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PREDICTION OF ULTIMATE LOAD ON RCC BEAM UTILIZING ANN ALGORITHM

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A B S T R A C T

In this research work, shows an analytical study regarding RCC (reinforced cement concrete) beam comprised with FRP (fiber reinforced polymers) bars. ANN is used in order to estimate and predict the ultimate load of a RCC beam along with the prediction of the failure load associated in the beam. A total of 40 dataset of simply supported beams are considered in the study. The neural network has been trained using MATLAB tool as it contains different training networks and application of training algorithm can be done easily. The data are arranged in a format such that 6 input parameters cover the geometrical and loading properties of beams and the corresponding output is the ultimate failure load. Several input parameters are considered in the study such as the length (L) in the range (900-3000 mm), width (b) in the range (80-250 mm), depth (d) in the range of (150-300 mm), compressive strength of concrete (Fc) in between range (25-80 Mpa), tensile strength (fu) in the range of (3.5-1300 Mpa), elasticity modulus (Ef) in the range of (23000-45000 Mpa) for the RCC beam, and only the ultimate load (40-248kN) is calibrated as the output variable. The input parameters have been taken as per the reference from previous works in the literature. The complete dataset is taken in five parts and depending on the reference papers. Further mean values of the ultimate load is calculated from each part in order to identify the type of beams suitable for use to bear the ultimate load. The results depict significant improvement in percentage for each of the data set which has been calculated. The predicted values from the five datasets gives 15.57%, 7.38%, 10.33%, 16.04% and 5.86% improvement respectively compared to actual ultimate load values. The results showed that using ANN method successfully predicted the values for the ultimate load of the beam. Separate graphs for each of the datasets have been plotted depicting the comparison between the actual ultimate load and predicted ultimate load. The predicted results were more accurate in terms of predicting the failure load. Scope of future work has been also discussed later in this study.

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Keywords:
RCC, FRP, ANN, concrete beam, MATLAB, ultimate load

1. Introduction

Artificial Neural Network (ANN) is a subfield of' the artificial intelligence technology that has gained strong popularity in it rather large array of engineering applications where conventional analytical methods arc difficult to pursue or show inferior performance. Specifically ANNs have shown a good potential to successfully model complex input/output relationships where the presence of non-linearity and inconsistent/noisy data adversely affects other approaches. ANN model is robust and Fault tolerant. ANN can also work with qualitative, uncertain and incomplete information, making it highly promising for inverse problems in structural engineering.

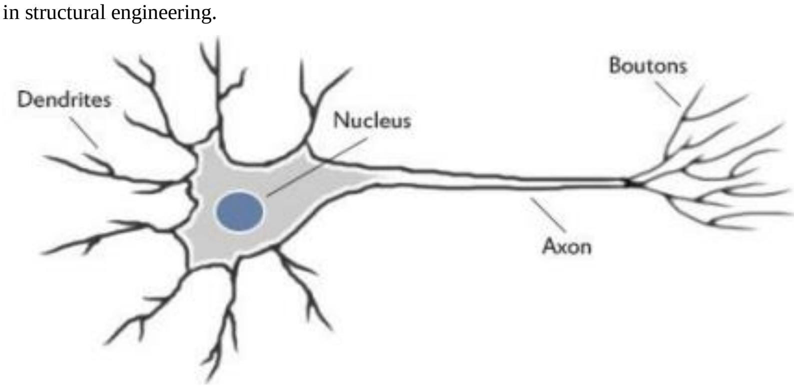

Figure 1 A biological neuron

1.1. The biological neural network

The structure and the functioning of the brain have been studied by many neurophysiologists. Even now the exact functional process of the human brain is not known. Only an overview of the functioning of the human brain is available at present. Basically, the brain functions with a very dense network of neurons. The biochemistry of the neurons is also not fully known. The brain contains as many as 10" neurons connected to each other by as many as 10" interconnections among them (Snell, 1992). Fig. 1.1 shows a typical biological neuron.

The biological neuron consists mainly of the following parts.

- The Cell Body
- The Axon
- The Dendrite

1.2. Structure of neural network

The neural networks can be single layered or multi-layered. A single layered neural network is composed of two input neurons and one output neuron. A multi-layered artificial neural network (ANN) consists of input layer, output layer and a hidden layer of neurons. The hidden layer of neurons is also called as intermediate layer of neurons. A three layered neural network is shown in the figure below.

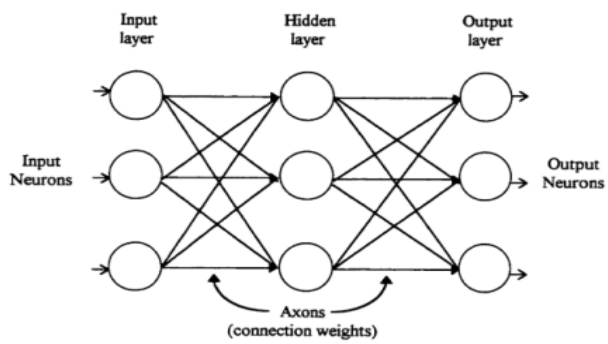

Figure 2 Simplified Neural Network Mode1

Each network is composed of three basic components as illustrates in Figure 2) input neurons or processing elements, which represent the input for the problem, 2) connecting "axons," which connect input and output neurons and represent the connection weights that associate the input to the output, and 3) output neurons or processing elements, which represent the output for the problem. Neural networks can be composed of a single Layer or many layers, according to the complexity of the architecture of the network Multi-layer neural networks may contain one or more middle layers. These middle or hidden" layers (see Figure 2) consist of neurons with no direct connection to either the input or the output of the network; rather, they are used to further refine training by adjusting the connection weights for the network These connection weights are applied at the links connecting the inputs to the outputs (axons in Figure 2) and they associate the contribution or effect of each of these inputs on each output.

2. Literature review

(S.H. Hashemi et. al 2008): Flexural Testing of High Strength Reinforced Concrete Beams Strengthened with CFRP Sheets

The objective of this study is to investigate the effectiveness of externally bonded CFRP sheets to increase the flexural strength of reinforced high strength concrete (HSC) beams. Four-point bending flexural tests to complete failure on six concrete beams, strengthened with different layouts of CFRP sheets were conducted. Three-dimensional nonlinear finite element (FE) models were adopted by ANSYS to examine the behavior of the test beams. More specifically, the strength and ductility of the beams is investigated, as the number of FRP layers and tensile reinforcement bar ratio changed. With the exception of the control beam, one to four layers of CFRP were applied to the specimens. The ductility characteristics of the test beams were evaluated in terms of the displacement, curvature and energy ductility index.

Conclusion: It was found that for all the reported beams, the energy ductility value is about two times higher than the displacement ductility values. The crack patterns in the beams are also presented. The load deflection plots obtained from numerical study show good agreement with the experimental results.

(Nebojsa Duranovic et. al 2000): Tests on Concrete Beams Reinforced with Glass Fibre Reinforced Plastic Bars

Results of tests on beams reinforced with steel and GFRP bars are presented. Three different approaches to design are examined by referring to the stiffness, area and strength of reinforcement. Analysis of experimental results shows that the classical approach of section analysis is valid and that predictable and repeatable results are obtained. The shear capacity of beam is also seen to be predictable, even though GFRP links have weaker characteristics than GFRP bars.

Conclusion:

1) The behaviour of beams reinforced with GFRP bars has been shown to be predictable by section analysis techniques normally used in design.

2) The behaviour of the beams is reliable and repeatable. The deformability of beams at failure is similar to that of steel reinforced beams.

3) Different approaches for design are discussed and illustrated with examples. The choice of design approach depends largely on the design constraints.

4) Shear capacity is predictable by using modifications to equations proposed by Clarke. However, the strength of GFRP links appears to be limited due to a number of factors.

(Maher A. Adam et. al 2015): Analytical and experimental flexural behavior of concrete beams reinforced with glass fiber reinforced polymers bars

This paper presents an experimental, numerical and analytical study of the flexural behavior of concrete beams reinforced with locally produced glass fiber reinforced polymers (GFRP) bars. The bars are locally produced by double parts die mold using local resources raw materials. A total of ten beams, measuring 120 mm wide 300 mm deep 2800 mm long, were cast and tested up to failure under four-point bending. The main parameters were reinforcement material type (GFRP and steel), concrete compressive strength and reinforcement ratio (μb, 1.7 μb and 2.7 μb; where lb is the reinforcement ratio at balanced condition). The mid-span deflection, crack width and GFRP reinforcement strains of the tested beams were recorded and compared.

Conclusions: The test results revealed that the crack widths and mid-span deflection were significantly decreased by increasing the reinforcement ratio. The ultimate load increased by 47% and 97% as the reinforcement ratio increased from μb to 2.7 μb. Specimens reinforced by 2.7 μb can produce some amount of ductility provided by the concrete. The recorded strain of GFRP reinforcement reached to 90% of the ultimate strains. A non-linear finite element analysis (NLFEA) was constructed to simulate the flexural behavior of tested beams, in terms of crack pattern and load deflection behavior. It can be considered a good agreement between the experimental and numerical results was achieved. Modifications to ACI 440.1R-06 equation for estimating the effective moment of inertia (μe) of FRP-reinforced concrete beams, using regression analysis of experimental results, is proposed by introducing empirical factors that effectively decrease the μe at high load level. The proposed equation is compared with different code provisions and previous models for predicting the deflection. It can proved that the proposed factors gives good estimation for the effective moment of inertia (μe) works well for FRP-reinforced concrete beams at high load level

(Iman Chitsazan et. al 2010) An experimental study on the flexural behavior of FRP RC beams and a comparison of the ultimate moment capacity with ACI

In this research, the authors have investigated flexural behavior in reinforced concrete beams with glass fiber-reinforced polymer (GFRP) and have analyzed the different kinds of failure, ultimate moment capacity, deflection, load of first crack, how to create and expand cracks, tensile and compressive strains created on beam and position of neutral axis (NA) during loading for different ratios of bars on 10 laboratorial specimens. Using high strength concrete instead of normal concrete and increasing the effective depth over the breadth on flexural behavior of concrete beams with GFRP had been studied. Results taken from the experimental tests have been compared with ACI 440 and they show that deflections, width of cracks and the cracks' extent are further used toward the usual RC beams.

Conclusions: High strength concrete instead of normal concrete is the ascended load of the first crack and it created more cracks, but with less width of crack. It is recommended that the selected ratio of effective depth over breadth (d/b) is slightly larger than 2. In addition, it can be said that the amount of the balanced bar provided by ACI 400 is not an exact criteria to determine the type of failure, and it is only in cases where the ratio of bars are lower than the balanced mode that ruptures occur in reinforcement area.

(C. Barris et. al 2009): An experimental study of the flexural behaviour of GFRP RC beams and comparison with prediction models

Although the number of analytical and experimental studies on RC beams with FRP reinforcement has increased in recent decades, it is still lower than the number of such studies related to steel RC structures. This paper presents the results and discussion of an experimental programme concerning concrete beams reinforced with glass-FRP (GFRP) bars with a relatively high modulus of elasticity. The main aim of the study is to evaluate the short-term flexural behaviour by varying the reinforcement ratio and the effective depth-to-height ratio.

Conclusions: Code formulations and other prediction models are examined and compared with experimental results at serviceability and ultimate limit states. For the tested beams current provisions predict reasonably well the behaviour up to service load. However, at the ultimate limit state, load capacity is underestimated. All the specimens behaved in a linear way until cracking and, due to lack of plasticity in the reinforcement. All beams demonstrated a concrete crushing mode of failure in line with design predictions. The experimental ultimate load is 51% and 17% higher than expected according to ACI 440.1R-06 and Eurocode 2 predictions, respectively.

(Saka, 2017) A comparative study was carried out for the use of multi-layer feed-forward neural networks in predicting the ultimate shear strength of simply supported deep beams subjected to two point loads acting symmetrically with respect to the centerline of the span. It is found that the strength values obtained from the artificial neural network are much more accurate than those determined from ACI code, strut-and-tie, or Mau-Hsu methods. Although the average value of the ratio of actual strength to predicted strength was 2.07 for all deep beams in the ACI method, 0.85 in the strut-and-tie method, and 0.84 in the Mau-Hsu method, it was only 0.99 in the neural network. These average ratios change to 2.44, 0.81, 0.78, and 0.97, respectively, when the methods are employed for 10 beams that are not used in training the network. These results clearly indicate the accuracy of the neural network in predicting the shear capacity of deep beams. Furthermore comparison has revealed that although the ACI, strut-and-tie, and Mau-Hsu methods were affected with the variations of L/d and a/d ratios and the compressive strength of concrete, neural network performance was unaffected by these variations.

(Indexed and Jawaharlal, 2017) The researches done earlier were to strengthen the beam-column joints in order to increase the overall performance under reversal loading and to enhance the energy absorption capacity of the joint under seismic loading and to increase the strength of weak joints which were originally not designed for seismic compliance and to strengthen the damages joints with different materials & techniques and in all the researches, only the incremental strength were focused, and no notable work on the required additional strength at a negative moment region required for the actual ground condition were analyzed. The FRP composites and the size of specimen were chosen arbitrarily to fit into the laboratory condition which will not suit to the field condition. Few researches carried out on internal beam-column joints have not taken care of the reaction from the upper columns and the strengthening schemes were worked on the slab area (the wrap were applied not exactly over the negative moment region). No notable researches were carried out on the corner beam-column joints ("L" junction in plan) to strengthen the negative moment region. There has been no scientific or empirical model has been established incorporating all relevant parameters like thickness or external strengthening materials, length to be glued, various modulus of material, exposure, property of substrate, existing strength of substrate, strain already attained, existing stress, etc.

(Chatterjee et al., 2016) The present work has considered a quite challenging in the field of machine learning as the traditionally well- known models based on neural networks fail to achieve the expected performance due to the premature convergence of the NNs while trained with local search-based optimization algorithms The NN-PSO-based model to predict the structural failure of a multistoried RC building was suggested, where the PSO algorithm was engaged to select the optimal weights for the NN classifier. The proposed model has been compared with NN and MLP-FFN that is trained with scaled conjugate gradient algorithm which has been found to be benchmarked against traditional back-propagation and other algorithms. Besides, cross-entropy has been used as the error estimator. The NN-PSO performance has been evaluated by different standard performance measure metrics. The experimental results established the dominance of the proposed model for detecting the structural status of a multistoried RC building structure.

3. Methodology

In general, the ultimate strength in reinforcing members depends on the type of reinforcement material and due to durability and corrosion problem of steel reinforcement other material like fiber reinforcement polymer have appeared to be an alternative reinforcement material. Talking about artificial neural network for the design of beam, then neural network is considered good for regression and classification task in practical cases which actually makes ANN a very efficient tool to solve and deal with many civil and structural engineering problems. And one of the most powerful use of neural network is function approximation. Neural networks which are also known as neural nets are actually the computing system which can be trained to learn a complex relationship between input variables and target data sets.

3.1. Algorithm for ANN Program

1) The experimental data is divided into two sets: training set and validation set.
2) The training of neural network is carried using the training data set.
3) The neural network is designed with three layers: input, hidden and output layer.
4) Input layer has x neurons to process the x inputs.
5) Hidden layer can have any number of neurons. By increasing the number of neurons, the accuracy increases, but it also results in increase in computational time.
6) The output layer has x neurons as x output variables are present.
7) The activation function for each neuron is chosen as atan(x).
8) The weights of the network are obtained by minimizing the error between neural network prediction and experimental data.
9) To minimize the error and determine the weights, the optimization procedure is carried in two steps.

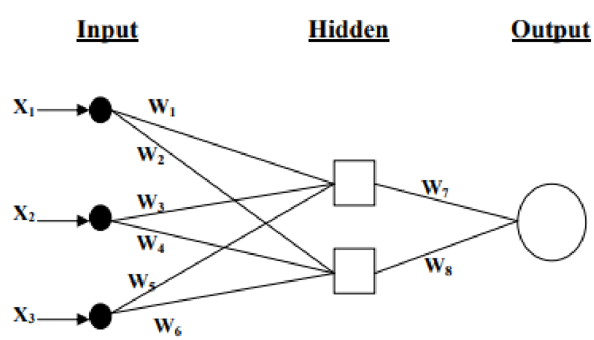

Figure 3 Schematic drawing of the topology of ANN

3.2. Neural network work for the beam

Since neural network allow using simple and basic operation to solve non-linear or complex problems and they are considered good for regression and classification task. Basically ANN has same topology but it uses the most common arrangement of neurons for input and output layers. And as said earlier in the previous chapter that it consists 3 layers which undergo some process to give the output on giving the input.

Neural network undergoes various processes, right from feeding input to training, testing, getting output, checking errors, etc… So, neural networks can be trained to learn a complex relationship between input variable and target data and for that:

1.) The learning process is considered to be the most important part of this process and the objective of this is to get the desired or at least consistent setoff output.

2.) A learning cycle starts with feeding the input vector which is then propagated to the forward propagation mode and ends with output vector.

3.) After that the network analyses the error between the desired output vector and the actual output network. According to learning rule it must tends to minimize the error and this process is known as "error back-propagation" or "back propagation".

4.) The adjusted weighs and biases are then used to start a new cycle.

3.3. Steps for the prediction of failure of beam:

1.) Selection of data set

The purpose of training a network is to get accurate answers and generalized future data. The network uses the training group to update values of the node or in other words it uses this group to get the relationship between the input and output variable.

The total actual (experimental) data used in this proposed neural model is taken from the literature done in previous chapter and its range has been made to implement and to train the network.

Table 1 Input and output variable

Input variable:	**Range:**
Width of beam, b, (mm)	80-250
Depth of beam, d, (mm)	150-300
Concrete compressive strength, fc, (Mpa)	25-80
FRP bars tensile strength, fu, (Mpa)	3.5-1300
FRP bars elasticity modulus, Ef, (Mpa)	23000-45000
Length of beam, L, (mm)	900-3000
Output variable:	**Range:**
Ultimate load, P, (KN)	40-248

3.4. Data set taken from the literature review:

Data set 1: Flexural testing of high strength reinforced concrete beams strengthened with CFRP sheets

4. 5. 6. **S.no**	**7. L (mm)**	**8. b (mm)**	**9. h(mm)**	**10. Concrete compressive strength, fc**	**11. FRP bars tensile strength, fu, (Mpa)**	**12. FRP bars elasticity modulus, Ef, (Mpa)**	**13. Ultimate load (P)**
14. 1	15. 3000	16. 150	17. 250	18. 77	19. 420.6	20. 3850	21. 75.4
22. 2	23. 3000	24. 150	25. 250	26. 77	27. 634.1	28. 3850	29. 90.2
30. 3	31. 3000	32. 150	33. 250	34. 77	35. 412.5	36. 3850	37. 115.4
38. 4	39. 3000	40. 150	41. 250	42. 77	43. 626.4	44. 3850	45. 140.2
46. 5	47. 3000	48. 150	49. 250	50. 77	51. 1250	52. 3850	53. 155.6
54. 6	55. 3000	56. 150	57. 250	58. 77	59. 1250	60. 3850	61. 172.3

For dataset 1:

The mean ultimate load = (75.4+90.2+115.4+140.2+155.6+172.3) / 6 = 124.87

Maximum value for ultimate load = 172.3 and minimum value for ultimate load = 75.4

Data set 2: Test on concrete beams reinforced with glass fibre reinforced plastic bars:

62. 7	63. 2500	64. 250	65. 150	66. 30.8	67. 1000	68. 45000	69. 97.8
70. 8	71. 2500	72. 250	73. 150	74. 38.1	75. 1000	76. 45000	77. 52.9
78. 9	79. 2500	80. 250	81. 150	82. 31.2	83. 1000	84. 45000	85. 105.1
86. 10	87. 2500	88. 250	89. 150	90. 32.9	91. 1000	92. 45000	93. 43.9
94. 11	95. 2500	96. 250	97. 150	98. 39.8	99. 1000	100. 45000	101. 103.6
102. 12	103. 2500	104. 250	105. 150	106. 39.8	107. 1000	108. 45000	109. 103
110. 13	111. 2500	112. 250	113. 150	114. 39.8	115. 1000	116. 45000	117. 97.95
118. 14	119. 2500	120. 250	121. 150	122. 39.8	123. 1000	124. 45000	125. 133.1
126. 15	127. 2500	128. 250	129. 150	130. 43.4	131. 1000	132. 45000	133. 90.6

For dataset 2:

The mean ultimate load = (97.8+52.9+105.1+43.9+103.6+103+97.95+133.1+90.6) / 9 = 91.99

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Maximum value for ultimate load = 133.1 and minimum value for ultimate load = 43.9

Data set 3: Analytical and experimental flexural behavior of concrete beams reinforced with GFRP:

134. 16	135. 2500	136. 120	137. 300	138. 25	139. 640	140. 30000	141. 74.2
142. 17	143. 2500	144. 120	145. 300	146. 25	147. 640	148. 30000	149. 45.9
150. 18	151. 2500	152. 120	153. 300	154. 25	155. 640	156. 30000	157. 40.7
158. 19	159. 2500	160. 120	161. 300	162. 25	163. 640	164. 30000	165. 75.2
166. 20	167. 2500	168. 120	169. 300	170. 45	171. 640	172. 30000	173. 55.8
174. 21	175. 2500	176. 120	177. 300	178. 45	179. 640	180. 30000	181. 81.9
182. 22	183. 2500	184. 120	185. 300	186. 45	187. 640	188. 30000	189. 109.8
190. 23	191. 2500	192. 120	193. 300	194. 70	195. 640	196. 30000	197. 84.6
198. 24	199. 2500	200. 120	201. 300	202. 70	203. 640	204. 30000	205. 132.7
206. 25	207. 2500	208. 120	209. 300	210. 70	211. 640	212. 30000	213. 145.1

For dataset 3:

The mean ultimate load = (74.2+45.9+40.7+75.2+55.8+81.9+109.8+84.6+132.7+145.1) / 10 = 84.69

Maximum value for ultimate load = 145.1 and minimum value for ultimate load = 40.7

Data set 4: An experimental study on the flexural behavior of FRP RC beams and a comparison of the ultimate moment capacity with ACI:

214. 26	215. 900	216. 130	217. 230	218. 41.4	219. 690	220. 40810	221. 98.8
222. 27	223. 900	224. 100	225. 200	226. 41.4	227. 690	228. 40810	229. 197.71
230. 28	231. 900	232. 90	233. 220	234. 41.4	235. 690	236. 40810	237. 141.11
238. 29	239. 900	240. 80	241. 190	242. 41.4	243. 690	244. 40810	245. 134.95
246. 30	247. 900	248. 130	249. 230	250. 73.9	251. 690	252. 40810	253. 100.94
254. 31	255. 900	256. 100	257. 200	258. 73.9	259. 690	260. 40810	261. 150.1
262. 32	263. 900	264. 90	265. 220	266. 41.4	267. 690	268. 40810	269. 127.48
270. 33	271. 900	272. 80	273. 190	274. 41.4	275. 690	276. 40810	277. 154.05
278. 34	279. 900	280. 130	281. 230	282. 41.4	283. 690	284. 40810	285. 106.42
286. 35	287. 900	288. 100	289. 200	290. 41.4	291. 690	292. 40810	293. 246.9
294. 36	295. 900	296. 120	297. 200	298. 70	299. 690	300. 40810	301. 167.22

For dataset 4:

The mean ultimate load = (98.8+197.71+141.11+134.95+100.9+150.1+127.48+154.05+106.42+246.9+167.22) /11 = 147.78

Maximum value for ultimate load = 246.9 and minimum value for ultimate load = 98.8

Data set 5: An experimental study of the flexural behavior of GFRP RC beams and comparison with prediction models:

302. 37	303. 2050	304. 140	305. 190	306. 59.8	307. 3.5	308. 26939	309. 43
310. 38	311. 2050	312. 140	313. 190	314. 56.3	315. 3.3	316. 26524	317. 50.9
318. 39	319. 2050	320. 140	321. 190	322. 55.2	323. 3.8	324. 24926	325. 40.5
326. 40	327. 2050	328. 140	329. 190	330. 39.6	331. 3.0	332. 23163	333. 47.2

For dataset 5:

The mean ultimate load = (43+50.9+40.5+47.2) /4 = 45.4

Maximum value for ultimate load = 50.9 and minimum value for ultimate load = 40.5

Hence, the mean values calculated from each of the data sets are:

Data set 1 = 124.87

Data set 2 = 91.99

Data set 3 = 84.69

Data set 4 = 147.78

Data set 5 = 45.4

Therefore, the mean value signifies type and range of beam to be used so as to calibrate the ultimate load value. For instance

The type of beam in Sets number 37-40 can be used if their ultimate load obtained is near by 45.4 P. Similarly, beam in the sets 16-25 can be used, if their ultimate load obtained is in between 45.4 – 84.69 P. Similarly, beam in the sets 7-15 can be used, if their ultimate load obtained is in between 84.69 – 91.99 P. In the same manner, beam in the sets 1-6 can be used, if their ultimate load obtained is in between 91.99-124.87 P. Similarly, beam in the sets 26-36 can be used, if their ultimate load obtained is in between 124.87-147.78 P

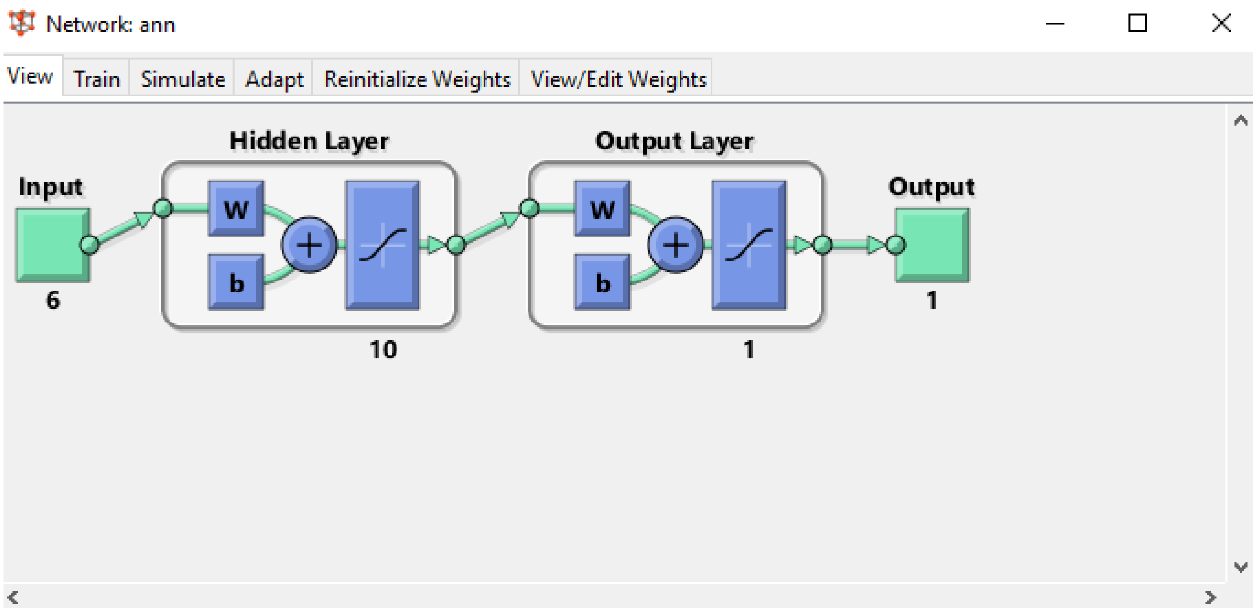

Figure 4 Artificial neural network model

4. Result

The problem's nature is the effective factor that state the defining of the input and output variables (parameters). Selection of the input variables is important to get an efficient network, while the selection of the output variables depends on what required from the network to know. In this study, the dimensions and properties of concrete and FRP bars are chosen as candidate input variables. While the output variable is only the ultimate load (P) of the considered concrete beams. For the proposed neural model, it is decided to use the following eight variables as input variables: the cross sectional width (b) of beams, cross sectional depth (h) of beams, cylinder concrete compressive strength (f'c), cross sectional area of FRP bars (Af), FRP bars tensile strength (fu), FRP bars elasticity modulus (Ef), effective span length (L) of beams, and shear span ratio (m). To minimize the input variables several attempts are tried to choose their proper number to represent the properties of the considered beams. In one attempt, the gross cross sectional area of concrete is used instead of its width and depth. Also in another attempt, the reinforcement ratio of FRP bars is used as an input variable. Although good performance in training is found, but the generalization is very poor. Therefore, it is decided to use the above input variables for the proposed model. So, nodes in the input layer and (1) node in the output layer are used in the proposed neural model.

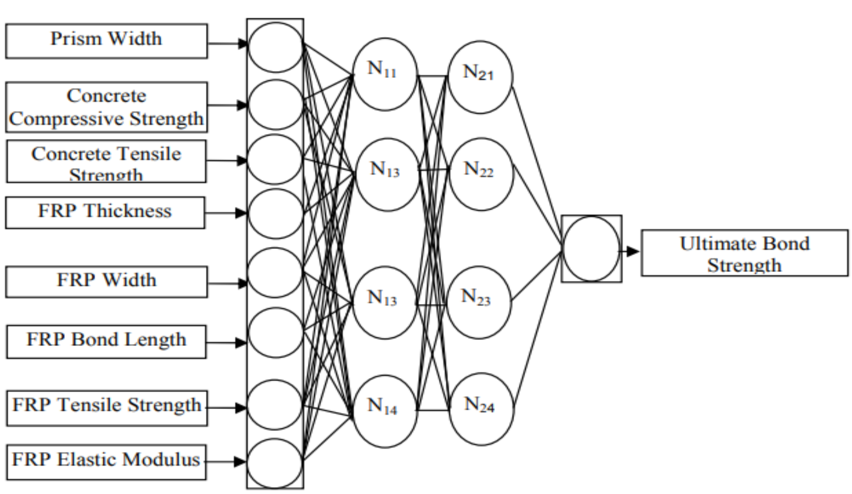

Figure 5 Architecture of the Artificial Neural Network model

After training the network, a regression analysis, Performance, Training state between obtained (predicted) results and actual values is performed to investigate the accuracy of proposed network. The regression coefficient of correlation (R) is used as index in this analysis. And thus the analysis is shown in the form of graphs.

After regression analysis the experimental values are plotted against regression equation. On training the network in ANN through MATLAB it gives the regression equation (Fig 5.2), then the experimental load values (based on literature survey) is put in this equation to get the ultimate load on which the beam will break.

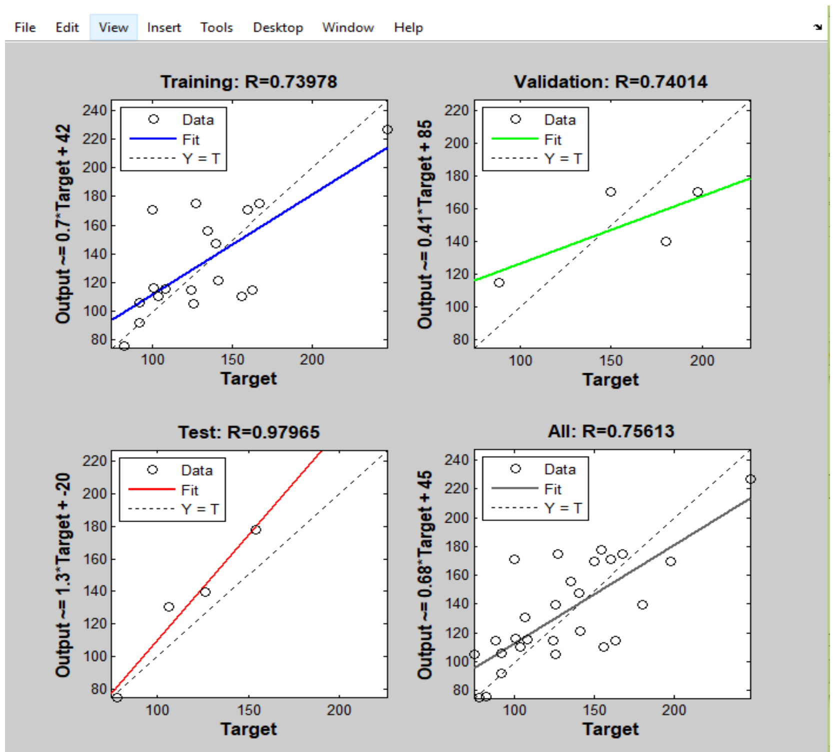

Figure 6 Regression analysis for training group

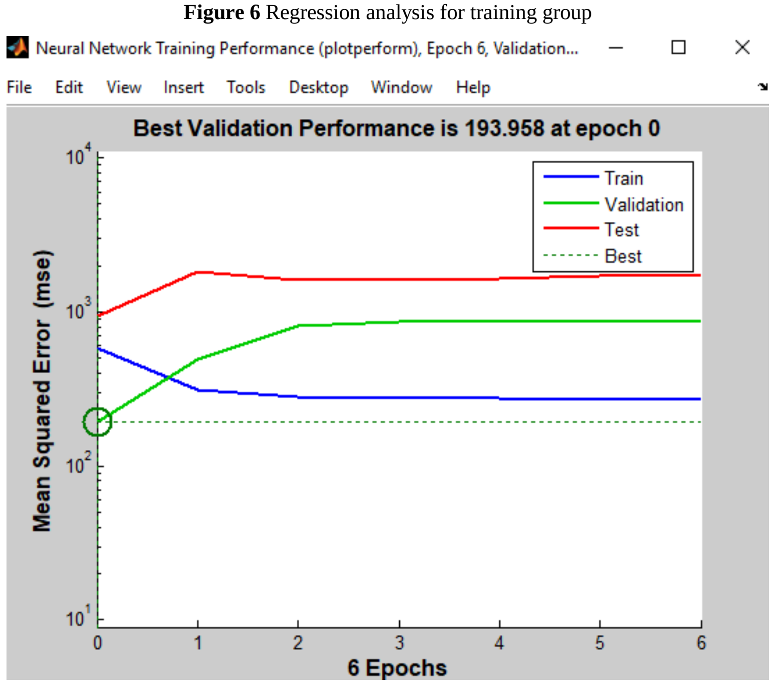

Figure 7 Performance analysis for training group

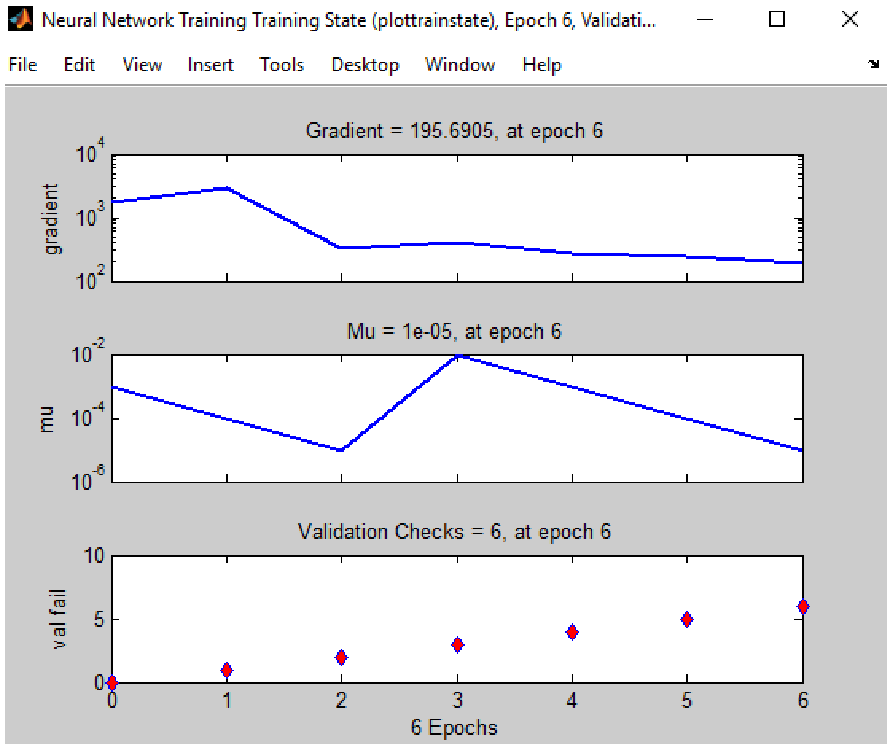

Figure 8 Training analysis for training group

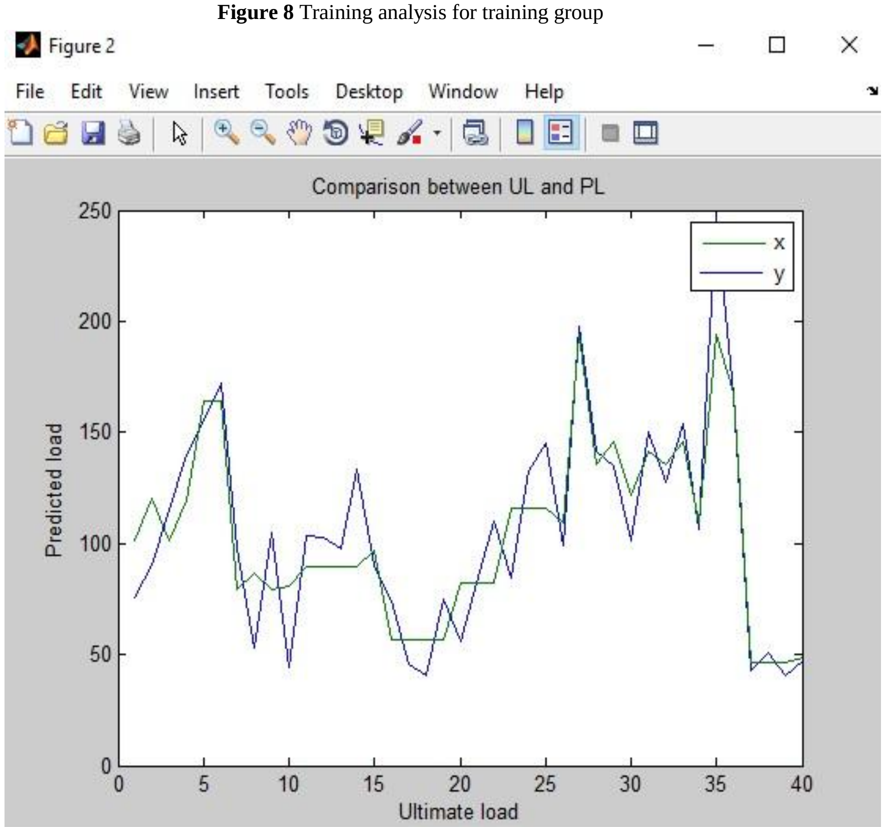

Figure 9 Experimental and ultimate load of beam

In terms of deviation ratio in percentage, it can be seen that the maximum value for ultimate load in actual dataset is 246.9 P. Therefore, calibrating from each of the dataset:

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If 246.9 is assumed to be 100%, then how much percent is 124.87 of 246.9:

100% = 246.9

x% = 124.87

From the above equations:

(100% / x%) = (246.9 / 124.87)

Taking the inverse and solving for x = 50.51 %

- The mean value of **data set 1** is 124.87 which is shows 50.51% deviation to the maximum value.
- The mean value of **data set 2** is 91.99 which is shows 37.25% deviation to the maximum value.
- The mean value of **data set 3** is 84.69 which is shows 34.3% deviation to the maximum value.
- The mean value of **data set 4** is 147.78 which is shows 59.85% deviation to the maximum value.
- The mean value of **data set 5** is 45.4 which is shows 18.388% deviation to the maximum value.

Comparison with the predicted ultimate values:

On the basis of the proposed work, the predicted values of ultimate for **data set 1** have the deviation up to 66.08% which shows improvement of 15.57%.

- Similarly, the predicted values of ultimate for **data set 2** have the deviation up to 44.63% which shows improvement of 7.38%.
- The predicted values of ultimate for **data set 3** have the deviation up to 42.3% which shows improvement of 10.33%.
- The predicted values of ultimate for **data set 4** have the deviation up to 75.89% which shows improvement of 16.04%.
- The predicted values of ultimate for **data set 5** have the deviation up to 24.24% which shows improvement of 5.86%.

4.1. Graphical comparison between the actual ultimate load and predicted value

The values of predicted load obtained for each of the data set is given below:

For Data set 1

Actual Ultimate load (KN)	Predicted Ultimate load (KN)
75.4	101.6071
90.2	120.4634
115.4	100.9016
140.2	119.785
155.6	163.8435
172.3	163.8435

For dataset 2

97.8	79.2656
52.9	86.5791
105.1	79.5215
43.9	80.7637
103.6	89.3485
103	89.3485
97.95	89.3485
133.1	89.3485
90.6	97.0847

For dataset 3

74.2	56.8932
45.9	56.8932
40.7	56.8932
75.2	56.8932
55.8	82.5861
81.9	82.5861
109.8	82.5861
84.6	115.5585
132.7	115.5585
145.1	115.5585

For dataset 4

98.8	109.0059
197.71	194.3575
141.11	135.3646
134.95	145.897
100.94	121.9452
150.1	141.5456
127.48	135.3646
154.05	145.897
106.42	109.0059
246.9	194.3575
167.22	168.0445

For dataset 5

43	46.3374
50.9	46.6444
40.5	46.6187
47.2	48.8433

5. Conclusions and Future Scope

1.) The proposed neural model, has been found to be very excellent for the prediction of ultimate load of the RC beam
2.) The artificial neural network (ANN) has proved its capability in predicting the ultimate load of RCC beam, and this procedure can be used as a reliable alternative to other complex or other costly test procedures.
3.) The configuration for the neural network model was found to be very typical.
4.) Artificial neural network can effectively use to predict the failure load of RCC beams.
5.) Artificial neural network is time – saving.
6.) Artificial neural network predicts the output with great and acceptable accuracy.
7.) For selecting the best configurations of network there are no special guideline.
8.) In this study it is found that the failure load values obtained are much more accurate than those obtained from Limit state theory.
Artificial neural networks are one typical example of a modern interdisciplinary subject that helps solving various different engineering problems which could not be solved by the traditional modelling and statistical methods. The main goal of this research was to explain the simplicity and the positive aspects of the usage of neural networks for solving engineering problems.

REFERENCES

1. Ã, A. W. C. O. (2004) 'Simulating size effect on shear strength of RC beams without stirrups using neural networks', 26, pp. 681–691. doi: 10.1016/j.engstruct.2004.01.009.
2. Adeli, H. (2001) 'Neural Networks in Civil Engineering : 1989 − 2000', 16, pp. 126–142.
3. Ahmadkhanlou, F. and Ã, H. A. (2005) 'Optimum cost design of reinforced concrete slabs using neural dynamics model', 18, pp. 65–72. doi: 10.1016/j.engappai.2004.08.025.
4. Al-jurmaa, M. A. (2011) 'Predicting the Ultimate Load Capacity of R . C . Beams by ANN', 18(1), pp. 56–66.
5. Amayreh, L. and Saka, M. P. (2005) 'FAILURE LOAD PREDICTION OF CASTELLATED BEAMS USING ARTIFICIAL NEURAL NETWORKS', 6, pp. 35–54.
6. Chatterjee, S. et al. (2016) 'Particle swarm optimization trained neural network for structural failure prediction of multistoried RC buildings', Neural Computing and Applications. Springer London. doi: 10.1007/s00521-016-2190-2.
7. Civil, I. and Goals, M. D. (2012) 'COMPARATIVE STUDY ON SHEAR STRENGTH OF REINFORCED CONCRETE BEAMS MADE FROM PHYLLITE AND GRANITE AGGREGATES WITHOUT SHEAR REINFORCEMENT', (March), pp. 285–299.
8. Govindaraj, V. and Ramasamy, J. V (2005) 'Optimum detailed design of reinforced concrete continuous beams using Genetic Algorithms', 84, pp. 34–48. doi: 10.1016/j.compstruc.2005.09.001.
9. Indexed, S. and Jawaharlal, D. (2017) 'COMPREHENSIVE STUDY ON METHODS OF STRENGTHENING OF REINFORCED CEMENT CONCRETE STRUCTURES', 8(7), pp. 1–12.
10. Kasperkiewicz, J. and Dubrawskp, A. (1996) 'BPe STRENGTH PREDICTION USING ARTIFICIAL NEURAL NETWORK By Janusz Kasperkiewicz ,] Janusz Racz , 2 and Artur DubrawskP', 9(4), pp. 279–284.
11. Michal, S. (2003) 'New approach to optimization of reinforced concrete beams ejnoha e j Lep', 81, pp. 1957–1966. doi: 10.1016/S0045-7949(03)00215-3.
12. Mukherjee, A. (2014) 'Modeling Initial Design Process using Artificial Neural Networks MODELING INITIAL DESIGN PROCESS USING ARTIFICIAL', 3801(July 1995). doi: 10.1061/(ASCE)0887-3801(1995)9.
13. Orleans, N. (1997) 'Engineering Computers', pp. 185–196.
14. Perea, C. et al. (2007) 'Design of reinforced concrete bridge frames by heuristic optimization'. doi: 10.1016/j.advengsoft.2007.07.007.
15. Press, A. I. N. (2002) 'Neural networks applications in concrete structures CO', (December).
16. Saka, M. P. (2017) 'Prediction of Ultimate Shear Strength of Reinforced-Concrete Deep Beams P REDICTION OF U LTIMATE S HEAR S TRENGTH OF R EINFORCED -', 9445(July 2001). doi: 10.1061/(ASCE)0733-9445(2001)127.
17. Senouci, A. B. (2000) 'PRELIMINARY DESIGN OF REINFORCED CONCRETE BEAMS USING NEURAL NETWORKS', 13.
18. Sobhani, J. et al. (2010) 'Prediction of the compressive strength of no-slump concrete : A comparative study of regression, neural network and ANFIS models', Construction and Building Materials. Elsevier Ltd, 24(5), pp. 709–718. doi: 10.1016/j.conbuildmat.2009.10.037.
19. S. A. Babiker, F. M. Adam and A. E. Mohamed "Design optimization of reinforced concrete beams using artificial neural network," International Journal of Engineering Inventions, vol. 1, no. 8, pp. 07-13, October, 2012.
20. M. A. Ismail, "Design optimization of structural concrete beams using genetic algorithms," M. S. thesis, Department of Civil Engineering, Islamic University of Gaza, Gaza, 2007.
21. D. M. Alex and L. Kottalil "Genetic algorithm Based design of a reinforced concrete cantilever beam," International Research Journal of Engineering and Technology, vol. 2, no.7, pp. 1249 -1252, IRJET, 2015.
22. S. T. Yousif and R. Najem "Optimum cost design of reinforced concrete continuous beams using genetic algorithm," International Journal of Applied Sciences and Engineering Research, vol. 2 no. 1, pp. 79-92, 2013.
23. S. A. Bhalchandra, P. K. Adsul "Cost optimization of doubly reinforced rectangular beam section," International Journal of Modern Engineering Research, vol. 2, no. 5, pp-3939-3942, IJMER, Sep.Oct., 2012.
24. Cladera A, Mari A R 2004 "Shear design procedure for reinforced normal and high strength concrete beams using artificial neural networks". Part I: Beams without stirrups. Eng. Struct. 26: 927–936.
25. Davis L 1991 Hand book of genetic algorithms, (New York: Van Nostrand Reinhold).