Computational Engineering and Physical Modeling 1-3 (2018) 100-110

Contents lists available at **CEPM**

Computational Engineering and Physical Modeling

Journal homepage: www.jcepm.com

Flexural Capacity Prediction for Reinforced Concrete Beams by Group Method of Data Handling Approach

A. Azimi[1], R. Farahnaki[2*]

1. Faculty of Civil Engineering, University of Birmingham, UK
2. University of Wollongong, New South Wales, Australia

Corresponding author: *rf847@uowmail.edu.au*

https://doi.org/10.22115/CEPM.2018.136502.1033

ARTICLE INFO

Article history:
Received: 19 June 2018
Revised: 29 September 2018
Accepted: 18 February 2019

Keywords:
Flexural capacity;
Reinforced concrete;
FRP;
GMDH.

ABSTRACT

Application of group method of data handling (GMDH) to predict the capacity of reinforced concrete beams strengthened with CFRP laminate has been investigated in this paper. The proposed model considers nine parameters including concrete compressive strength, width of beam, effective depth, area of tension reinforcement, area of compression reinforcement, yield strength of steel, modulus of elasticity of steel, width of CFRP sheet, length of CFRP sheet. There are fourteen second order polynomials in three middle layers and an output layer. The coefficients of these polynomials are determined based on a collection of experimental laboratory tests, which were collected from the literature. In addition, 66 datasets were used to estimate unknown coefficients of the polynomials. To validate the model, 17 datasets were considered from the collected database. The results of the proposed GMDH showed that it can use as a predictive model for determining the ultimate flexural capacity of reinforced concrete beams strengthened with CFRP laminates.

How to cite this article: Azimi A, Farahnaki R. Flexural Capacity Prediction for Reinforced Concrete Beams by Group Method of Data Handling Approach. Comput Eng Phys Model 2018;1(3):100–110. https://doi.org/10.22115/cepm.2018.136502.1033

1. Introduction

One of the most important issues in civil engineering is retrofitting of existing structures to increase their capacity. In this regard, FRP materials are one of the first choices for concrete structures, because of their strength (Fig. 1). In recent years, the design and analysis of strengthened elements with FRP [1,2] as well as laboratory studies has been widely investigated by researchers due to the importance of performance and assurance of the ability of this type of material for desired purposes. Despite the ability of analytical methods such as finite element, there are some problems that occur during the analysis of complex elements in these methods [3] and therefore, it is necessary to another methods that require no complex analysis and calculation for determining the final capacity of structural elements.

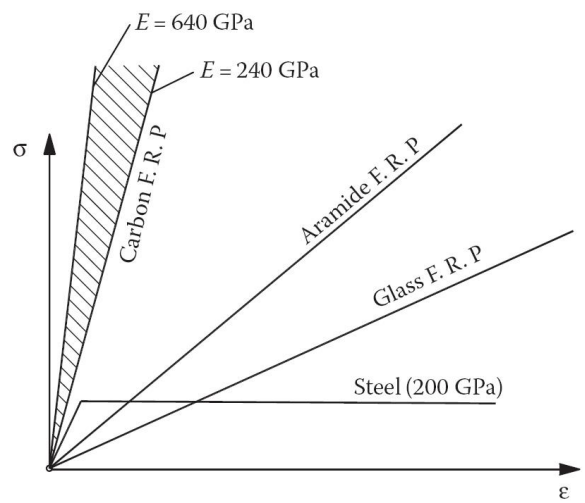

Fig. 1. Stress-Strain diagrams for several types of FRP materials [4].

Despite the high performance of methods such as conventional neural networks or fuzzy systems in civil engineering[5–18] they cannot consider as the first choice due to the lack of access to a simple mathematical structure. In this article, Group method of data handling (GMDH) is used to estimate the ultimate flexural capacity in reinforced concrete beams strengthened with CFRP laminates. This method is a mathematical model based on second order polynomials that can determines the optimal output by combining two variables in a few steps [19]. The final equation can use for the considered prediction and for this purpose, the model is presented in details.

2. Definition of the parameters

In this paper, a collection of the experimental results of RC beams strengthened with FRP is considered which is published in several researches [20,21,30–36,22–29]. This database includes 83 data that has been used in two groups of 66 and 17 for training and also testing the model. Table 1 and also Fig. 2 show the details and description of the considered database, inputs of the model and also the output. It should be noted that these inputs are selected based on try and error method to find the best structure for the proposed GMDH model.

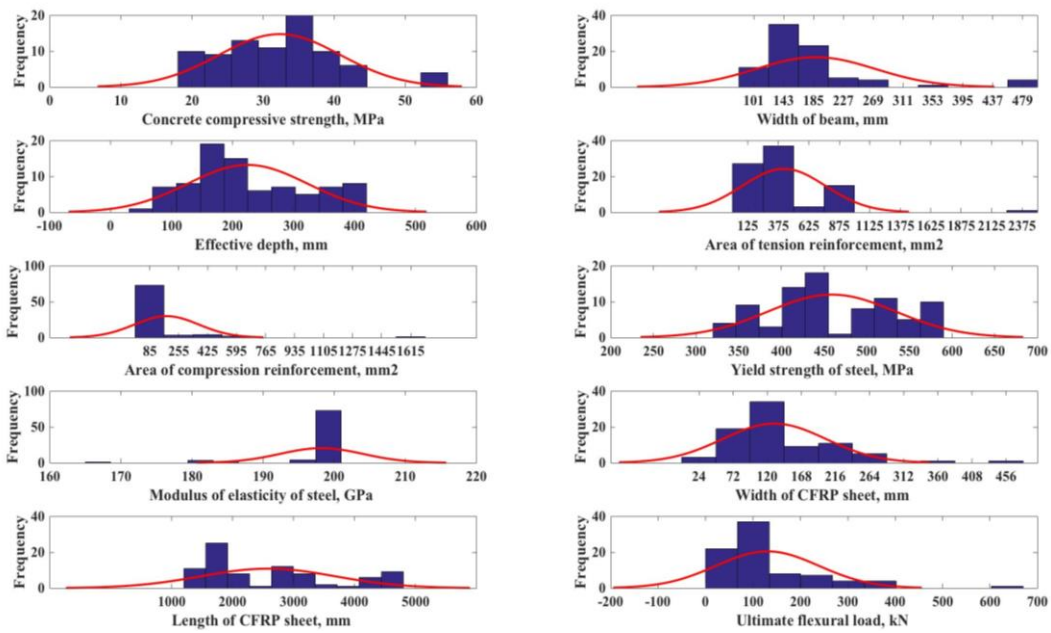

Fig. 2. Histograms of the selected variables.

To decrease the interval of the using parameters, the authors use Eq.1 to convert each of considered variables to a value between 0 to 1.

$$X_1 = \frac{x_1 - 18}{37.2},\ X_2 = \frac{x_2 - 100}{400},\ X_3 = \frac{x_3 - 100}{400},\ X_4 = \frac{x_4 - 71}{2342},\ X_5 = \frac{x_5 - 28}{1581}$$

$$X_6 = \frac{x_6 - 335}{255},\ X_7 = \frac{x_7 - 165}{36},\ X_8 = \frac{x_8 - 25}{455},\ X_9 = \frac{x_9 - 1200}{3600} \tag{1}$$

Table 1
Details of the considered parameters for the proposed model.

Variable	Description	Minimum	Maximum
x_1	Concrete compressive strength, *MPa*	18	55.2
x_2	Width of beam, *mm*	100	500
x_3	Effective depth, *mm*	50.8	419
x_4	Area of tension reinforcement, *mm2*	71	2413
x_5	Area of compression reinforcement, *mm2*	28	1609
x_6	Yield strength of steel, *MPa*	335	590
x_7	Modulus of elasticity of steel, *GPa*	165	201
x_8	Width of CFRP sheet, *mm*	25	480
x_9	Length of CFRP sheet, *mm*	1200	4800
Y	Ultimate flexural load, *kN*	16.1	669.3

3. Definition of the proposed GMDH model

The proposed GMDH in this paper have five layers (Fig. 3), including input layer, three middle layer and also one output layer. There are nine nodes in the first layer as inputs. In the second layer, a combination of each of two inputs makes a node. This layer has seven nodes that are Eq.2 to Eq.8.

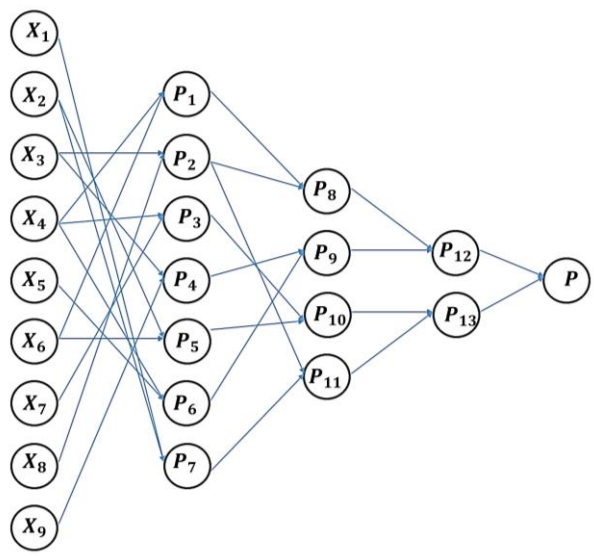

Fig. 3. GMDH structure of the proposed model.

$$P_1 = 0.046 + 0.9118X_4 - 0.2235X_6 - 0.2927X_4^2 + 0.2956X_6^2 + 0.2317X_4X_6 \tag{2}$$

$$P_2 = -0.007 - 0.0865X_3 + 0.2598X_8 + 0.3943X_3^2 - 0.2251X_8^2 + 0.6439X_3X_8 \tag{3}$$

$$P_3 = -0.219 + 1.1019X_4 + 0.8382X_7 - 0.3705X_4^2 - 0.6177X_7^2 + 0.1131X_4X_7 \tag{4}$$

$$P_4 = 0.060 + 0.084X_3 - 0.2544X_9 + 0.2519X_4^2 + 0.2084X_9^2 + 0.1822X_3X_9 \tag{5}$$

$$P_5 = 0.050 + 1.2622X_2 - 0.5804X_6 - 1.1992X_2^2 + 0.6732X_6^2 + 0.1461X_2X_6 \tag{6}$$

$$P_6 = -0.036 + 1.2767X_4 + 0.6731X_5 - 3.7431X_4^2 - 5.7456X_5^2 + 7.9044X_4X_5 \tag{7}$$

$$P_7 = -0.108 + 0.1759X_1 + 2.1544X_2 + 0.0509X_1^2 - 1.2811X_2^2 - 1.7019X_1X_2 \tag{8}$$

In the third layer, there are four nodes, which are P8,…,P11 (Eq.9 to Eq.12). Each of these four nodes are a second order polynomial and with two variables, which are determined in the previous layer.

$$P_8 = -0.014 + 0.3026P_1 + 0.7883P_2 - 1.3212P_1^2 - 1.9347P_2^2 + 3.5150P_1P_2 \tag{9}$$

$$P_9 = 0.042 - 0.6569P_4 + 0.9389P_6 + 2.2137P_4^2 - 0.3087P_6^2 + 0.001P_4P_6 \tag{10}$$

$$P_{10} = 0.031 + 0.6130P_3 - 0.3945P_5 - 0.4186P_3^2 + 1.8087P_5^2 + 1.1369P_3P_5 \tag{11}$$

$$P_{11} = -0.029 + 1.1590P_2 - 0.0388P_7 + 0.1120P_2^2 + 1.3956P_7^2 - 1.4039P_2P_7 \tag{12}$$

There are two nodes in the fourth layer including P12 and P13, which are determined by Eq.13 and Eq.14. The combination of these two nodes creates the last node of the output layer, P.

$$P_{12} = 0.003 + 0.9125P_8 + 0.0036P_9 - 0.3124P_8^2 + 0.9767P_9^2 - 0.4322P_8P_9 \tag{13}$$

$$P_{13} = -0.001 + 0.2167P_{10} + 0.7570P_{11} + 0.1125P_{10}^2 - 1.4966P_{11}^2 + 1.5521P_{10}P_{11} \tag{14}$$

$$P = -0.005 + 0.1216P_{12} + 0.9537P_{13} - 0.7366P_{12}^2 - 3.1273P_{13}^2 + 3.7229P_{12}P_{13} \tag{15}$$

Based on the proposed structure for GMDH, which is showed in Fig. 2, a set of second order polynomials containing seven, four, two and finally one polynomial for each of three middle layers as well as the output layer were used. In the last step, the amount of obtained *P* from the GMDH should return to its corresponding value as the final output, because this output is the normal value of the target (between 0 to 1). To do this, the amount of minimum and maximum values reported in Table 1 are used. The proposed equation as the predictive model of this paper is Eq.16:

$$V(kN) = 653.2P - 16.1 \tag{16}$$

4. Comparison results

A comparison study on the obtained results based on the laboratory datasets, for the considered database is presented in this section. The error for the 66 training data as well as for 17 testing data are shown in Fig. 4. According to this figure, the maximum error reported for the proposed model is 100 kN, which appears to be a reasonable number in comparison with the amount of whole interval of the output (669.3-16.1=653.2 kN).

For better comparison, Fig. 5 and Fig. 6 are presented for the test and train data. Error mean (Mean) for train data is 20.64% with standard deviation equal to 22.07 for 66 datasets. Also, it can be seen from the Fig. 5 that the Mean value for the test data was 25.13% with standard deviation equal to 30.76 for 17 datasets.

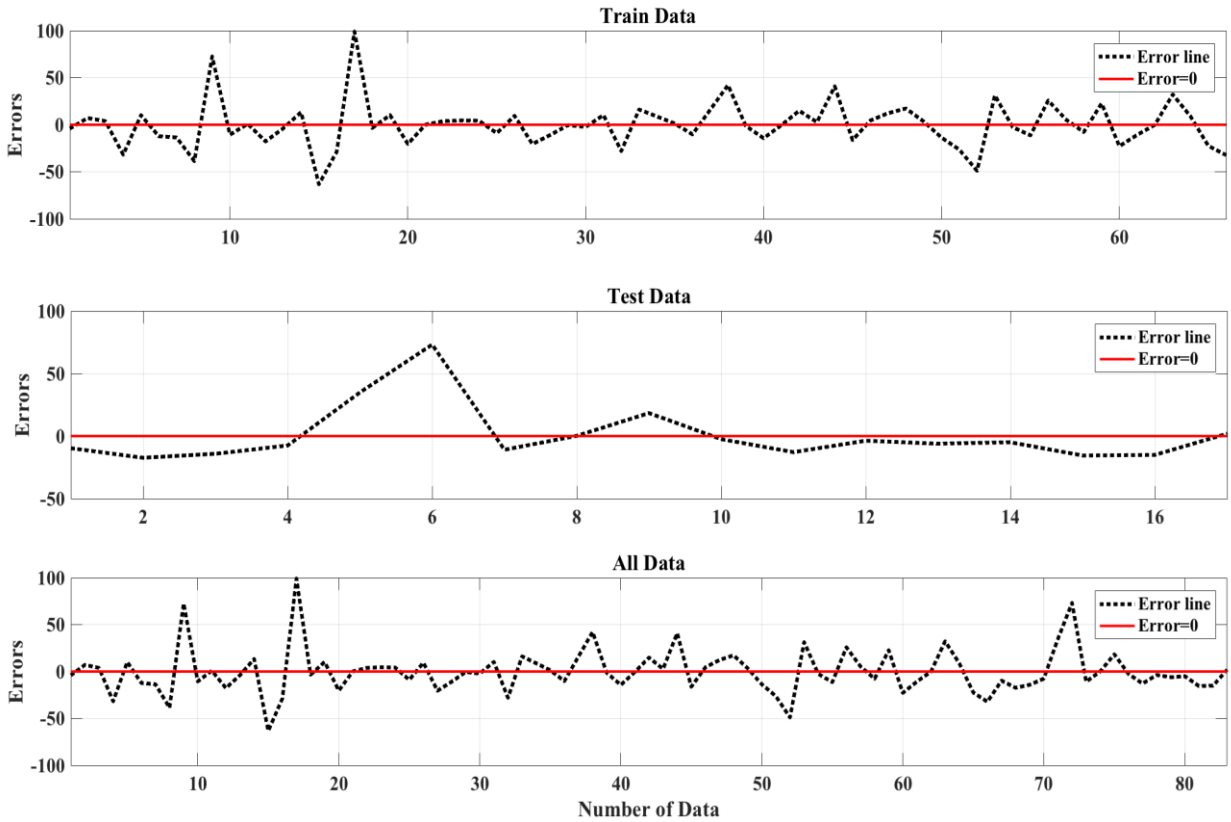

Fig. 4. Errors for the GMDH model.

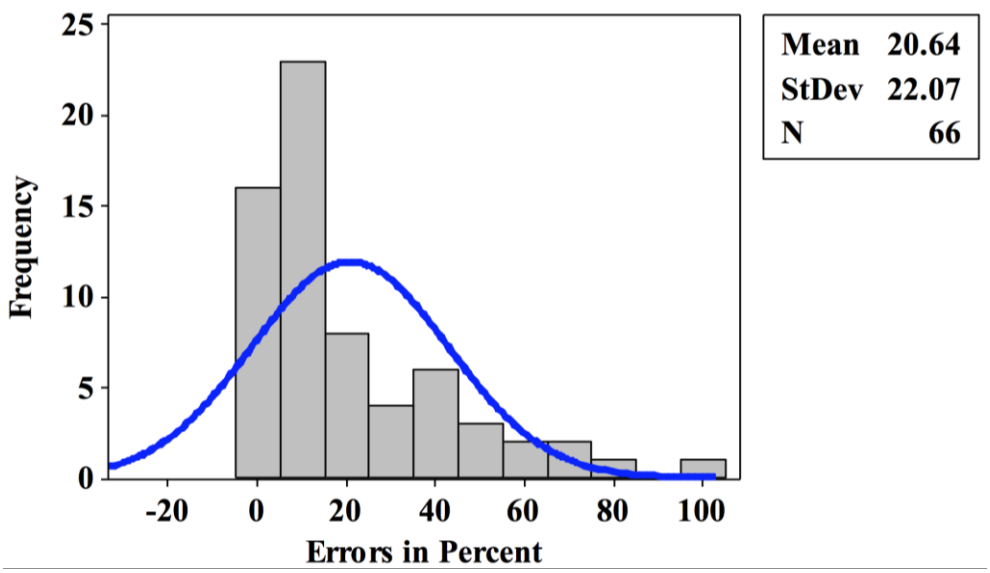

Fig. 5. Histogram of errors for the train data.

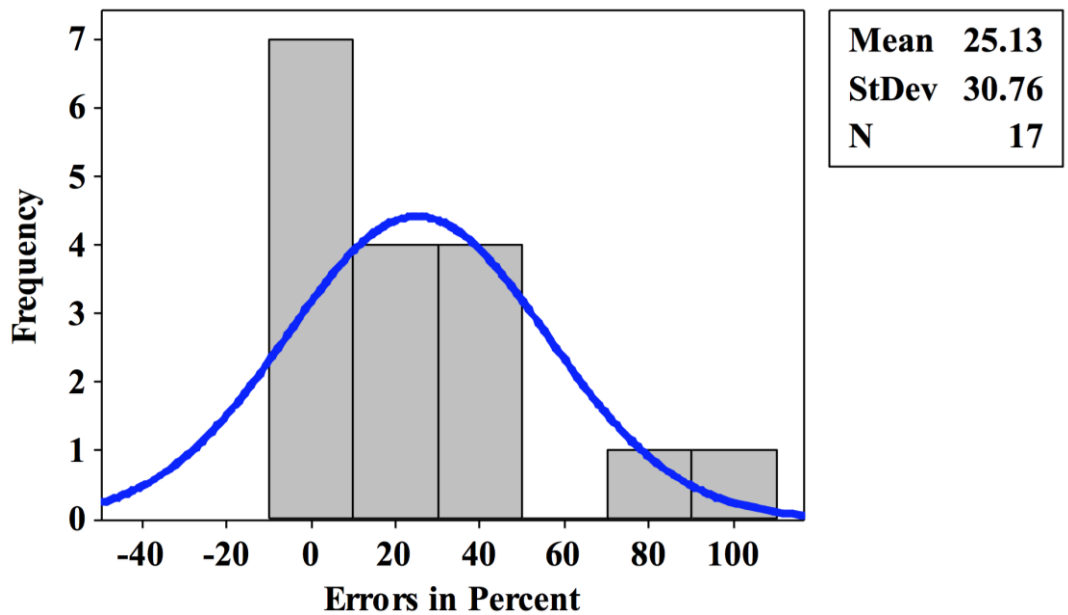

Fig. 6. Histogram of errors for the test data.

Plot regressions for the train, test and also all data are illustrated in Fig. 7 to Fig. 9. Also, the results are compared with the ACI 440. It can be seen from the figures that GMDH had better results than ACI in many cases. This result showed that the presented equations of this research can be used as predictive system.

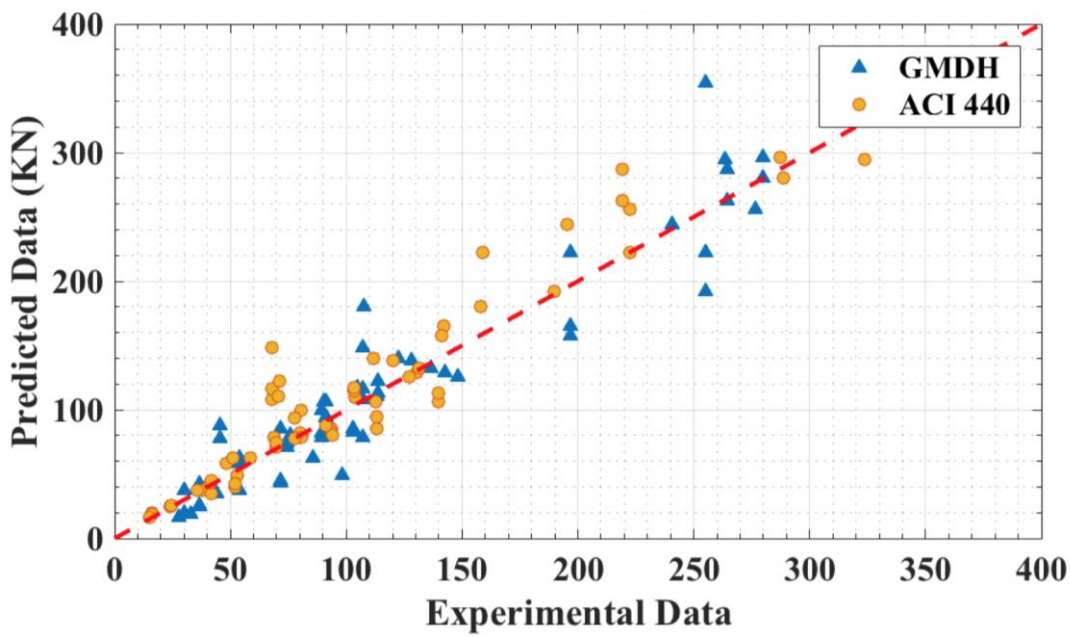

Fig. 7. Regression plot for the train data.

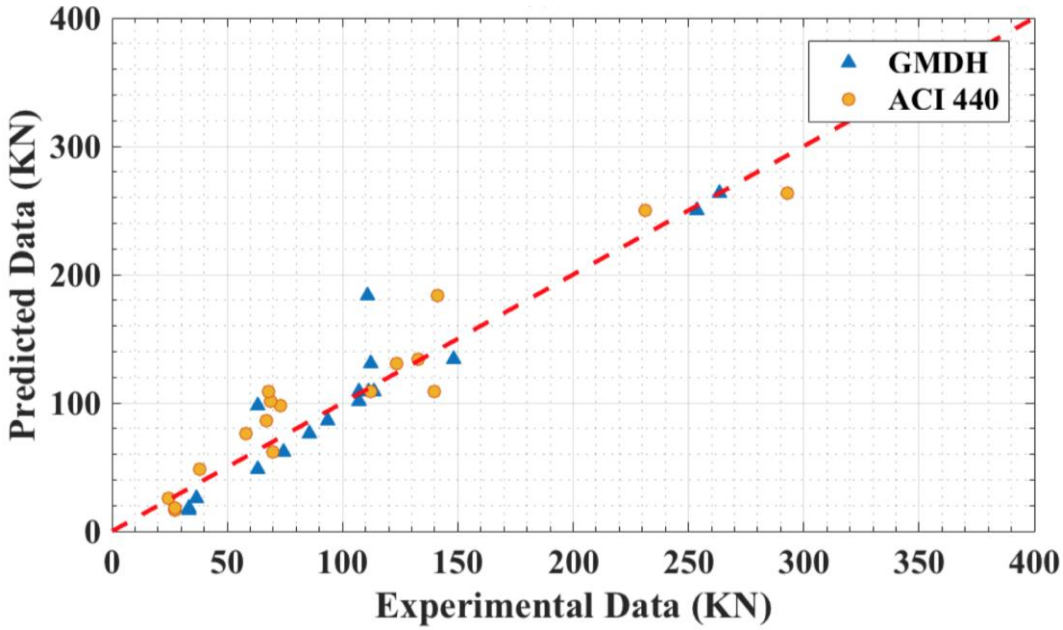

Fig. 8. Regression plot for the test data.

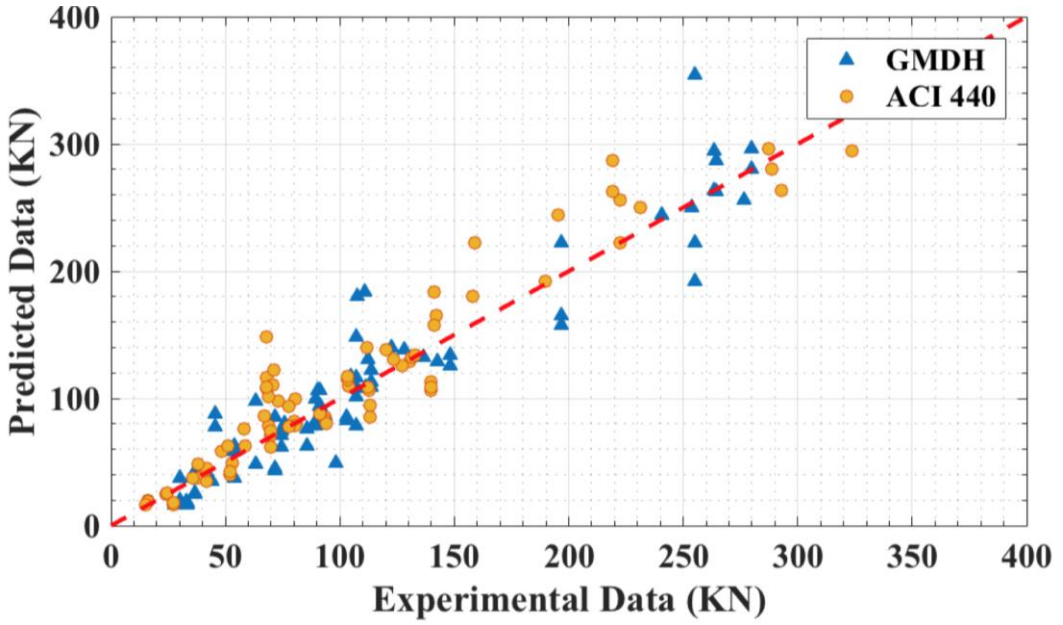

Fig. 9. Regression plot for all data.

Fig.10 shows the performance of the proposed model against the results of laboratory data as well as ACI 440. The proposed model seems to have worked very well in some cases, but there are also more errors than the code in some points. This issue relates to the number of using laboratory data. In fact, because of the structure of the GMDH which is such that its coefficients determine based on laboratory data, the higher number of data increase the accuracy of the model. Also, the high number of parameters considered in this paper for estimating output has affected on this issue. However, it may be a benefit because the proposed model considers the more variables than regulations.

5. Conclusion

The application of group method of data handling (GMDH) is studied in this paper with the aim of prediction the ultimate flexural capacity of reinforced concrete beams strengthened with CFRP laminates. Nine inputs including concrete compressive strength, width of beam, effective depth, area of tension reinforcement, area of compression reinforcement, yield strength of steel, modulus of elasticity of steel, width of CFRP sheet, length of CFRP sheet were considered to estimate the output. The proposed GMDH model consists of fourteen second order polynomials in three middle layer. the obtained results of the proposed GMDH structure indicated that this model, can be used as a predictive model. The results also compared with ACI 440 and it was showed that GMDH had suitable output in many cases.

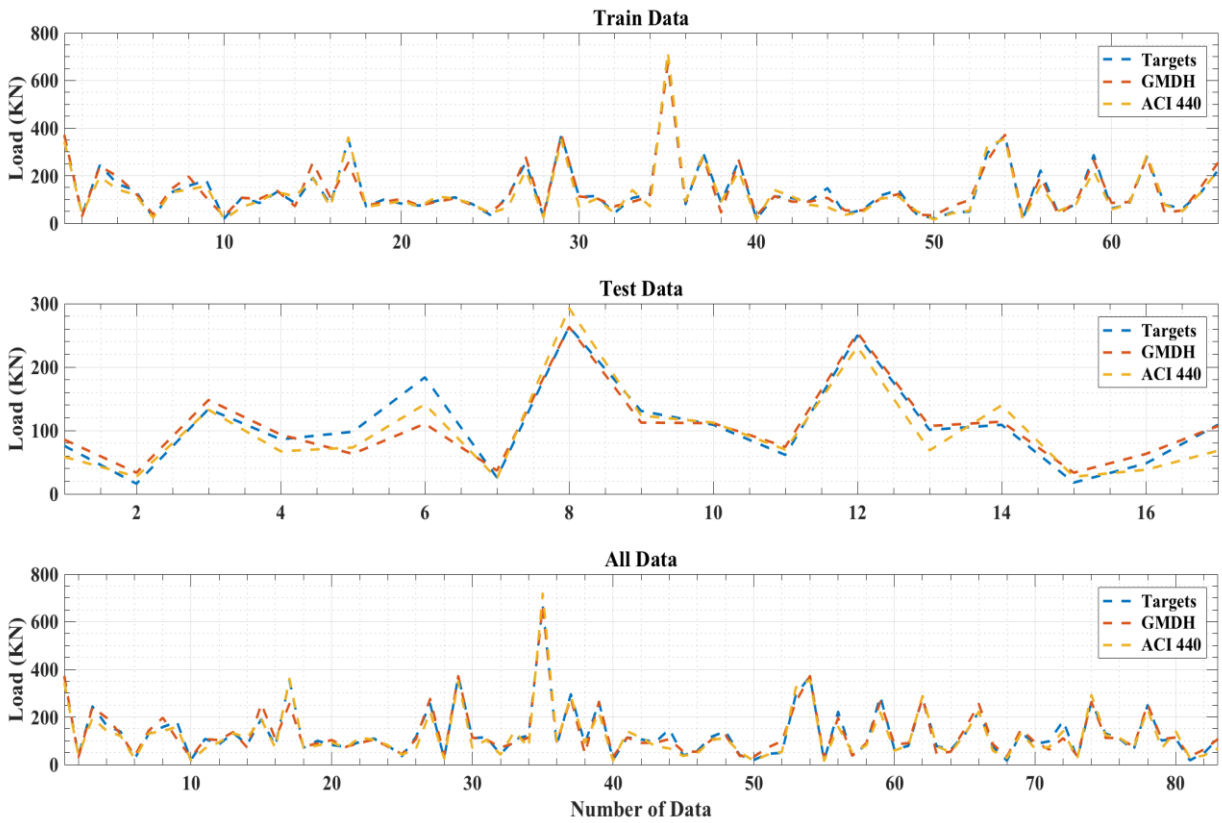

Fig. 10. Comparison between GMDH, ACI 440 and experimental results.

References

[1] Qu HC, Wu CQ, Chen LL. Numerical Analysis on the Load-Carrying Capacity for the FRP Reinforced Four-Point Bending Concrete Beam. Adv Mater Res 2011;287–290:1130–4. doi:10.4028/www.scientific.net/AMR.287-290.1130.

[2] Xu X. Calculation Method and Analysis of Bearing Capacity of FRP Rebar Concrete Beam. ICTE 2011, Reston, VA: American Society of Civil Engineers; 2011, p. 1572–7. doi:10.1061/41184(419)260.

[3] Kheyroddin A, Mirrashid M, Arshadi H. An Investigation on the Behavior of Concrete Cores in Suspended Tall Buildings. Iran J Sci Technol Trans Civ Eng 2017;41:383–8. doi:10.1007/s40996-

017-0075-y.

[4] Penelis GG, Penelis GG. Concrete Buildings in Seismic Regions. 2nd Ed. | Boca Raton : Taylor & Francis, CRC Press, 2018.: CRC Press; 2018. doi:10.1201/b22364.

[5] Jafari M, Mirrashid M, Vahidnia A. Prediction of chloride penetration in the concrete containing magnetite aggregates by Adaptive Neural Fuzzy Inference System (ANFIS). 7th Internatinal Symp. Adv Sci Technol(5thsastech), Bandare Abbas, Iran 2013.

[6] Mirrashid M. Earthquake magnitude prediction by adaptive neuro-fuzzy inference system (ANFIS) based on fuzzy C-means algorithm. Nat Hazards 2014;74:1577–93. doi:10.1007/s11069-014-1264-7.

[7] Naderpour H, Mirrashid M. Shear Strength Prediction of RC Beams Using Adaptive Neuro-Fuzzy Inference System. Sci Iran 2018:0–0. doi:10.24200/sci.2018.50308.1624.

[8] Naderpour H, Mirrashid M. An innovative approach for compressive strength estimation of mortars having calcium inosilicate minerals. J Build Eng 2018;19:205–15. doi:10.1016/j.jobe.2018.05.012.

[9] Naderpour H, Rafiean AH, Fakharian P. Compressive strength prediction of environmentally friendly concrete using artificial neural networks. J Build Eng 2018;16:213–9. doi:10.1016/j.jobe.2018.01.007.

[10] Naderpour H, Vahdani R, Mirrashid M. Soft Computing Research in Structural Control by Mass Damper (A review paper). 4st Int. Conf. Struct. Eng. Tehran, Iran, 2018.

[11] Mirrashid M. Comparison study of soft computing approaches for estimation of the non-ductile RC joint shear strength. Soft Comput Civ Eng 2017;1:12–28.

[12] Mirrashid M, Bigdeli S. Genetic Algorithm for Prediction the Compressive Strength of Mortar Containing Wollastonite. 1st Natl. Congr. Counstruction Eng. Proj. Assessment, Gorgan, Iran, 2014.

[13] Mirrashid M, Givehchi M, Miri M, Madandoust R. Performance investigation of neuro-fuzzy system for earthquake prediction 2016.

[14] Mirrashid M, Jafari M, Akhlaghi A, Vahidnia A. Prediction of compressive strength of concrete containing magnetite aggregates using Adaptive Neural Fuzzy Inference System (ANFIS) 2013.

[15] Naderpour H, Mirrashid M. Application of soft computing to reinforced concrete beams strengthened with fibre reinforced polymers: a state-of-the-art review. Comput Tech Civ Struct Eng 2015;38:305–23.

[16] Naderpour H, Mirrashid M. Compressive Strength of Mortars Admixed with Wollastonite and Microsilica. Mater Sci Forum 2017;890:415–8. doi:10.4028/www.scientific.net/MSF.890.415.

[17] Naderpour H, Mirrashid M. Ultimate Capacity Prediction of Concrete Slabs Reinforced with FRP Bars. 3rd Int. 7th Natl. Conf. Mod. Mater. Struct. Civ. Eng. Bu-Ali Sina Univ. Hamedan, IRAN, 2018.

[18] Naderpour H, Mirrashid M. Application of group method of data handling to Estimate the Shear Strength of RC Beams Reinforced with FRP Bars. 3rd Int. 7th Natl. Conf. Mod. Mater. Struct. Civ. Eng. Bu-Ali Sina Univ. Hamedan, IRAN, 2018.

[19] Ivakhnenko AG. Polynomial Theory of Complex Systems. IEEE Trans Syst Man Cybern 1971;SMC-1:364–78. doi:10.1109/TSMC.1971.4308320.

[20] HAJELA P, BERKE L. Neurobiological Computational Models in Structural Analysis and Design. 31st Struct. Struct. Dyn. Mater. Conf., Reston, Virigina: American Institute of Aeronautics and Astronautics; 1990. doi:10.2514/6.1990-1133.

[21] Saadatmanesh H, Ehsani MR. RC Beams Strengthened with GFRP Plates. I: Experimental Study. J Struct Eng 1991;117:3417–33. doi:10.1061/(ASCE)0733-9445(1991)117:11(3417).

[22] Ross CA, Jerome DM, Tedesco JW, Hughes ML. Strengthening of reinforced concrete beams with externally bonded composite laminates. Struct J 1999;96:212–20.

[23] Ni H-G, Wang J-Z. Prediction of compressive strength of concrete by neural networks. Cem Concr Res 2000;30:1245–50. doi:10.1016/S0008-8846(00)00345-8.

[24] Béton. F. I.Du. Externally bonded FRP reinforcement for RC structures, Bulletin FIB 2001;14:138.

[25] Sanad A, Saka MP. Prediction of Ultimate Shear Strength of Reinforced-Concrete Deep Beams Using Neural Networks. J Struct Eng 2001;127:818–28. doi:10.1061/(ASCE)0733-9445(2001)127:7(818).

[26] Dong Y, Zhao M, Ansari F. Failure characteristics of reinforced concrete beams repaired with CFRP composites. Strain 2002;304:12–7.

[27] Dai JG, Ueda T, Sato Y, Ito T. Flexural strengthening of RC beams using externally bonded FRP sheets through flexible adhesive bonding. Int. Symp. Bond Behav. FRP Struct. (BBFS 2005), Hong Kong, 2005, p. 7–9.

[28] Ebead UA, Marzouk H. Tension-stiffening model for FRP-strenghened RC concrete two-way slabs. Mater Struct 2005;38:193–200. doi:10.1007/BF02479344.

[29] Kotynia R. Debonding failures of RC beams strengthened with externally bonded strips. Proc. Int. Symp. Bond Behav. FRP Struct. (BBFS 2005), 2005.

[30] Lundqvist J, Nordin H, Täljsten B, Olofsson T. Numerical analysis of concrete beams strengthened with CFRP: a study of anchorage lengths. Int. Symp. Bond Behav. FRP Struct. 07/12/2005-09/12/2005, International Institute for FRP in Construction; 2005, p. 239–46.

[31] Maalej M, Leong KS. Effect of beam size and FRP thickness on interfacial shear stress concentration and failure mode of FRP-strengthened beams. Compos Sci Technol 2005;65:1148–58. doi:10.1016/j.compscitech.2004.11.010.

[32] Coronado CA, Lopez MM. Sensitivity analysis of reinforced concrete beams strengthened with FRP laminates. Cem Concr Compos 2006;28:102–14. doi:10.1016/j.cemconcomp.2005.07.005.

[33] Reeve BZ. Effect of adhesive stiffness and CFRP geometry on the behavior of externally bonded CFRP retrofit measures subject to monotonic loads 2006.

[34] Abdalla JA, Elsanosi A, Abdelwahab A. Modeling and simulation of shear resistance of R/C beams using artificial neural network. J Franklin Inst 2007;344:741–56. doi:10.1016/j.jfranklin.2005.12.005.

[35] Esfahani MR, Kianoush MR, Tajari AR. Flexural behaviour of reinforced concrete beams strengthened by CFRP sheets. Eng Struct 2007;29:2428–44. doi:10.1016/j.engstruct.2006.12.008.

[36] Neagoe CA. Concrete beams reinforced with CFRP laminates 2011.