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ORIGINAL ARTICLE

Moment capacity estimation of spirally reinforced concrete columns using ANFIS

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Abstract
This paper presents a predictive model based on adaptive neuro-fuzzy inference system namely ANFIS to determine the moment capacity of spiral-reinforced concrete columns. For this purpose, five input parameters including the longitudinal reinforcement index, transverse reinforcement index, axial force, diameter to length ratio and also shear force were considered to estimate the moment capacity. A collection of experimental database was applied to train and test the proposed system. This database includes 82 spiral-reinforced concrete columns (with flexure failure) which were reported in the literature and modified by PEER as a uniform database of cantilever columns. The model is created by fuzzy C-means algorithm with four cluster and Gaussian membership functions, also trained and tested by 70 and 12 datasets, respectively. It was concluded that the model of this study with high accuracy could be able to estimate the moment capacity.

Keywords Flexure failure · Moment capacity · Neuro-fuzzy system · Reinforced concrete · Spiral-reinforced concrete column

Introduction

One of the most complex issues in structural engineering is the investigation of the structural elements behaviors and estimation of final capacities. This issue is essential in determining the damages and the failures of elements under loading such as an earthquake. There are many efforts to investigate this topic which were published in the literature, and some of them are reviewed here by the authors. Panagiotako et al. [1] studied the effect of capacity design for Reinforced Concrete (RC) column under seismic loading and showed that in some cases, damage of the element could not be prevented by full capacity design. Hernandez et al. [2] investigated the effect of longitudinal reinforcement on the capacity of concrete columns and presented a method to determine a suitable combination of reinforcement. An experimental study on the compressive capacity of RC columns was done by Chen et al. [3]. They presented an analytical approach for their purpose and based on the experimental results, showed that their method could determine the considered behavior of special-shaped reinforced concrete columns. Some researchers studied the capacity of RC columns which made by recycled aggregate [4–6].

Today, soft computing (SC) has many applications in engineering problems [7–10]. There are numerous articles on the use of SC in civil engineering such as earthquakes [11, 12] dams [13], concrete [14] and structural control [15]. Also, these methods are considered to estimate the capacity of structural elements [16, 17] instead of finite element analysis which is a time-consuming approach [18, 19]. Liu et al. [20] studied the application of artificial neural networks to predict the shear strength of RC columns and verified their model with an experimental database. Jakubek [21] used fuzzy weight neural networks to predict the critical axial load of bulking tests in RC columns. Xu et al. [22] identified the seismic damages of RC columns by neural networks based on images. Their results indicated that these soft computing approaches could be used for damage detection of RC columns.

The current research investigated the application of a powerful soft computing approach namely ANFIS (adaptive neuro-fuzzy inference system) to determine the moment capacity in spiral-reinforced concrete columns. The

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presented model is trained and tested by a collection of the experimental database. Details of the proposed ANFIS structure are provided in the mathematical framework to increase the ability to use it by engineers.

ANFIS

Adaptive neuro-fuzzy inference system (ANFIS) is a fuzzy inference model in a neural network structure for function approximation [23]. It used a Sugeno-type fuzzy system in the five-layer network [23]. ANFIS contains an input vector with some Membership Function (MF) for each input. ANFIS used a hybrid approach, which is a combination of backpropagation and least squares methods, to find its unknown parameters. This type of soft computing method is widely considered as a powerful system because it has the ability of both artificial neural networks and fuzzy systems simultaneously [7, 23–31].

Database

Neuro-fuzzy inference system needs a database to determine its unknown coefficients, and in this paper, a collection of spiral-reinforced columns tests results, which were presented by other researchers [32–65] and modified by PEER [66], was used. This database contains three types of cantilever column including octagonal, circular and square. More information can be seen in the PEER report. Also, five input variables which are described in Table 1 and presented in "Appendix" are used in this study. The two first parameters can also be defined by Eqs. 1 and 2:

Table 1 Description of the considered variables

Parameter	Notation	Description
Input 1	X_1	Longitudinal reinforcement index
Input 2	X_2	Transverse reinforcement index
Input 3	X_3	Axial force (kN)
Input 4	X_4	D/L[a]
Input 5	X_5	Shear load (kN)
Output	M	Moment capacity (kN m)

[a] D diameter of column (mm), L length of equivalent cantilever (mm)

$$x_1 = \frac{\rho_l f_{yl}}{f'_c}, \tag{1}$$

$$x_2 = \frac{\rho_s f_{ys}}{f'_c}, \tag{2}$$

where $\rho_l, f_{yl}, \rho_s, f_{ys}, f'_c$ are longitudinal reinforcement ratio (%), the yield stress of longitudinal reinforcement (MPa), volumetric transverse reinforcement ratio (%), the yield stress of transverse reinforcement (MPa) and also the compressive strength of concrete (MPa), respectively. Table 2 shows the details of the collected database.

In this paper, the authors used Eq. 3 as a normalization relationship to convert all amounts of the database into a value between −1 and +1. In this equation, the parameters x_n, x_{min}, x_{max} are indicated to the normal, minimum and maximum values of x_i.

$$x_n = 2\frac{x_i - x_{min}}{x_{max} - x_{min}} - 1 \tag{3}$$

Based on Table 2 and also Eq. 3, the amount of the variables is normalized by Eqs. 4–9 before using in training and testing the proposed ANFIS model.

$$X_1 = 2\frac{x_1 - 6.78}{65.60} - 1 \tag{4}$$

$$X_2 = 2\frac{x_2 - 1.05}{36.99} - 1 \tag{5}$$

$$X_3 = 2\frac{x_3}{6770} - 1 \tag{6}$$

$$X_4 = 2\frac{x_4 - 0.07}{0.6} - 1 \tag{7}$$

Table 2 Description of the considered parameters

Parameter	X_1	X_2	X_3	X_4	X_5	M
Minimum	6.78	1.05	0.00	0.07	14.00	22.00
Maximum	72.37	38.05	6770.00	0.67	957.00	1300.00
Median	27.86	12.72	552.50	0.22	136.00	220.00
Average	30.15	14.48	917.33	0.27	199.87	368.28
St. deviation	13.70	7.16	1078.75	0.14	209.56	340.19
Mode	15.27	13.70	222.00	0.22	77.00	394.00
Range	65.60	36.99	6770.00	0.60	943.00	1278.00

$$X_5 = 2\frac{x_5 - 14}{943} - 1 \tag{8}$$

$$Y = 2\frac{M - 22}{1278} - 1 \tag{9}$$

Proposed ANFIS model

As mentioned in the previous sections, ANFIS uses some membership functions for each input. In this research, four Gaussian membership functions (Eq. 10) were used for each of the five inputs in the proposed ANFIS structure (Fig. 1). The parameters of the membership functions for all inputs are presented in Table 3. These functions can be seen in Fig. 2:

$$C_i(x;\sigma,c) = \mathrm{e}^{\frac{-(x-c)^2}{2\sigma^2}}, \tag{10}$$

where c is the mean and σ is the variance for x.

The proposed ANFIS uses linear-type functions (Eq. 5) as the output of each node with five coefficients and one constant value. Table 4 presents the details of these linear functions and their coefficients.

$$f_j = a_{1j}X_1 + a_{2j}X_2 + a_{3j}X_3 + a_{4j}X_4 + a_{5j}X_5 + C_j \quad j = 1,\ldots,4, \tag{11}$$

where X_i is the normalized value of inputs and $a_1,\ldots,a_5$ are coefficients of the linear function. C is also the constant value of the equation. In this equation, j denotes the number of linear functions.

There are four rules in the proposed ANFIS. The weight of each rule W_i ($j=1,\ldots,4$) is calculated by Eq. 12. In these equations, MF is a membership function value of each input, which can be calculated by Eq. 10 based on the presented amounts of Table 3.

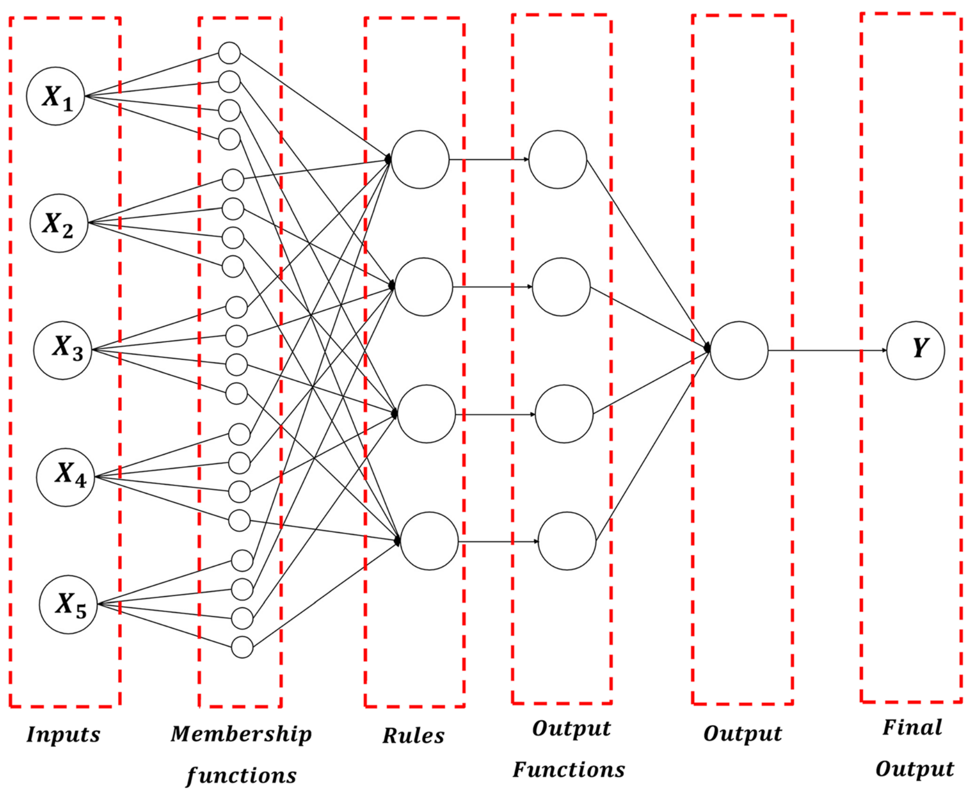

Fig. 1 Proposed ANFIS structure

Table 3 Details of the membership function

	MF1		MF2		MF3		MF4	
	σ	c	σ	c	σ	c	σ	c
$X1$	0.202	−0.05196	0.2011	−0.3444	0.1633	−0.2706	0.1842	−0.3268
$X2$	0.2793	0.1796	0.1853	−0.3405	0.1488	−0.36	0.1507	−0.4305
$X3$	0.09427	−0.8847	0.1438	−0.8701	0.1301	−0.6938	0.1196	−0.6849
$X4$	0.2928	0.07414	0.1706	−0.4769	0.227	−0.1356	0.2035	−0.552
$X5$	0.1236	−0.7507	0.1644	−0.8406	0.2803	−0.1641	0.1116	−0.6885

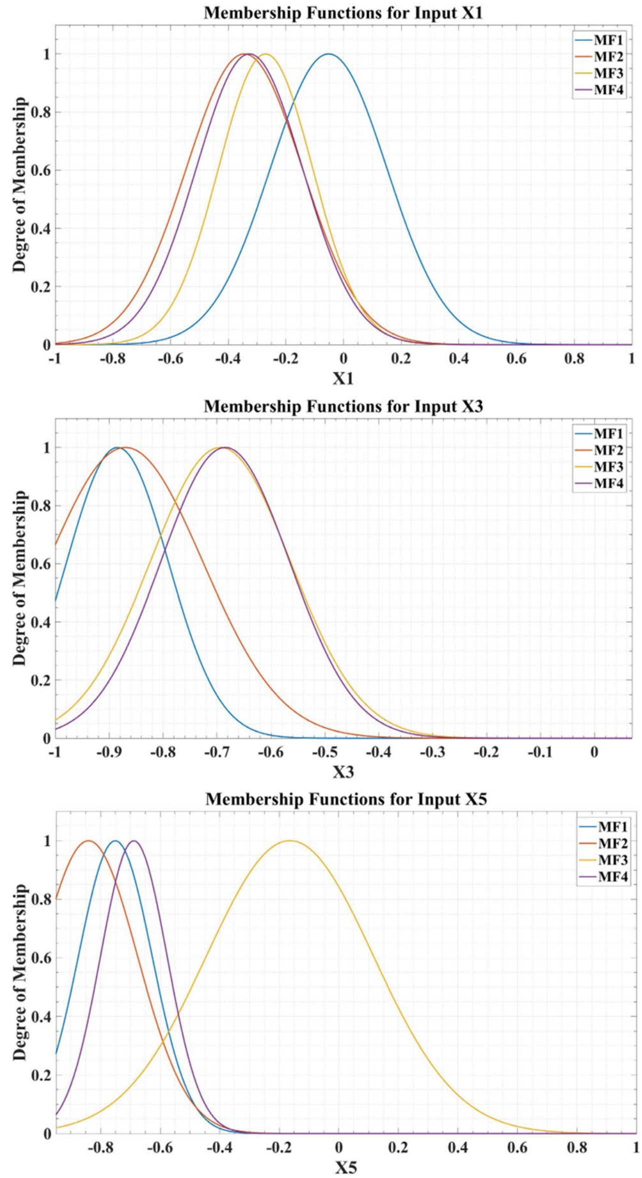

Fig. 2 Membership functions of the input parameters

Table 4 The parameters of Eq. 11

Function	Coefficients					Constant
	a_1	a_2	a_3	a_4	a_5	C
f_1	−0.0351	−0.0275	0.0110	−0.0642	0.4107	−0.5734
f_2	0.1251	0.2258	−0.0757	−0.2742	0.8458	−0.2343
f_3	−0.3503	−0.0999	−0.1728	−1.5300	1.6980	−0.0266
f_4	−0.1095	0.0262	−1.4740	−1.9110	4.2500	1.0400

$$
\begin{aligned}
W_1 &= \mathrm{MF}_{1,X1}\mathrm{MF}_{1,X2}\mathrm{MF}_{1,X3}\mathrm{MF}_{1,X4}\mathrm{MF}_{1,X5}\\
W_2 &= \mathrm{MF}_{2,X1}\mathrm{MF}_{2,X2}\mathrm{MF}_{2,X3}\mathrm{MF}_{2,X4}\mathrm{MF}_{2,X5}\\
W_3 &= \mathrm{MF}_{3,X1}\mathrm{MF}_{3,X2}\mathrm{MF}_{3,X3}\mathrm{MF}_{3,X4}\mathrm{MF}_{3,X5}\\
W_4 &= \mathrm{MF}_{4,X1}\mathrm{MF}_{4,X2}\mathrm{MF}_{4,X3}\mathrm{MF}_{4,X4}\mathrm{MF}_{4,X5}
\end{aligned}
\tag{12}
$$

The final output of the proposed ANFIS model is determined by Eq. 13:

$$
-1 \leq \left(Y = \frac{\sum_{j=1}^{4} W_j f_j}{\sum_{j=1}^{4} W_j} \right) \leq 1. \tag{13}
$$

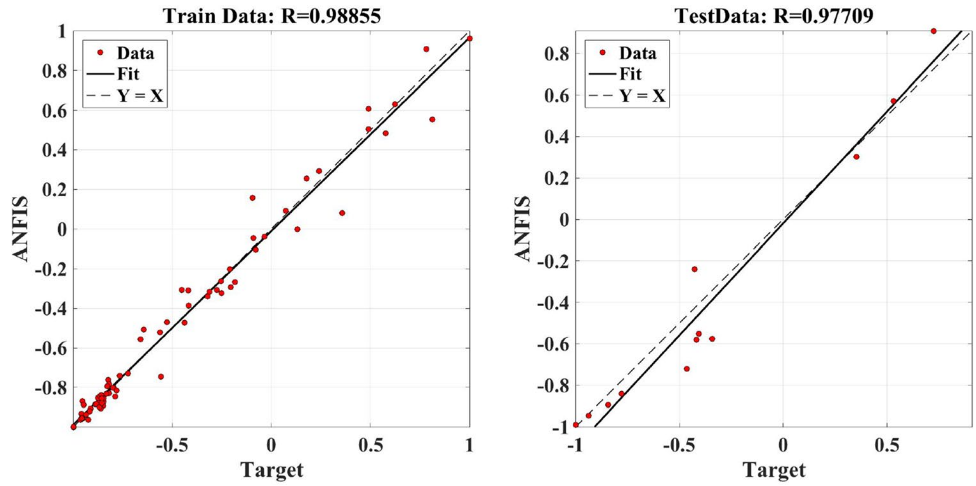

Fig. 3 Regression plots of the results based on normal values

As mentioned in the previous section, the result of the ANFIS is a normal value between − 1 and 1, and therefore, it needs to convert to the corresponding real value (22–1300 kN m) by Eq. 14:

$$M(\text{kN m}) = 1278\frac{Y+1}{2} + 22. \tag{14}$$

Results of the ANFIS

The training of the proposed system was done by 70 datasets, and the results of this phase showed that the model was trained very well. Also, to validate the ANFIS, 12 datasets were applied to the trained system. The results of regression plots (Fig. 3) for the normal values showed the correlation coefficients equal to 0.99 and 0.98 for the train and test phases, respectively.

Figure 4 shows the obtained results by ANFIS against the experimental values after converting the normalized values into their corresponding real values for the considered database. It is clear from the figure that the proposed ANFIS was able to estimate the moment capacity of spiral-reinforced concrete columns.

The amount of root means squared error for the train, and test phases (Figs. 5, 6) were 50.36 and 92.11 which was shown that the ANFIS could be used as a suitable tool for

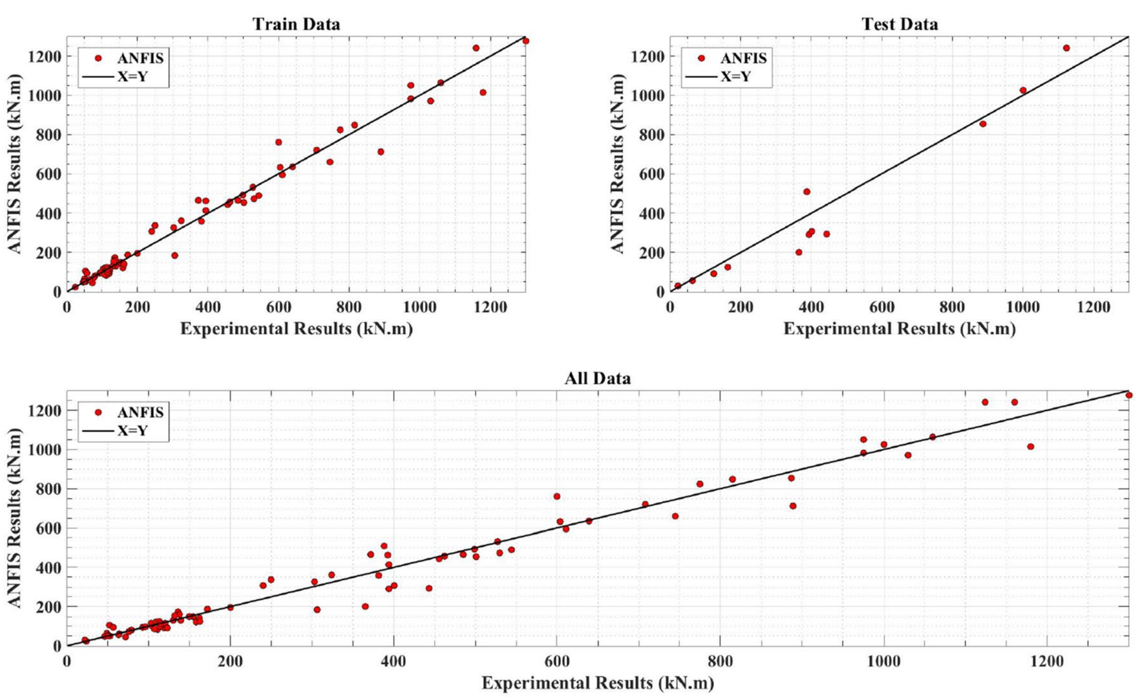

Fig. 4 The results of the ANFIS vs. experimental values

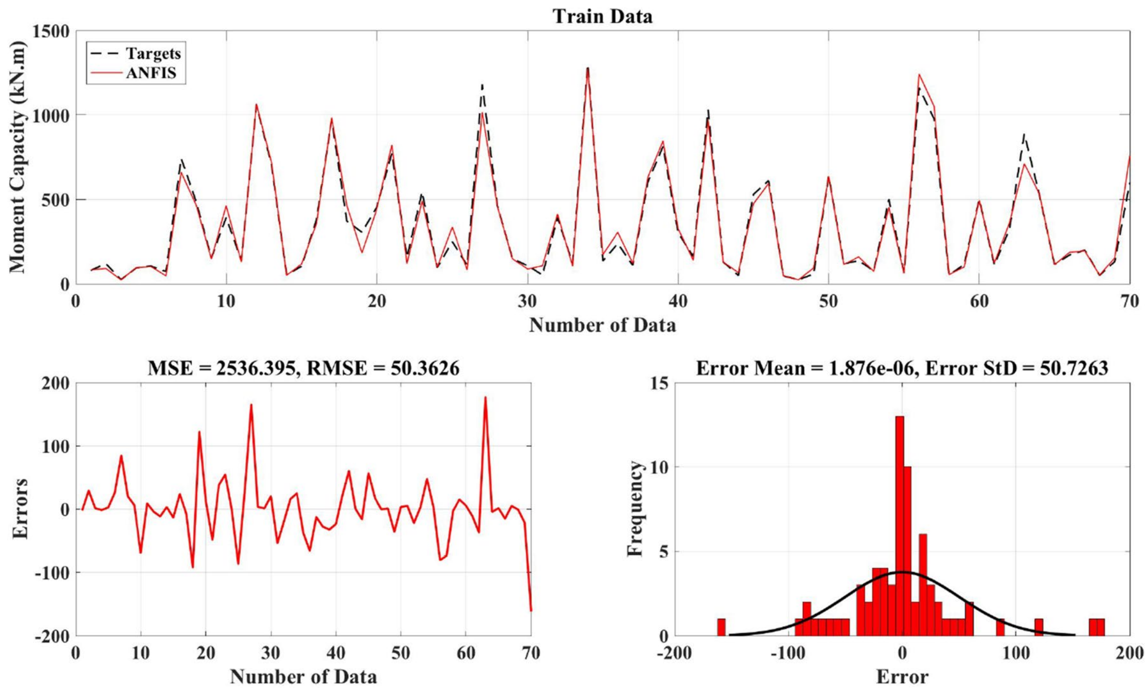

Fig. 5 Results for the train data

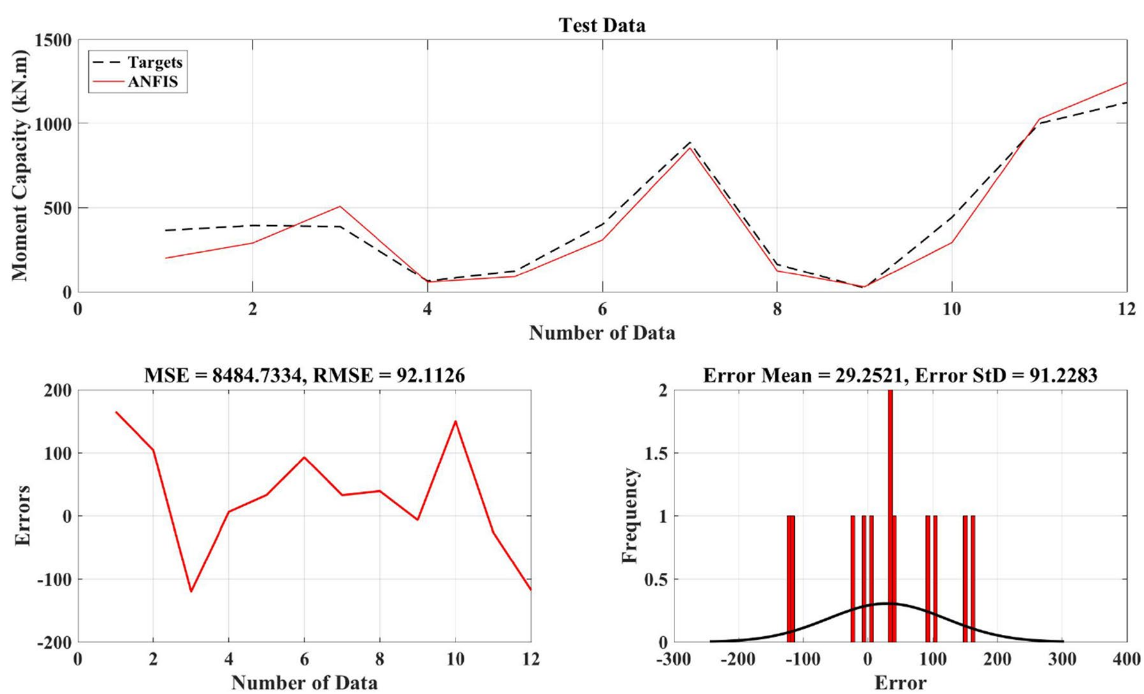

Fig. 6 Results for the test data

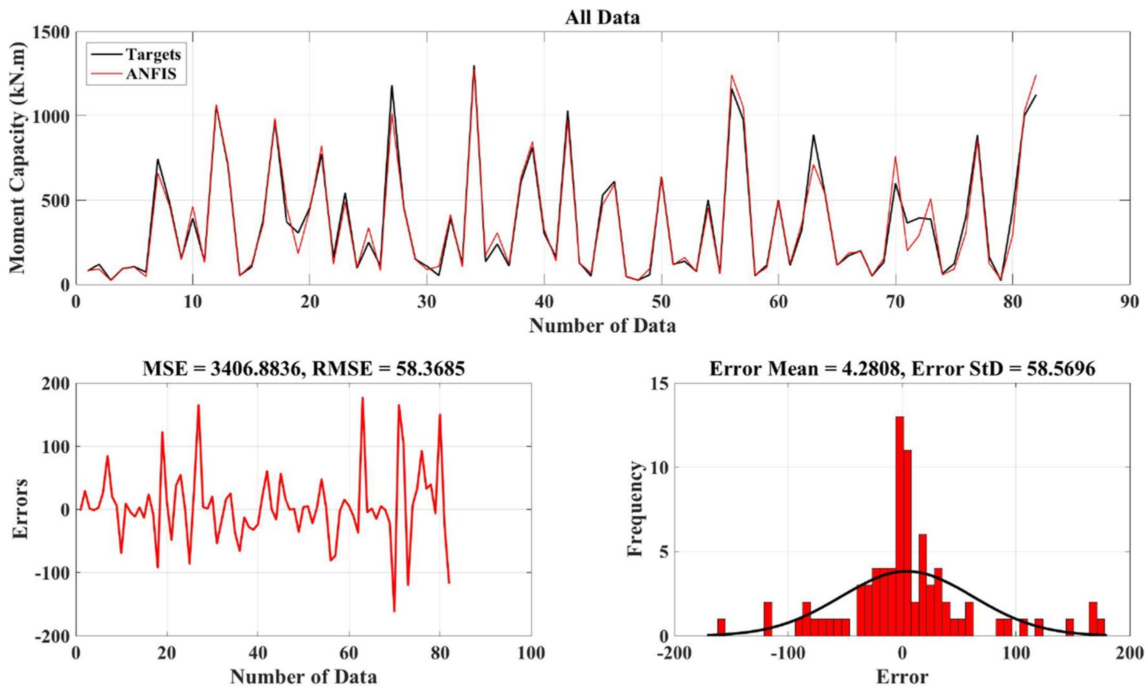

Fig. 7 Results for all data

prediction. Figure 7 illustrated the results of ANFIS for all of 82 datasets.

Figure 8 shows the effect of changes in input variables ($X1$, …, $X5$) on the output parameter (Y). In drawing each of these graphs, the values of the three variables from the five input variables are considered constant, which is equal to its corresponding median value (see Table 2), and the values of the other two variables have been varied between − 1 and 1. Then, the output value for this database is calculated and plotted.

Conclusion

This paper presents a neuro-fuzzy inference system namely ANFIS to predict the moment capacity of spiral-reinforced concrete columns which are failed in flexure. For this purpose, a collection of 82 datasets were used to train and test the model. The system created based on five input parameters including longitudinal reinforcement, transverse reinforcement index, axial force, diameter to length ratio and also a shear force to calculate the target (moment capacity). The proposed ANFIS used Fuzzy C-means approach to determine its unknown coefficients. Also, four clusters and Gaussian membership functions are applied to creating the neuro-fuzzy model. The results of the paper in both training and testing phases indicated that this type of soft computing methods with high accuracy could be considered for predicting the moment capacity of the considered RC columns. The model presented in this article has many applications in the design of concrete structures. Also, due to the proposed neuro-fuzzy model in a mathematical framework, it is an efficient and feasible model. Therefore, it is easy for engineers to understand the equations of this paper and to use them for their purposes. In the future works, other soft computing methods can be used to estimate the moment capacity of the RC columns.

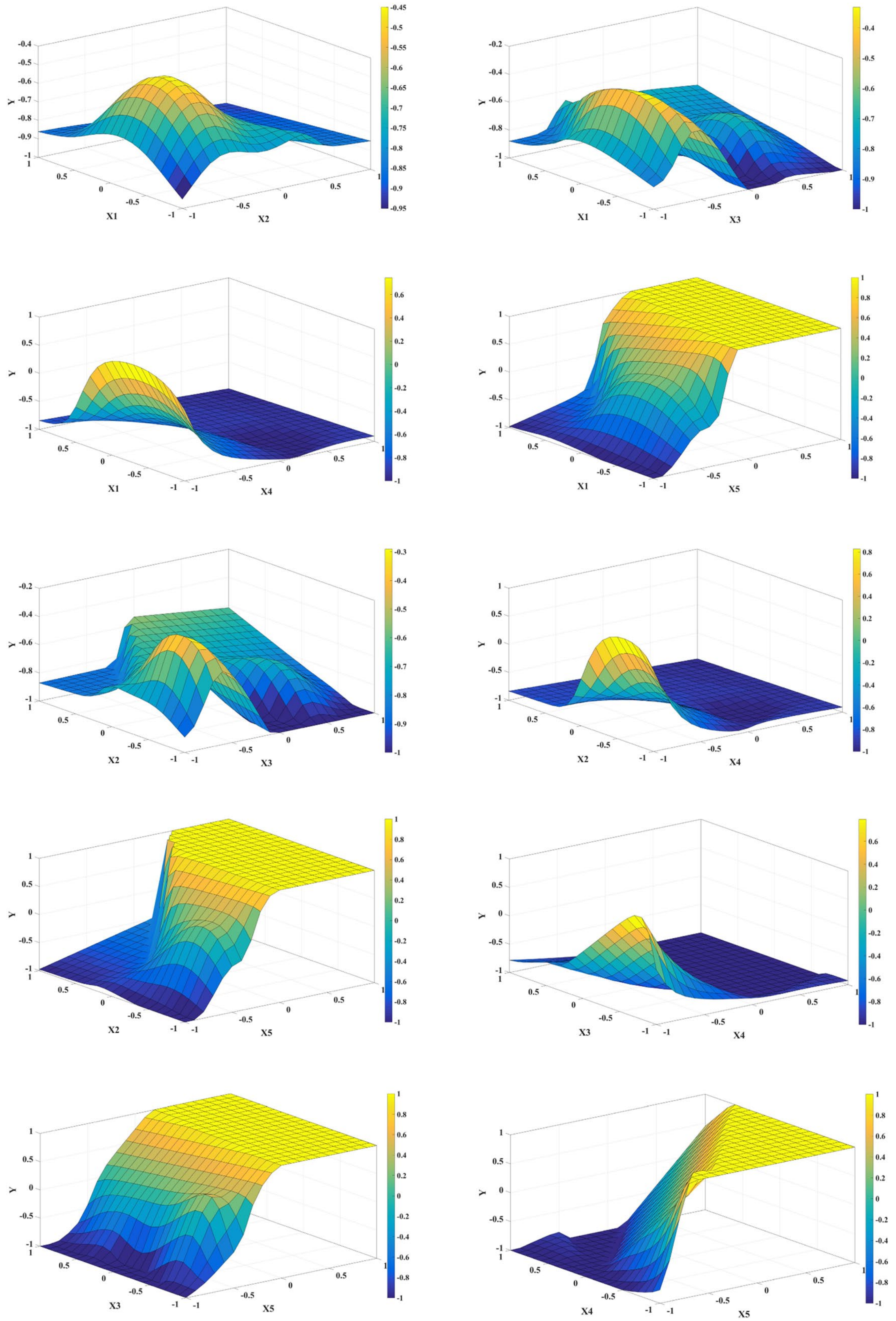

Fig. 8 The effect of input changes on the considered output

Appendix

Data ID in PEER report [48]	X1	X2	X3	X4	X5	Y
1	29.3232	4.1349	380	0.1818	180	527
2	27.8250	3.9448	380	0.2857	334	600
3	28.8027	4.4521	380	0.1538	142	485
4	19.5963	12.2535	26.4	0.1832	133	365
5	22.3319	14.0117	16.9	0.1866	36	49
6	20.1345	15.5564	550	0.2688	61	72
7	28.7862	9.0031	680	0.2500	139	250
8	26.2611	15.0316	2111	0.2500	163	303
9	25.9257	7.9225	1920	0.5000	687	887
11	22.3796	10.2857	3785	0.5000	781	1000
12	22.9542	22.4862	3385	0.5000	812	1060
13	22.9542	22.4862	6770	0.5000	937	1124
22	47.9465	12.6903	751	0.4000	364	401
39	25.3533	8.9449	555	0.2500	142	240
40	30.3300	19.3304	2080	0.2500	175	324
41	21.5670	5.9520	2652	0.2500	212	393
42	22.1200	12.7400	3620	0.2500	207	394
43	35.6211	11.2105	907	0.5000	461	394
45	41.0811	11.5135	1813	0.5000	579	499
50	72.3293	26.0580	151	0.1333	14	22
51	72.3293	26.0580	151	0.2667	37	24
52	72.3293	26.0580	220	0.2667	36	24
55	36.6423	25.8012	120	0.3333	59	50
56	38.2286	26.9182	239	0.3333	73	63
57	34.7669	12.7433	120	0.1667	32	57
58	36.1918	25.4840	120	0.3333	63	51
59	36.3407	25.5889	239	0.3333	77	64
60	37.9004	13.8918	120	0.1667	30	52
61	6.7755	38.0453	184	0.6667	117	46
63	11.9858	11.6981	322	0.5000	102	53
66	28.0585	36.0964	322	0.5000	146	76
80	44.6502	16.3112	0	0.6111	176	79
84	47.6980	17.4246	215	0.6111	209	96
85	45.8213	7.8698	215	0.4583	151	93
90	45.2282	7.7680	430	0.4583	167	104
93	31.5145	14.0676	200	0.2223	74	115
94	31.5145	14.0676	200	0.2223	75	120
95	25.7442	11.4918	222	0.2223	72	111
96	25.7442	11.4918	222	0.2223	77	123
97	25.7442	11.4918	222	0.2223	77	119
98	27.8634	12.4378	222	0.2223	79	120
99	27.8634	12.4378	222	0.2223	68	107
100	28.1206	12.5526	222	0.2223	75	114
101	33.8489	15.1096	200	0.2223	74	113
102	33.8489	15.1096	200	0.2223	68	103
103	33.8489	15.1096	200	0.2223	72	109
106	29.4477	8.9650	1780	0.1667	285	1300
107	26.9001	12.8049	1928	0.5022	535	530
109	26.1491	12.4474	970	0.5022	510	501
112	72.3743	37.7307	1914	0.5022	957	975
113	47.1787	11.1858	1780	0.1250	101	544
114	43.1685	6.5550	1780	0.1250	124	639
115	44.7342	10.6062	1780	0.1250	117	611
116	22.2041	13.7010	653.856	0.2500	269	708
117	22.2041	13.7010	653.856	0.1250	130	745
118	22.2041	13.7010	653.856	0.0670	80	604
119	11.1766	13.7010	653.856	0.2500	172	443
120	44.4082	13.7010	653.856	0.2500	448	1180
121	34.9187	15.6526	911.84	0.3333	525	1030
122	34.9187	15.6526	911.84	0.1250	172	975
123	34.9187	15.6526	911.84	0.0670	157	1160
125	24.8601	6.7266	400	0.3333	411	775
126	26.8218	10.6527	400	0.3333	433	815
127	21.1434	23.6923	1000	0.1520	55	138
128	21.1434	22.5508	1000	0.1520	53	132
129	15.2702	17.1111	1850	0.1520	56	163
130	15.2702	11.2778	1850	0.1520	55	162
131	15.2702	8.1200	1850	0.1520	57	154
132	15.2702	17.1111	925	0.1520	59	139
133	15.2702	17.1111	1850	0.1520	55	158
134	15.2702	16.0067	1850	0.1520	71	200
136	8.2647	1.0506	1139	0.3333	279	456
141	18.5048	11.4175	1308	0.2500	207	889
150	15.4853	11.4719	987.5	0.2129	144	372
151	15.0447	11.4719	987.5	0.2129	152	388
152	35.9624	12.2208	231.3	0.1875	180	462
153	34.3851	11.6848	231.3	0.1875	150	382
154	37.0969	12.6063	231.3	0.1875	94	306
155	34.6894	11.7882	231.3	0.1875	70	130
156	26.8745	4.1345	700	0.1596	74	136
157	14.6971	10.0410	0	0.2192	143	150
158	14.6971	10.0410	0	0.2192	164	172

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