Journal of Soft Computing in Civil Engineering 4-4 (2020) 24-35

Contents lists available at SCCE

Journal of Soft Computing in Civil Engineering

Journal homepage: www.jsoftcivil.com

Compressive Strength Estimation of Mesh Embedded Masonry Prism Using Empirical and Neural Network Models

S. Kanchidurai[1*], P.A. Krishnan[2], K. Baskar[2]

1. Assistant Professor, School of Civil Engineering, SASTRA Deemed to be University, Thanjavur, India
2. Professor, Department of Civil Engineering, National Institute of Technology, Trichy, India

Corresponding author: *kanchidurai@civil.sastra.edu*

https://doi.org/10.22115/SCCE.2020.228611.1213

ARTICLE INFO

Article history:
Received: 26 April 2020
Revised: 16 August 2020
Accepted: 09 September 2020

Keywords:
Masonry;
PNM mesh;
Compressive strength;
Analytical modelling;
Statistical;
Artificial neural network (ANN);
Multiple linear regression predictive model (MLRPM).

ABSTRACT

Presently, the mesh embedment in masonry is becoming a trendy research topic. In this paper, the mesh embedded masonry prism was cast and tested. The experimental data were used for the analytical modelling. Compressive strength (CS) test was conducted for forty five masonry prism specimens with and without poultry netting mesh (PNM) embedment in the bed joints. The small mesh embedment in the masonry prism provides the better strength improvement as well as the endurance. The size of masonry prism was 225×105×176 mm. Uniformity was maintained in all prisms as per the guidelines given in ASTM C1314. Compressive strength experimental results are compared with a new proposed regression equation. The equation needs nine input parameters and two adjustment coefficients. The masonry mortar strength and mesh embedment are considered as input parameter. The experimental results were predicted by proposed Artificial Neural Network model. The validated results were gives better and more accuracy compared to the statistical and MLRPM models.

How to cite this article: Kanchidurai S, Krishnan PA, Baskar K. Compressive strength estimation of mesh embedded masonry prism using empirical and neural network models. J Soft Comput Civ Eng 2020;4(4):24–35. https://doi.org/10.22115/scce.2020.228611.1213.

Nomenclature

$f_{masonry}$	*Strength of masonry unit*	t_m	*Thickness of bed joint mortar*
K_m	*Material coefficient for the mesh*	β_m	*Characteristic strength of mortar*
f_{mo}	*Strength of mortar*	α	*Co-efficient for an embedded mesh*
f_b	*Compressive strength of brick*	W_b	*Weight of one brick*
h_p	*Height of masonry prism*	A_m	*Area of masonry*
t_p	*Thickness of masonry prism*	CSC	*Compressive Strength of Control specimen*
CSP	*Compressive Strength of Poultry netting mesh embedment*		

1. Introduction

This complete study was related to the brittle material compressive strength prediction by the three different model. Masonry analysis was changing because of its different failure pattern. So the prediction may gives to understand better for execution. ANN model give more accuracy for the brittle material like experimentation. The entire structural engineering studies were referred from the failure analysis then design part takes place. The ANN model gives better prediction than the others and it is reliable and fast. Table 1 shows the quantitative models of existing works in this field. The existing research proves the perfect reliability for the brittle materials like bricks, concrete etc. earlier there was many complication in the masonry strength prediction, but the work shows the positives results in modelling [1–7]. In concrete construction, concrete strength was determined using various computational methods. The sustainable concrete mix started rapidly for the construction works, since the aggregate was in demand for the constructions, the recycled and waste materials takes place. Fangming et al [8] finding the compressive strength of recycled concrete using deep learning algorithm, the different replacement and addition of concrete mix considered as a parameter. Here the water cement ratio, fine aggregate and coarse aggregate replacements, addition of fly ash content was considered as a main parameter. 74 sets of different mix made for deep learning, its achieved good results. On other hand, Slawomir et al [9] probed the prediction of concrete strength by its thickness using ANN, the different thickness was analyzed for the existing structure with Non Destructing Testing (NDT). The five different NDT methods data was well trained and tested successfully.

Table 1
Existing research of masonry analytical model.

Ref	Research area	Target of prediction	Sample	Input parameter	ANN R^2	Mean error
[1]	Masonry panel with FRP	Shear strength	113	6	0.91-0.96	7-24%
[2]	Earth block masonry	Compressive strength	72	3	0.946	< 6%
[3]	Clay brick masonry	Compressive strength	96	2	0.99	< 20%
[4]	Solid masonry prism with concrete fill	Compressive strength	102	3	Close to 1	Very low
[5]	Masonry wall	Axial behaviour	1944	3	0.93-0.99	Very low
[6]	Ferrocement wall	Moment capacity	75	5	0.97-0.98 (ANFIS)	1.7%
[7]	Ferrocement wall	Moment capacity	74	5	0.98	7.8%

Jinjun et al [10] was determined the parametric sensitive analysis of concrete strength by added materials mechanical strength, the mechanical properties of materials was simulated by multiple nonlinear regression (MNR) and ANN, found the strength prediction was highly promising. Alessio et al [11] modeled the ANN to predict the compressive strength of concrete column with fiber reinforced polymer (FRP) column, wrapping the column and finding buckling strength is quite difficult, but with the ANN model coefficient of correlation up to 0.83 was achieved. Farid et al [12] found the ANN model for the masonry veneer fragility because of seismic effect, the model gives better understand of masonry veneers against 200 artificial earth motions. The modeling of masonry failure and the management of bridge system could be done perfectly with the ANN algorithms [13,14]. The neural networks and adaptive systems was performing well for the many cases, shear capacity of reinforced grouted masonry wall and compressive strength of concrete with zero slump predicting results were finer than the empirical formulas [15,16]. Iman et al [17] explored the experimental data with neuro fuzzy and ANN, the deboning strength was evaluated for a part in masonry construction and explored for the different cases, comparing to other mathematical model results the ANN and ANIFS performed well. Also the masonry mortar with different cement grades could be analyzed with ANN perfectly [18]. This study objective is to determine the compressive and flexural strength analytically. Since the mathematical model is complex in predicting the masonry strength with mesh embedment. ANN model with minimum input parameter used to predict accurately the masonry strength. The main objective is to arrive at the effective mesh embedment for the masonry construction, and to predict compressive and flexural bond strength by using statistical analysis and Artificial Neural network.

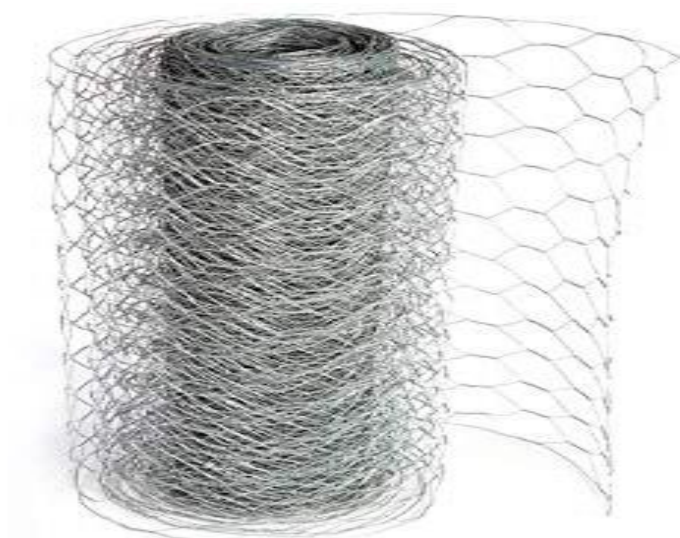


Fig. 1. Poultry netting mesh PNM for masonry embedment.

3. Experimental Work

In the present research work, compressive strength of brick masonry units with and without mesh embedment is studied in detail. The effect of adding simple wire mesh changes was noted extensively by experimentation. The standard size of brick was 225 × 105 × 82mm. The compressive strength of masonry units with PNM mesh embedment and without mesh embedment was studied experimentally with 45 specimens. The Poultry netting mesh (Fig.1) was used as mesh embedment of 0.3mm thickness and 28 × 13mm hexagonal shape. The masonry unit was prepared by stretcher bond with 12 mm mortar thickness. The masonry mortar was prepared with 1:3, 1:4 and 1:5 mix (Cement: Sand) to evaluate the compressive strength variation with and without mesh embedment at the bed joint. The embedment was maintained for single layer or double layer at bed joint. The specification given in ASTM C 1314 [19] was followed to make forty-five numbers of specimens. The speed of testing for all compressive strength testing specimen was maintained at 20 kN per minute and the height to width ratio 1.6 was considered to calculated for CS. The compressive strength test of masonry prism was performed as shown in the experimental set-up (Fig.2). The solid masonry units were cast with 12 mm mortar thickness uniformly. The test specimen curing was done by normal water for 28 days. The maximum compressive strength was noted and fixed as a target data for statistical and artificial neural network. The experimental test was performed for complete collapse of the masonry prism by compression testing machine CTM. Table 2 shows the experimental results of 45 masonry prism and the specimen details are described in list of abbreviations.

Fig. 2. Experimental set-up of compressive strength test on masonry unit.

4. Model development and discussions

4.1. Statistical model

Statistical analysis is used in many fields. It is provide the logical investigation of dealing with quantitative data. It summarizes a philosophy of gathering data, order, representation, and understanding of information acquired. In this research, the compressive strength of masonry prism was modelled with a suitable expression and compared with the experimental data. Statistical thinking and operative behavioural science research are essential from a variety of standpoints. Statistics permit the use of a descriptive language which is more efficient and exact in communication; they disallow any vague conclusions and emphasize on arriving at particular ones. Statistics further enables us to draw generalization and make predictions.

Table 2
Experimental results of compressive strength of masonry prism.

No	Specimen	(Cement: Sand)	Mesh	Avg. mortar strength in MPa	Target in MPa
1	CSC -13 -01	1:3	0	13.46	7.14
2	CSC -13 -02	1:3	0	13.46	7.81
3	CSC -13 -03	1:3	0	13.46	5.57
4	CSC -13 -04	1:3	0	13.46	7.43
5	CSC -13 -05	1:3	0	13.46	6.94
6	CSP-131 -01	1:3	1298	13.46	6.52
7	CSP-131 -02	1:3	1298	13.46	8.71
8	CSP-131 -03	1:3	1298	13.46	6.90
9	CSP-131 -04	1:3	1298	13.46	6.46
10	CSP-131 -05	1:3	1298	13.46	7.90
11	CSP-132 -01	1:3	2596	13.46	7.86
12	CSP-132 -02	1:3	2596	13.46	9.01
13	CSP-132 -03	1:3	2596	13.46	6.21
14	CSP-132 -04	1:3	2596	13.46	7.69
15	CSP-132 -05	1:3	2596	13.46	6.34
16	CSC -14 -01	1:4	0	11.79	7.36
17	CSC -14 -02	1:4	0	11.79	6.92
18	CSC -14 -03	1:4	0	11.79	6.03
19	CSC -14 -04	1:4	0	11.79	6.30
20	CSC -14 -05	1:4	0	11.79	6.42
21	CSP-141 -01	1:4	1298	11.79	6.96
22	CSP-141 -02	1:4	1298	11.79	7.08
23	CSP-141 -03	1:4	1298	11.79	7.54
24	CSP-141 -04	1:4	1298	11.79	6.81
25	CSP-141 -05	1:4	1298	11.79	4.75
26	CSP-142 -01	1:4	2596	11.79	8.30
27	CSP-142 -02	1:4	2596	11.79	7.69
28	CSP-142 -03	1:4	2596	11.79	5.96
29	CSP-142 -04	1:4	2596	11.79	8.70
30	CSP-142 -05	1:4	2596	11.79	5.80
31	CSC -15 -01	1:5	0	9.03	4.59
32	CSC -15 -02	1:5	0	9.03	4.93
33	CSC -15 -03	1:5	0	9.03	3.92
34	CSC -15 -04	1:5	0	9.03	5.73
35	CSC -15 -05	1:5	0	9.03	4.86
36	CSP-151 -01	1:5	1298	9.03	7.34
37	CSP-151 -02	1:5	1298	9.03	5.48
38	CSP-151 -03	1:5	1298	9.03	5.17
39	CSP-151 -04	1:5	1298	9.03	6.59
40	CSP-151 -05	1:5	1298	9.03	4.58
41	CSP-152 -01	1:5	2596	9.03	8.29
42	CSP-152 -02	1:5	2596	9.03	6.96
43	CSP-152 -03	1:5	2596	9.03	3.6
44	CSP-152 -04	1:5	2596	9.03	6.50
45	CSP-152 -05	1:5	2596	9.03	5.49

Research in behavioural science will be weaker without the use of statistical analysis. The statistical equation (1) is discussed below with the parameters from the brick specimens, and the experimental results are compared with the statistical data. Table 4 represents the mathematical prediction. Here the co-efficient α and K_m are assumed values (Table 3) with reasonable conditions. The masonry weight, the thickness of mortar, height, the strength of mortar and bricks and width of masonry prism are considered as parameter in statistical work.

$$f_{masonry}(in\ MPa) = \left(K_m \times \sqrt{{f_{mo}}^2 + {f_b}^2} \times \frac{h_p \times t_p}{t_m} \times \alpha \times W_b\right) \div (A_m \times \beta_m) \quad (1)$$

Strength of masonry $f_w = k_w \sqrt{(f_b / f_m)}$ (2)

Where, k_w = a coefficient which depends on the layout of brick and joints (0.275 and 0.303), f_b= strength of brick, and f_m = strength of masonry

The equation-2 was developed based on experimental investigations undertaken at I.I.T Kanpur by Dr. Pasala Dayaratnam, 'Brick and reinforced brick structures' (1981) [20]. In this research, the statistical works were carried out by proposed equation (1) considering equ (2) as base.

Table 3
Proposed numerical co-efficient.

Percentage mesh embedment	K_m	α
0	0.91	10.2
0-5	0.92	10.4
5-10	0.93	10.6
10-15	0.94	10.8
15-20	0.95	11
20-25<	0.96	15

Table 4
Empirical model results of masonry compressive strength.

Description	Avg. for five specimen Experimental Results in MPa	K_m	α	Statistical Results in MPa	Error in %
Control 1:3	6.9	0.91	10.2	6.95	0.4
PNM single	7.3	0.92	10.4	7.17	1.8
PNM double	7.4	0.93	10.6	7.38	0.6
Control 1:4	6.6	0.91	10.2	6.56	0.8
PNM single	6.6	0.92	10.4	6.76	1.8
PNM double	7.3	0.93	10.6	6.96	4.7
Control 1:5	4.8	0.91	10.2	5.82	17.3
PNM single	5.8	0.92	10.4	5.78	1.0
PNM double	6.2	0.93	10.6	7.38	16.3

4.2. Artificial Neural Network (ANN)

ANN is the part of artificial intelligence, which can predict the experimental data for an upcoming event with best accuracy. It could be displaying results of complicated practices. There are many intelligent systems like Genetic algorithm (GA), Neural network (NN), Adaptive resonance theory (ART), Ant algorithm (AA), artificial life (AL), Rules-based system (RBS), Fuzzy logic (FL), etc. which used by many researchers in civil engineering. In this research, the experimental data were trained in the ANN program by using MATLAB. Single layer perception (SLP) is the one consisting only one weighting function and input functions are represented by W_i & U_i respectively. Actual weight indicates perfect connection and negative weights indicate discomfort. These weights, along with the inputs to the cell, decide the performance of the network. Fig. 3 shows the single-layer network perception; in this the cell includes three data (U_1, U_2, and U_3). A bias input (W_0) is provided. Each input connection also consists of a weight (W_1, W_2, and W_3).

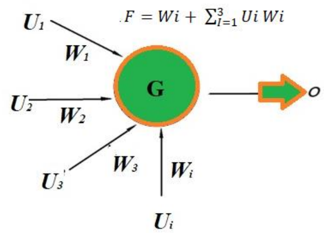


Fig. 3. Single Layer Perception.

MLN provides a more accurate solution for the complex problem, here one input layer and one output layer forms SLP. Also, the more hidden layers are formed to predict the output data (Fig. 4). The input layer represents the inputs to the network and is not composed of neurons in the traditional sense. Sigmoid functions are applied in the intermediate layer. The feed-forward network provides the network information of input, hidden and output layers, also, the network moves only one direction in MLN and SLP. At the same way the another similar network known as Back Propagation or back drop (BP), BP algorithm assign the best training to fit target data.

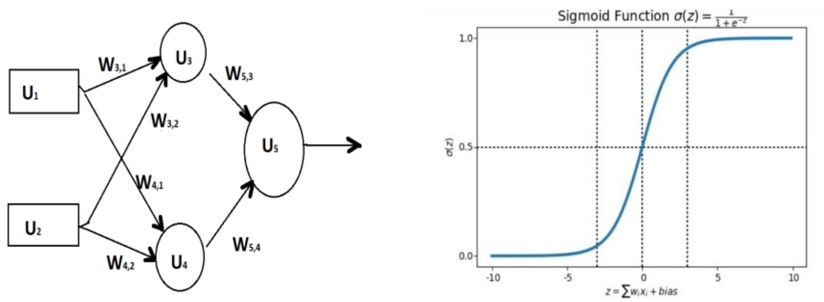


Fig. 4. Multiple Layer Networks and Sigmoid Function.

In this research, the network architecture uses different input layers and one hidden layer function to get prediction. In compressive strength of the masonry prism, the two input layer was mesh area and strength of the mortar, for a training nine, hence totally 27 experimental input data was used for prediction. In the output layer Purelin function was used, network architecture is shown in Fig. 5.

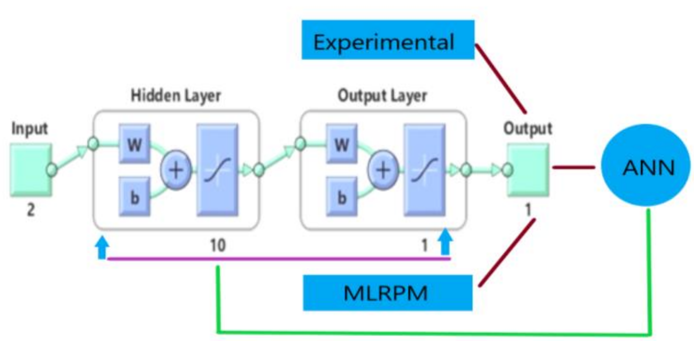


Fig. 5. Network architecture.

The ANN modelling results was shown in table 5. The average compressive strength was compared with ANN prediction; the absolute error was very low when compared with statistical regression equation. The mean absolute deviation was noted as 0.22 and the mean square error also 0.22. The root mean square error was 0.051 and the mean absolute error was much lower 0.003. Hence the predicated results were better than the statistical work, analysis for the brittle materials is complex but the ANN makes this much simpler. Fig.6 and Fig.7 shows the comparison of ANN model against experimental data and Best training, validation and test masonry output data simulated by model. The coefficient of correlation was found 0.94 when compared with experimental results. Table 7 and figure 8 shows the Comparison data of Experimental, prediction by ANN and MLRPM.

Table 5
Validation of masonry compressive strength results against experimental.

Set	Mortar	mesh	Average CS (MPa)	Testing data (MPa)	ANN (MPa)	Error (MPa)	Absolute Error (A)	Square of Error(S)	A/S
CSC13	13.46	0	6.98	6.79	6.84	0.13	0.14	0.02	0.020
CSP131	13.46	1298	7.3	7.01	7.31	0.01	0.01	0.00	-0.001
CSP132	13.46	2596	7.42	7.09	7.4	0.01	0.02	0.00	0.003
CSC14	11.79	0	6.61	6.53	6.67	0.06	0.06	0.00	-0.009
CSP141	11.79	1298	6.63	6.54	7.08	0.45	0.45	0.20	-0.068
CSP142	11.79	2596	7.29	7.00	7.35	0.06	0.06	0.00	-0.008
CSC15	9.03	0	4.81	5.27	4.97	0.16	0.16	0.03	-0.033
CSC151	9.03	1298	5.83	5.98	6.22	0.38	0.39	0.15	-0.067
CSC152	9.03	2596	6.17	6.22	6.93	0.76	0.76	0.58	-0.123
					Sum	2.02	2.05	4.20	-0.287
					AVG	0.22	0.22	0.051	0.003
						MAD*	MSE*	RMSE*	MAPE*

MAD - Mean absolute deviation, MSE - Mean square error
RMSE - Root mean square error, MAPE - Mean absolute percentage error

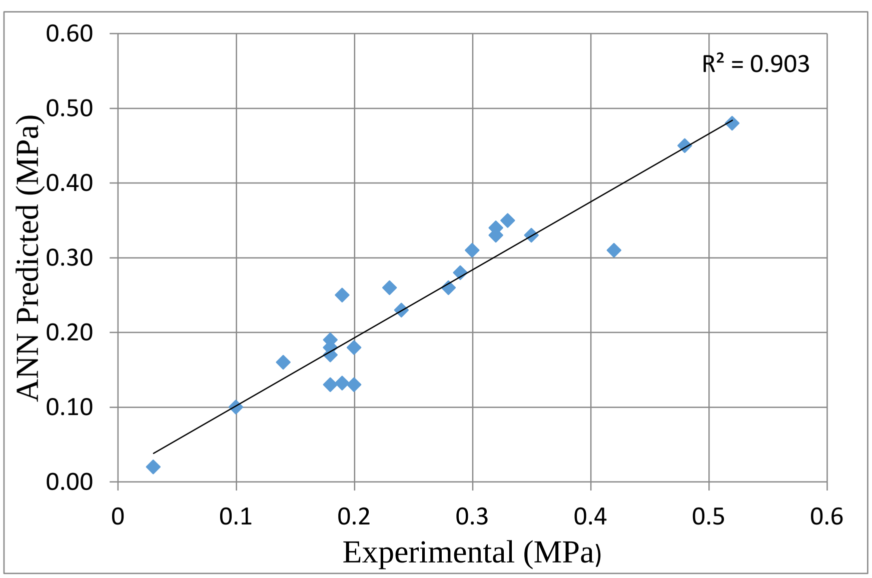
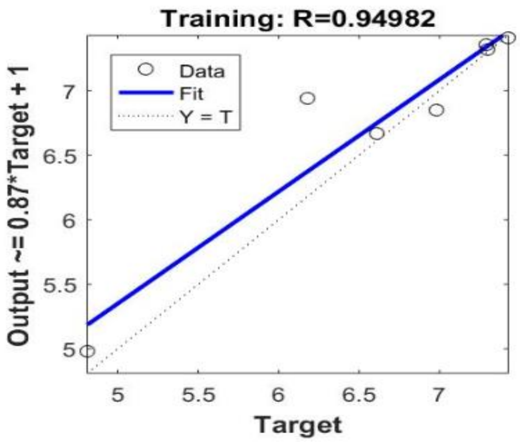
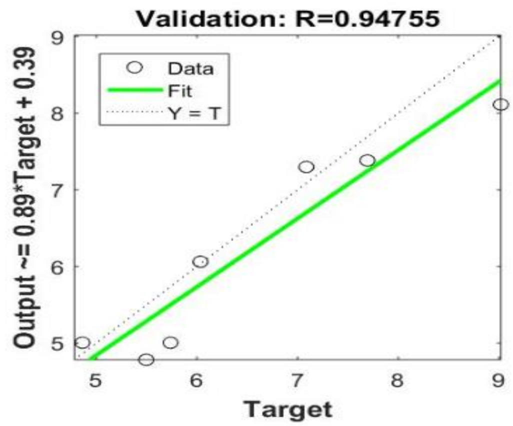


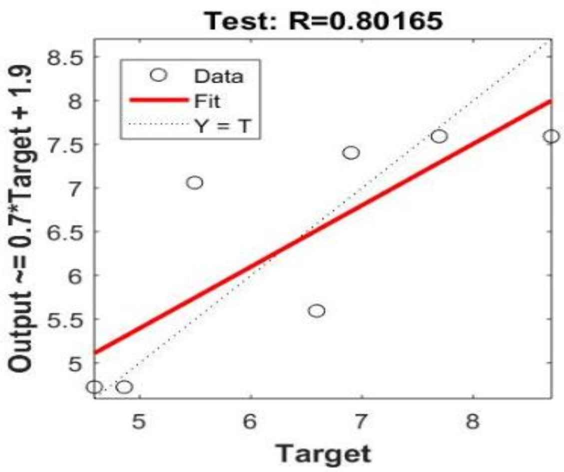
Fig. 6. Verification of compressive strength predicted by ANN against experimental data.



(a) Training data



(b) Validation data



(c) Testing data

Fig. 7. ANN Model Output prediction (a) Training data (b) Validation data and (c) Testing data.

Table 7
Results by Multiple linear regression predictive model (MLRPM).

Observation	Predicted	Residuals		
CSC13	6.91	0.07		
CSP131	7.32	-0.02		
CSP132	7.74	-0.32		
CSC14	6.28	0.33	Regression Statistics	
CSP141	6.70	-0.07	Multiple R	0.96
CSP142	7.11	0.18	R Square	0.92
CSC15	5.25	-0.44	Adjusted R Square	0.89
CSC151	5.66	0.17	Standard Error	0.28
CSC152	6.07	0.10	Observations	9

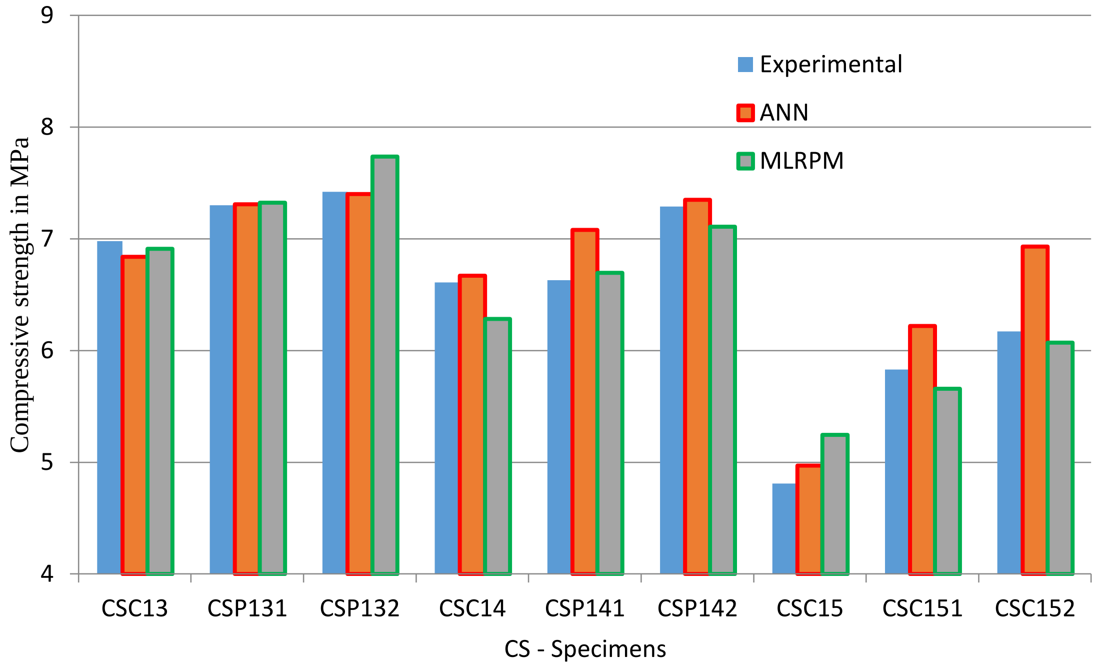


Fig. 8. Comparison data of Experimental, prediction by ANN and MLRPM.

5. Conclusions

In this study, the PNM was embedded in masonry prism with different mortar proportion. The experimental data are fitted in the regression equation. The results of the new proposed equation can be used for further research in mesh embedded masonry. The better compressive strength results were achieved for PNM double layer mesh. ANN validation for compressive strength of mesh embedded masonry prism shows better results than the regression. The regression equation shows the error range from 0.4% to 17.3%. Hence, ANN mean absolute percentage error was 0.003 compared to experimental. The co-efficient of correlation (R^2) by ANN model was 0.94. Another mathematical model MLRPM prediction results was slightly less ($R^2 = 0.02$) compare to the ANN model, the coefficient of correlation was measured 0.92. Finally, the properties of mesh embedment are sufficient to predict compressive strength.

Acknowledgement

The authors would like to thank the Vice-Chancellor of SASTRA DEEMED TO BE UNIVERSITY and Director of National institute of Technology Tiruchirappalli for having provided experimental facilities in the Civil Engineering Department to do this research activity.

References

[1] Cascardi A, Micelli F, Aiello MA. Analytical model based on artificial neural network for masonry shear walls strengthened with FRM systems. Compos Part B Eng 2016;95:252–63. doi:10.1016/j.compositesb.2016.03.066.

[2] Lan G, Wang Y, Zeng G, Zhang J. Compressive strength of earth block masonry: Estimation based on neural networks and adaptive network-based fuzzy inference system. Compos Struct 2020;235:111731. doi:10.1016/j.compstruct.2019.111731.

[3] Garzón-Roca J, Marco CO, Adam JM. Compressive strength of masonry made of clay bricks and cement mortar: Estimation based on Neural Networks and Fuzzy Logic. Eng Struct 2013;48:21–7. doi:10.1016/j.engstruct.2012.09.029.

[4] Zhou Q, Wang F, Zhu F. Estimation of compressive strength of hollow concrete masonry prisms using artificial neural networks and adaptive neuro-fuzzy inference systems. Constr Build Mater 2016;125:417–26. doi:10.1016/j.conbuildmat.2016.08.064.

[5] Garzón-Roca J, Adam JM, Sandoval C, Roca P. Estimation of the axial behaviour of masonry walls based on Artificial Neural Networks. Comput Struct 2013;125:145–52. doi:10.1016/j.compstruc.2013.05.006.

[6] Naderpour H, Rezazadeh Eidgahee D, Fakharian P, Rafiean AH, Kalantari SM. A new proposed approach for moment capacity estimation of ferrocement members using Group Method of Data Handling. Eng Sci Technol an Int J 2020;23:382–91. doi:10.1016/j.jestch.2019.05.013.

[7] Kalman Sipos T, Parsa P. Empirical Formulation of Ferrocement Members Moment Capacity Using Artificial Neural Networks. J Soft Comput Civ Eng 2020;4:111–26. doi:10.22115/scce.2020.221268.1181.

[8] Deng F, He Y, Zhou S, Yu Y, Cheng H, Wu X. Compressive strength prediction of recycled concrete based on deep learning. Constr Build Mater 2018;175:562–9. doi:https://doi.org/10.1016/j.conbuildmat.2018.04.169.

[9] Czarnecki S. Non-destructive Evaluation of the Bond between a Concrete Added Repair Layer with Variable Thickness and a Substrate Layer Using ANN. Procedia Eng 2017;172:194–201. doi:10.1016/j.proeng.2017.02.049.

[10] Xu J, Zhao X, Yu Y, Xie T, Yang G, Xue J. Parametric sensitivity analysis and modelling of mechanical properties of normal- and high-strength recycled aggregate concrete using grey theory, multiple nonlinear regression and artificial neural networks. Constr Build Mater 2019;211:479–91. doi:10.1016/j.conbuildmat.2019.03.234.

[11] Cascardi A, Micelli F, Aiello MA. An Artificial Neural Networks model for the prediction of the compressive strength of FRP-confined concrete circular columns. Eng Struct 2017;140:199–208. doi:10.1016/j.engstruct.2017.02.047.

[12] Khosravikia F, Kurkowski J, Clayton P. Fragility of masonry veneers to human-induced Central U.S. earthquakes using neural network models. J Build Eng 2020;28:101100. doi:10.1016/j.jobe.2019.101100.

[13] Lee J, Sanmugarasa K, Blumenstein M, Loo YC. Improving the reliability of a Bridge Management System (BMS) using an ANN-based Backward Prediction Model (BPM). Autom Constr 2008;17:758–72. doi:10.1016/j.autcon.2008.02.008.

[14] Plevris V, Asteris PG. Modeling of masonry failure surface under biaxial compressive stress using Neural Networks. Constr Build Mater 2014;55:447–61. doi:10.1016/j.conbuildmat.2014.01.041.

[15] Zhou Q, Zhu F, Yang X, Wang F, Chi B, Zhang Z. Shear capacity estimation of fully grouted reinforced concrete masonry walls using neural network and adaptive neuro-fuzzy inference system models. Constr Build Mater 2017;153:937–47. doi:10.1016/j.conbuildmat.2017.07.171.

[16] Sobhani J, Najimi M, Pourkhorshidi AR, Parhizkar T. Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models. Constr Build Mater 2010;24:709–18. doi:10.1016/j.conbuildmat.2009.10.037.

[17] Mansouri I, Kisi O. Prediction of debonding strength for masonry elements retrofitted with FRP composites using neuro fuzzy and neural network approaches. Compos Part B Eng 2015;70:247–55. doi:10.1016/j.compositesb.2014.11.023.

[18] Eskandari H, Nik MG, Eidi MM. Prediction of Mortar Compressive Strengths for Different Cement Grades in the Vicinity of Sodium Chloride Using ANN. Procedia Eng 2016;150:2185–92. doi:10.1016/j.proeng.2016.07.262.

[19] American Society for Testing and Materials (ASTM). Standard Test Method for Compressive Strength of Masonry Prisms. ASTM C1314 – 16 2018.

[20] Dayaratnam P. Brick and Reinforced Brick Structures. M. Primlani; 1987.