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SHEAR STRENGTH OF FIBRE REINFORCED POLYMERS (FRP) USED AS INTERNAL REINFORCEMENT FOR REINFORCED CONCRETE (RC) BEAMS

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Abstract. *The main aim of the study was to perform selection procedure in order to find the optimal predictors for the shear strength of fibre reinforced polymers (FRP) used as internal reinforcement for reinforced concrete (RC) beams. The procedure was performed by adaptive neuro fuzzy inference system (ANFIS) and all available parameters are included. The ANFIS model could be used as simplification of the shear strength analysis of the FRP-RC beams. MATLAB software was used for the ANFIS application for the shear strength prediction of the FRP-RC beams. The results from the searching procedure indicated that "beam width" and "effective depth" form the optimal combination of two input attributes or two predictors for the shear strength prediction of the FRP-RC beams. This selected two predictors could be used effectively to estimate the strength of the FRP-RC beams.*

Key words: *FRP; predictors; shear strength; reinforced concrete; ANFIS.*

1. INTRODUCTION

Steel reinforcement corrosion represents one of the main issues for the deterioration of reinforced concrete (RC) structures. In order to solve the issue, fiber reinforced polymer (FRP) has been included into the RC structures as internal reinforcement instead of the conventional steel. FRP members have high resistance to corrosion and high ratio strength to weight. However, the FRP members have lower modulus of elasticity than conventional structures.

In paper [1] has been presented the use Machine Learning (ML) techniques to study the behavior of shear-deficient reinforced concrete (RC) beams strengthened in shear with

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side-bonded and U-wrapped fiber-reinforced polymers (FRP) laminates and results indicated that the ML with the selected parameters was capable of predicting the FRP shear capacity more accurately. Based on the comparison of different performance evaluators in article [2], it can be concluded that the present ANFIS model has better performance in the prediction of the shear contribution of FRP. A parametric study was also conducted to study the effect of individual parameters on the shear contribution of FRP composites. The accuracy of the soft computing models is quite satisfactory as compared to experimental results for modeling of strength enhancement of FRP (fiber–reinforced polymer) confined concrete cylinders [3]. In the case of FRP-confined concrete cylinder with a strain-hardening response, it is found that the ultimate Poisson's ratio of FRP-confined concrete trends to an asymptotic value [4]. FRP-confined steel-reinforced concrete (FCSRC) column with high strength concrete (HSC) is a promising type of hybrid structural element that enables effective utilization of both HSC and high-performance FRP [5]. Compressive behavior of FRP-confined (FRP)-confined recycled glass aggregate concrete (RGAC) is comparable to that of FRP-confined normal concrete when the replacement ratio of RGAs is not large than 50%, although the compressive behavior of RGAC has a notable decrease with increasing replacement ratio of recycled glass aggregates (RGAs) [6]. Using large rupture strain FRP (LRS-FRP) significantly improved the ductility and ultimate strength of the confined concrete compared to small rupture strain FRP (SRS-FRP) confined concrete [7]. The results obtained in this study [8] showed that expansion of shear zone for unconfined concrete is more localized than FRP-confined specimens. In paper [9], a 3-dimensional geometrical approach is proposed to interpret the general theory of analysis-oriented models based on three general equations. FRP composites have been widely used in the retrofitting of earthquake-damaged concrete structures [10].

In this study is performed a selection procedure for optimal predictors for shear strength of fibre reinforced polymers (FRP) used as internal reinforcement for reinforced concrete (RC) beams. To perform the selection procedure data set was collected and arranged from published literature. Adaptive neuro fuzzy inference system (ANFIS) [11] is used for the selection procedure of the data samples.

2. METHODOLOGY AND MATERIALS

2.1. Experimental procedure

To study the behavior of FRP-RC (Fibre Reinforced Polymers (FRP) used as internal reinforcement for Reinforced Concrete (RC) beams and check the performance of the proposed ANFIS model. Data samples are collected and arranged from literature [12]. Table 1 shows input and output data samples. The used inputs are: concrete compressive strength (fc (MPa)), beam width (bw (mm)), effective depth (d (mm)), beam shear span (a (mm)), shear span to depth ratio (a/d), reinforcement ratio of longitudinal FRP bars (ρf (%)), and modulus of elasticity of the reinforcing bar (Ef (GPa)). The output represents the shear strength (Vexp (KN)) of FRP-RC beams.

Table 1 Experimental data samples [12]

In1	In2	In3	In4	In5	In6	In7	output
fc (MPa)	bw (mm)	d (mm)	a (mm)	a/d	ρf (%)	Ef (GPa)	Vexp (KN)
36.3	229	225	914	4.1	1.11	40.3	39.1
36.3	229	225	914	4.1	1.11	40.3	38.5
36.3	229	225	914	4.1	1.11	40.3	36.8
36.3	178	225	914	4.1	1.42	40.3	28.1
36.3	178	225	914	4.1	1.42	40.3	35
36.3	178	225	914	4.1	1.42	40.3	32.1
36.3	229	225	914	4.1	1.66	40.3	40
36.3	229	225	914	4.1	1.66	40.3	48.6
36.3	229	225	914	4.1	1.66	40.3	44.7
36.3	279	225	914	4.1	1.81	40.3	43.8
36.3	279	225	914	4.1	1.81	40.3	45.9
36.3	279	225	914	4.1	1.81	40.3	46.1
36.3	254	224	914	4.1	2.05	40.3	37.7
36.3	254	224	914	4.1	2.05	40.3	51
36.3	254	224	914	4.1	2.05	40.3	46.6
36.3	229	224	914	4.1	2.27	40.3	43.5
36.3	229	224	914	4.1	2.27	40.3	41.8
36.3	229	224	914	4.1	2.27	40.3	41.3
40	1000	165	1000	6	0.39	114	140
40	1000	165	1000	6	0.78	114	167
40	1000	161	1000	6.2	1.18	114	190
40	1000	162	1000	6.2	0.86	40	113
40	1000	159	1000	6.3	1.7	40	142
40	1000	162	1000	6.2	1.71	40	163
40	1000	159	1000	6.3	2.44	40	163
40	1000	154	1000	6.5	2.63	40	168
50	250	326	1000	3.1	0.87	128	77.5
50	250	326	1000	3.1	0.87	39	70.5
44.6	250	326	1000	3.1	1.24	134	104
44.6	250	326	1000	3.1	1.22	42	60
43.6	250	326	1000	3.1	1.72	134	124.5
43.6	250	326	1000	3.1	1.71	42	77.5
40.5	200	225	600	2.7	0.63	145	47.2
40.5	200	225	800	3.6	0.5	145	49.7
40.5	200	225	950	4.2	0.5	145	38.5
28.9	150	168	667	4	0.45	38	12.5
28.9	150	212	667	3.1	0.71	32	17.5
28.9	150	263	667	2.5	0.86	32	25
37.3	160	346	952	2.8	0.72	42	54.5
37.3	160	346	952	2.8	0.72	42	63.7
43.2	160	346	1149	3.3	1.1	42	42.7
43.2	160	346	1149	3.3	1.1	42	45.5
34.1	160	325	1151	3.5	1.54	42	48.7
34.1	160	325	1151	3.5	1.54	42	44.9
37.3	130	310	949	3.1	0.72	120	49.2

In1	In2	In3	In4	In5	In6	In7	output
fc (MPa)	bw (mm)	d (mm)	a (mm)	a/d	ρf (%)	Ef (GPa)	Vexp (KN)
37.3	130	310	949	3.1	0.72	120	45.8
43.2	130	310	1150	3.7	1.1	120	47.6
43.2	130	310	1150	3.7	1.1	120	52.7
34.1	130	310	1150	3.7	1.54	120	55.9
34.1	130	310	1150	3.7	1.54	120	58.3
39.7	457	360	1219	3.4	0.96	40.5	108.1
39.9	457	360	1219	3.4	0.96	37.6	94.7
40.3	457	360	1219	3.4	0.96	47.1	114.8
42.3	457	360	1219	3.4	1.92	40.5	137
42.5	457	360	1219	3.4	1.92	37.6	152.6
42.6	457	360	1219	3.4	1.92	47.1	177
24.1	178	279	750	2.7	2.3	40	53.4
24.1	178	287	750	2.6	0.77	40	36.1
24.1	178	287	750	2.6	1.34	40	40.1
34.7	200	260	700	2.7	1.3	130	62.2
34.3	150	250	750	3	1.51	105	45
39.8	250	305	763	2.5	0.86	46.3	61
39.8	250	305	1068	3.5	0.86	46.3	43.7
34.5	250	310	465	1.5	0.42	144	87.3
34.5	250	310	775	2.5	0.42	144	64.6
34.5	250	310	1085	3.5	0.42	144	58.9
44.7	250	440	1100	2.5	0.9	46.3	77.2
37.4	250	584	1460	2.5	0.91	46.3	103.7
37.4	300	734	1762	2.4	0.91	46.3	129.4
42.4	300	460	1150	2.5	0.45	144	74.1
37	250	594	1485	2.5	0.43	144	112.9
42.4	300	744	1786	2.4	0.4	144	137.3
37.4	300	310	775	2.5	0.33	46.3	72.7
39.8	250	296	740	2.5	1.43	46.3	65.5
42.4	250	296	740	2.5	1.43	46.3	70.9
37.4	250	455	1138	2.5	0.35	46.3	68
37.4	250	434	1085	2.5	1.47	46.3	92.2
42.4	250	310	775	2.5	0.18	144	58.7
34.5	250	310	775	2.5	0.67	144	72.5
42.4	250	460	1150	2.5	0.22	144	70.3
42.4	250	439	1098	2.5	0.65	144	82.5
74.2	300	449	1123	2.5	0.69	144	100.4
74.2	250	594	1485	2.5	0.65	144	146.1
74.2	300	442	1105	2.5	1.27	46.3	116.1
74.2	250	578	1445	2.5	1.38	46.3	155.2
65.3	250	310	775	2.5	0.42	144	71.6
88.3	250	310	775	2.5	0.42	144	77.9
65.3	250	291	728	2.5	0.89	46.3	75.6
88.3	250	291	728	2.5	0.89	46.3	80.2
29.6	457	889	2756	3.1	0.6	4.1	159
42.8	150	223	491	2.2	1.28	45	44.7
42.8	150	223	245	1.1	1.28	46	81
38.1	150	210	767	3.7	1.31	45	26.5
35	450	438	1524	3.5	0.55	37	86

In1	In2	In3	In4	In5	In6	In7	output
fc (MPa)	bw (mm)	d (mm)	a (mm)	a/d	ρf (%)	Ef (GPa)	Vexp (KN)
35	450	194	762	3.9	0.66	37	54.5
36	450	857	3051	3.6	2.23	37	232
35	450	405	1527	3.8	2.36	37	138
35	450	188	761	4.1	2.54	37	74
29.5	457	883	2746	3.1	0.59	40.7	154.1
38.8	457	883	2746	3.1	0.59	40.7	158.9
32.1	114	294	914	3.1	0.59	40.8	19.3
32.1	114	294	914	3.1	0.59	40.8	18.1
32.1	229	147	457	3.1	0.59	40.8	36.8
29.5	457	880	2737	3.1	1.18	40.7	220.7
30.7	457	880	2737	3.1	1.18	41.4	216.2
63	250	326	1000	3.1	1.71	135	130
63	250	326	1000	3.1	1.71	42	87
63	250	326	1000	3.1	2.2	42	115.5
61.8	159	141	910	6.5	0.58	139	19.8
61.8	159	141	910	6.5	0.58	139	17
81.4	89	143	910	6.4	0.47	139	8.8
81.4	89	143	910	6.4	0.47	139	11.7
81.4	89	143	910	6.4	0.47	139	8.9
81.4	121	141	910	6.5	0.76	139	14.3
81.4	121	141	910	6.5	0.76	139	15.3
81.4	121	141	910	6.5	0.76	139	16.6

2.2. ANFIS methodology

ANFIS network has five layers as it shown in Figure 1. The main core of the ANFIS network is fuzzy inference system. Layer 1 receives the inputs and convert them in the fuzzy value by membership functions. In this study bell shaped membership function is used since the function has the highest capability for the regression of the nonlinear data.

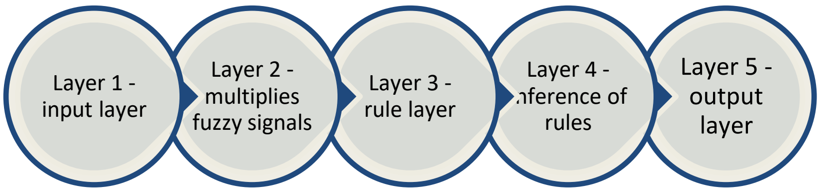

Fig. 1 ANFIS layers

Bell-shaped membership functios is defined as follows:

$$\mu(x) = bell(x; a_i, b_i, c_i) h_{ci} = \frac{1}{1 + \left[\left(\frac{x - c_i,}{a_i,} \right)^2 \right]^{b_i}} \tag{1}$$

where $\{a_i, b_i, c_i\}$ is the parameters set and x is input.

Second layer multiplies the fuzzy signals from the first layer and provides the firing strength of as rule. The third layer is the rule layers where all signals from the second layer are normalized. The fourth layer provides the inference of rules and all signals are converted in crisp values. The final layers summarized the all signals and provied the output crisp value.

3. Results

ANFIS methodology was used for selection of the optimal predictors for shear strength of FRP-RC beams. The selection is important as preprocessing of the input parameters to remove the inputs with small relevance. The data set is obtained from the data file in Table 1. The dataset is then partitioned into a training set (odd-indexed samples) and a checking set (even-indexed samples) by following command in MATLAB Software:

```
>>[data] = shear;
>>trn_data = data(1:2:end,:);
>>chk_data = data(2:2:end,:);
```

The function "exhsrch" performs an exhaustive search within the available inputs to select the set of inputs that most influence the shear strength of FRP-RC beams. The first parameter to the function specifies the number if input combinations to be tried during the selection procedure. Essentially, "exhsrch" builds an ANFIS model for each combination and trains it for one epoch and reports the performance achieved. The following command line is used for determine the one most influential attribute in predicting the output:

```
>> exhsrch(1,trn_data,chk_data);
```

The following results are obtained (Figure 2):

```
ANFIS model 1: in1 --> trn=47.6685, chk=50.4654
ANFIS model 2: in2 --> trn=28.7684, chk=29.9848
ANFIS model 3: in3 --> trn=38.5202, chk=39.6556
ANFIS model 4: in4 --> trn=35.9930, chk=39.0937
ANFIS model 5: in5 --> trn=46.9295, chk=51.8274
ANFIS model 6: in6 --> trn=47.4247, chk=50.3212
ANFIS model 7: in7 --> trn=47.7124, chk=53.5527
```

Fig 2 Predictors' influence on the shear strength of FRP-RC beams

The lest-most input variable (in2) in Figure 2 has the least error or in other words the most relevance with respect to the output. The plot and results from the function clearly indicate that the input attribute "beam width" is the most influential. The training and checking errors are comparable, which implies that there is no overfitting. This means we can push a little further and explore if we can select more than one input attribute to build the ANFIS model.

Intuitively, one can simply select "beam width" and "beam shear span" directly since they have the least errors as shown in the Figure 2. However, this will not necessarily be the optimal combination of two inputs that results in the minimal training error. To verify this, one can use:

```
>> exhsrch(2,trn_data,chk_data);
```

The following results are obtained (Figure 3):

```
ANFIS model 1: in1 in2 --> trn=22.9756, chk=36.3469
ANFIS model 2: in1 in3 --> trn=32.8510, chk=41.5568
ANFIS model 3: in1 in4 --> trn=31.7283, chk=51.7965
ANFIS model 4: in1 in5 --> trn=34.4541, chk=45.8268
ANFIS model 5: in1 in6 --> trn=44.0512, chk=49.8283
ANFIS model 6: in1 in7 --> trn=44.0962, chk=50.6159
ANFIS model 7: in2 in3 --> trn=15.4313, chk=23.3665
ANFIS model 8: in2 in4 --> trn=18.1118, chk=24.2689
ANFIS model 9: in2 in5 --> trn=21.6377, chk=26.7704
ANFIS model 10: in2 in6 --> trn=26.4107, chk=30.2595
ANFIS model 11: in2 in7 --> trn=24.9798, chk=35.7504
ANFIS model 12: in3 in4 --> trn=24.0954, chk=209.7226
ANFIS model 13: in3 in5 --> trn=19.6570, chk=92.5814
ANFIS model 14: in3 in6 --> trn=34.8755, chk=75.9777
ANFIS model 15: in3 in7 --> trn=30.2766, chk=172.0246
ANFIS model 16: in4 in5 --> trn=18.9079, chk=177.1485
ANFIS model 17: in4 in6 --> trn=33.8664, chk=58.3976
ANFIS model 18: in4 in7 --> trn=34.5913, chk=104.2876
ANFIS model 19: in5 in6 --> trn=38.4331, chk=46.0639
ANFIS model 20: in5 in7 --> trn=33.4146, chk=54.6191
ANFIS model 21: in6 in7 --> trn=44.5389, chk=65.6771
```

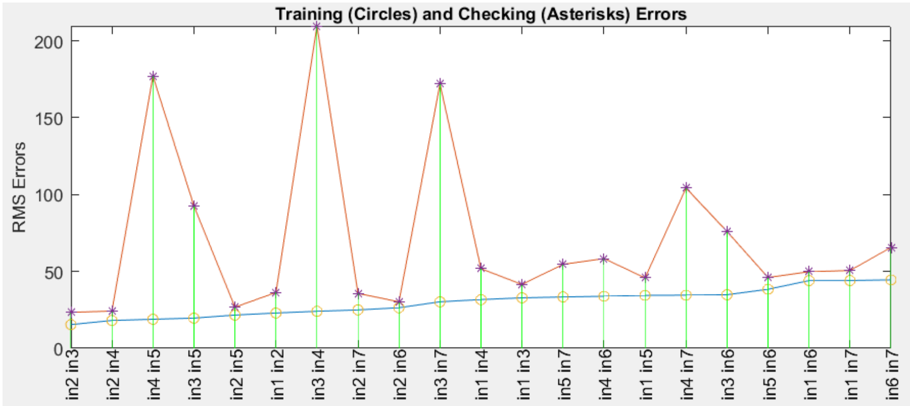

Fig 3 All two predictors combinations influence on the shear strength of FRP-RC beams

The results from "exhsrch" indicate that "beam width" and "effective depth" form the optimal combination of two input attributes or two predictors. The training and checking errors are getting distinguished which indicates the outset of overfitting. It may be not preferable to use more than two input for building the ANFIS model. However, one can confirm the premise to verify its validity by following command line:

```
>> exhsrch(3,trn_data,chk_data);
```

The following results are obtained (Figure 4):

ANFIS model 1: in1 in2 in3 --> trn=11.2498, chk=162.8687
ANFIS model 2: in1 in2 in4 --> trn=12.6280, chk=101.0679
ANFIS model 3: in1 in2 in5 --> trn=15.6878, chk=559.0779
ANFIS model 4: in1 in2 in6 --> trn=14.1832, chk=50.9990
ANFIS model 5: in1 in2 in7 --> trn=15.2771, chk=110.3073
ANFIS model 6: in1 in3 in4 --> trn=14.7596, chk=522.1914
ANFIS model 7: in1 in3 in5 --> trn=13.9229, chk=92.3709
ANFIS model 8: in1 in3 in6 --> trn=22.0726, chk=250.5787
ANFIS model 9: in1 in3 in7 --> trn=18.3099, chk=459.7988
ANFIS model 10: in1 in4 in5 --> trn=14.1184, chk=134.6110
ANFIS model 11: in1 in4 in6 --> trn=21.6134, chk=1194.7738
ANFIS model 12: in1 in4 in7 --> trn=22.0705, chk=473.0779
ANFIS model 13: in1 in5 in6 --> trn=28.0365, chk=64.7652
ANFIS model 14: in1 in5 in7 --> trn=27.0283, chk=108.5869
ANFIS model 15: in1 in6 in7 --> trn=32.7692, chk=211.8272
ANFIS model 16: in2 in3 in4 --> trn=10.2168, chk=799.1103
ANFIS model 17: in2 in3 in5 --> trn=10.4146, chk=237.0670
ANFIS model 18: in2 in3 in6 --> trn=8.4013, chk=211.8117
ANFIS model 19: in2 in3 in7 --> trn=8.8978, chk=851.6215
ANFIS model 20: in2 in4 in5 --> trn=11.1824, chk=370.7922
ANFIS model 21: in2 in4 in6 --> trn=13.4324, chk=459.2600
ANFIS model 22: in2 in4 in7 --> trn=11.2578, chk=1617.5548
ANFIS model 23: in2 in5 in6 --> trn=15.4825, chk=180.2330

ANFIS model 24: in2 in5 in7 --> trn=17.6976, chk=151.3632
ANFIS model 25: in2 in6 in7 --> trn=19.9275, chk=95.7980
ANFIS model 26: in3 in4 in5 --> trn=13.4424, chk=6156.9596
ANFIS model 27: in3 in4 in6 --> trn=17.0637, chk=805.7227
ANFIS model 28: in3 in4 in7 --> trn=13.4865, chk=19362.0331
ANFIS model 29: in3 in5 in6 --> trn=11.5879, chk=81.4807
ANFIS model 30: in3 in5 in7 --> trn=12.9908, chk=281.5371
ANFIS model 31: in3 in6 in7 --> trn=17.6058, chk=194.4082
ANFIS model 32: in4 in5 in6 --> trn=10.8919, chk=138.6010
ANFIS model 33: in4 in5 in7 --> trn=13.5533, chk=291.5226
ANFIS model 34: in4 in6 in7 --> trn=24.1216, chk=332.4736
ANFIS model 35: in5 in6 in7 --> trn=27.3702, chk=89.2608

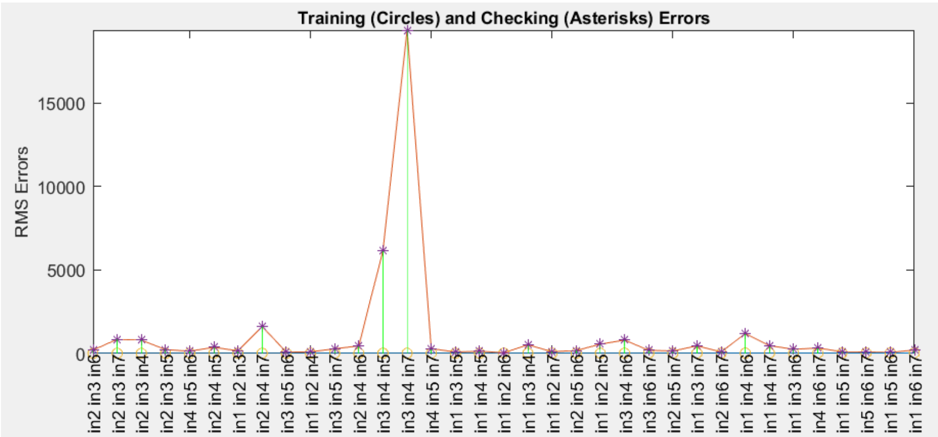

Fig 4 All three predictors combinations influence on the shear strength of FRP-RC beams

The Figure 4 shows the results of selecting three predictors, in which “weight”, “effective depth” and “reinforcement ratio of longitudinal FRP bars” are selected as the best combination of three predictors. However, the minimal training and checking error do not reduce significantly from that of the best two predictors model, which indicates that the newly added predictor “reinforcement ratio of longitudinal FRP bars” does not improve the prediction much. For better generalization it is preferable to pick a model with simple structure. For further analysis model with two predictors will be extracted.

The function “exhsrch” only trains each of the ANFIS model for a single epoch to be able to quickly select the optimal input attributes. In the next step, after extraction of the two optimal predictors, 100 epochs are used for training the new ANFIS model. Figure 5 shows error curve for 100 epochs of the ANFIS training for two predictors. The green curve presents the training errors and the red curve presents the checking errors. The minimal checking error occurs at epoch 100, which is indicated by a circle. Notice that the checking error curve is almost constant after epoch 70, indicating that further training over fitch the data and produces worse generalization.

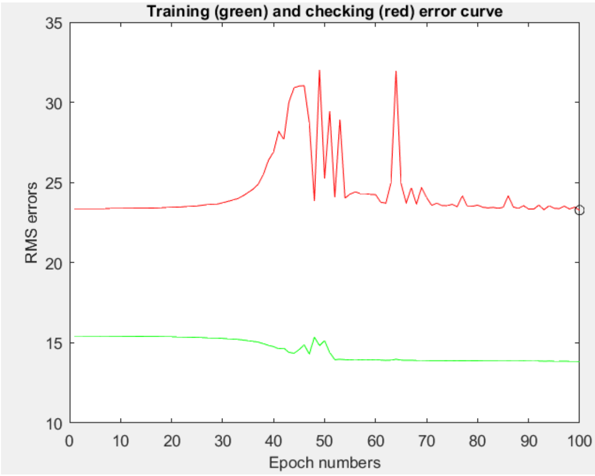

Fig 5 Training and checking errors for two optimal predictors

The ANFIS model could be compared against a linear regression model by comparing their respective RMSE values against checking data. ANFIS RMSE value against checking data is 29.978, while linear regression RMSE value against checking data is 35.656.

Figure 6 shows input/output surface of the ANFIS model at the minimal checking error during the training process. The surface shown in the figure 6 is a nonlinear and monotonic surface and illustrates how the ANFIS model will respond to varying values of beam width and effective depth.

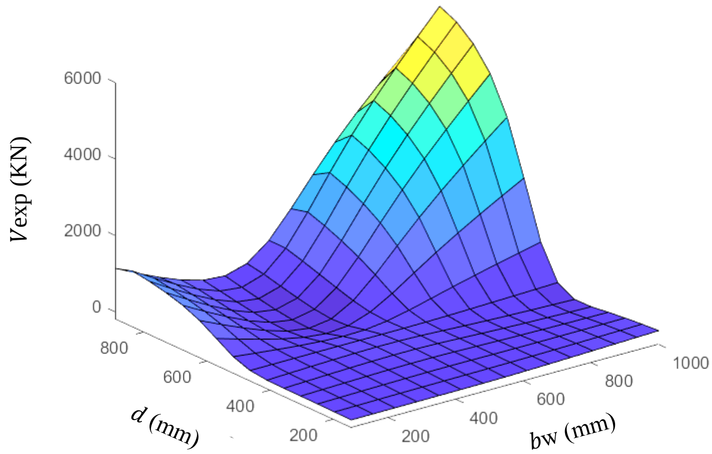

Fig 6 Input/output surface for trained ANFIS model

4. CONCLUSION

A computational intelligence model for the shear strength estimation of fibre reinforced polymers (FRP) used as internal reinforcement for reinforced concrete (RC) beams has been proposed in this paper. A set of experimental data from the published literature has been collected and divided into input and output parameters.

Adaptive neuro fuzzy inference system or ANFIS was used for optimization of the predictors for the shear strength of the FRP-RC beams. Based on the input/output data pairs ANFIS models were created. The results from the searching procedure indicated that “beam width” and “effective depth” form the optimal combination of two input attributes or two predictors for the shear strength prediction of the FRP-RC beams. This selected combination of two predictors could be used effectively to estimate the strength of confined ultimate concrete.

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SMICANJE OJAČANIH VLAKNASTIH POLIMERA U PRIMENI KOD UNUTRAŠNJIH BETONSKIH STUBOVA

Osnovni cilj istraživanja prikazanog u radu je analiza procedure selekcije, kako bi se pronašli optimalne prediktore za smicanje ojačanih vlaknastih polimera, u primeni kod unutrašnjih ojačanih betonskih stubova. Procedura selekcije je urađena primenom adaptivne neuro fazi logike, ANFIS, i svi dostupni parametri su bili uključeni. ANFIS model bi mogao da se koristi kao primer ne suviše komplikovane analize smicanja unutrašnjih betonskih stubova. MATLAB softver je korišćen za ANFIS aplikaciju. Rezultati su pokazali da širina stuba i efektivna dubina stuba čini optimalnu kombinaciju od dva ulazna parametra za predikciju smicanja stubova.

Ključne reči: *FRP; prediktori; smicanje; ojačani beton; ANFIS.*