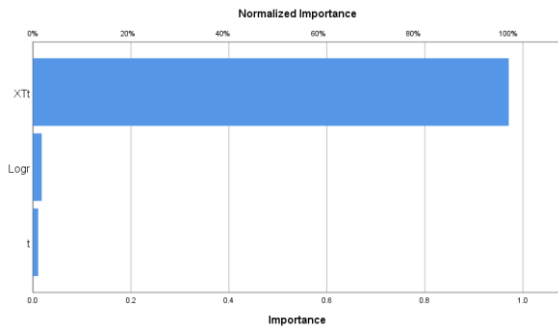**Figure 3C:** Representation of predicted compressive strength Vs residual

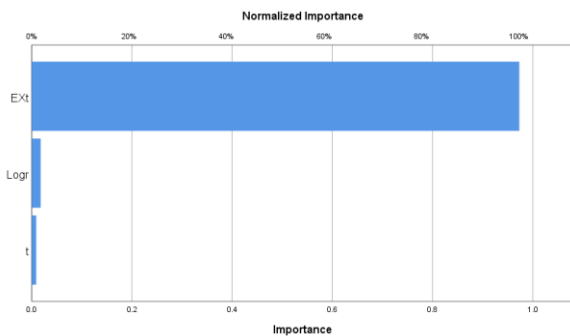**Figure 4A:** Representation importance of variables for tensile strength

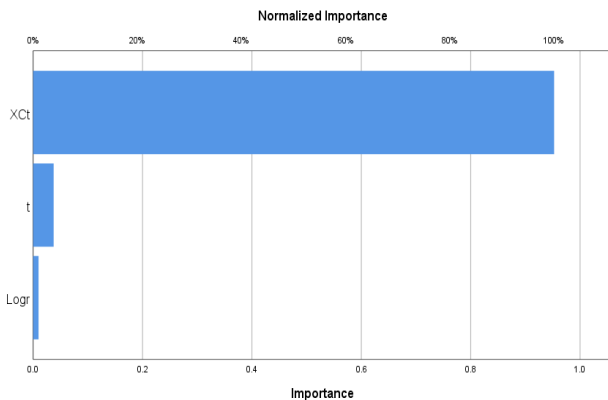**Figure 4B:** Representation of importance of variables for modulus of elasticity

Figure 4C: Representation of importance of variables for compressive strength

V. CONCLUSIONS

Neural network models (computational intelligent method) can be built that provide a quick mean of predicting 28-day strength (tensile, modulus of elasticity, compressive) of concrete based on some of its impact factors which will be beneficial to civil engineers.

Neural network models accomplish excellent prediction accuracy (R^2=0.99 for tensile strength and modulus of elasticity, R^2=0.981 for compressive strength figure 2A, 2B and 2C) hence the relevance of neural network models to concrete strength prediction is significant.

The importance of variables (Figure 4A, 4B, 4C) reveals that the strength depends on time lag and blend ratio.

REFERENCES

1. Ahmed, M., Mallick, J., & Hasan, M. A. (2016). A study of factors affecting the flexural tensile strength of concrete. Journal of King Saud University - Engineering Sciences, 28(2), 147–156. https://doi.org/10.1016/j.jksues.2014.04.001
2. Bairagi, N. K., Goyal, A. S., and Joshi, P. A. (1989). Strength of Composite Mixes Using Selfing and Crossing Theory. Indian Concretes Journal, 63 (12), 600–604.
3. Bairagi, N. K., and Jhaveri. (1977). Strength Variation of Composite Mixes by Pure Selfing Theory. Indian Concrete Journal, 51 (3), 87-89.
4. Snell, L. M., Roekel, J.V., and Wallace, N. D (1989). Predicting Early Concrete Strength. Concrete International, 43-47
5. Marcia J Simon(MclLean, V., & Kenneth(NIT Gaitherburg, M. (n.d.). 917028.pdf (1997th ed.). Proceeding of the PCI/FHWA.

Mr. Kisan L.Bidkar is working as Associate Professor in Civil Engineering Department in Sandip Foundation's Sandip Institute of Engineering & Management Nashik. His research interest includes behaviour of remix concrete.

Second Author Dr. Pradip D. Jadhao is presently working as Professor & Head of Civil Engineering Department, K. K. Wagh Institute of Engineering Education & Research, Nashik. His areas of interest are Geotechnical Engineering and concrete technology.