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ANN AND STATISTICAL MODELLING TO PREDICT THE DEFLECTION OF CONTINUOUS REINFORCED CONCRETE DEEP BEAMS

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ABSTRACT: - This comparative study investigates the adoption of artificial neural networks and statistical modelling in the prediction of the deflection under ultimate strength of continuous reinforced concrete deep beams. All experimental data collected from the literature covers a case of a continuous deep beam with two point loads acting symmetrically in each span. The data set consist of many input parameters cover the geometrical and material properties. The corresponding output value was the deflection under ultimate strength of the continuous deep beam. The model takes into account the effects of the effective depth, shear span-to-depth ratio, length of one span, section width, ratio of reinforcement, and compressive strength of concrete cubes. Training, validation and testing of the developed neural network have been achieved using a comprehensive database compiled from 75 continuous deep beam specimens. The results show high correlation through using ANN modeling with 99.13% and 97.27% for extended and original data set. This model was compared with the multi-linear model which was of 81.16% correlation coefficient. Both model reflect high correlation with observed data and proved that they can be used to predict the deflection of deep beam with high degree of confidence.
KEYWORDS: Deep beam, ultimate strength, ANN modeling, Regression modelling, prediction.

1- INTRODUCTION

Neural Network Forecasting

Artificial neural network (ANN) was successfully adopted as modeling tools in many construction and structural contexts, mostly due to its precise non-linear properties and adaptive behavior that simulate the ability to cope with the non-linear phenomena usually found in construction processes.

Many researchers adopted the ANN forecasting for different field in construction. Studies have shown that it is possible to identify structural sub-processes within a trained ANN architecture [1, 2]. Different ANN architectures have found use among construction. In particular, feed-forward neural networks (FNNs) have been largely employed due to their proven performances, consolidated training methods and universal approximation capability [3]. When carrying out the training process to map the unknown input–output relationship into the FNN architecture, the preferred techniques are first and second-order local search methods, such as the conjugate gradient (CG) and the Levenberg–Marquardt (LM) method [4].

Structural Forecasting Using ANN

This work focus on continuous deep beams constructed using reinforced concrete, which are fairly common structural elements. These specimens are characterized as being relatively short and deep, having a small thickness relative to their span or depth. There are many important applications of deep beams such as (but not limited) transfer girders, pile caps, tanks, folded plates and foundation walls, often receiving many small loads in their own plane and transferring them to a small number of reaction points. Elastic solutions of reinforced concrete deep beams provide a good description of the behavior before cracking, but after cracking, a major redistribution of stresses occurs and hence the beam capacity must be predicted by inelastic analysis [5].

The behavior of deep beam differs from the normal beam behavior in various ways according to the small ratio (i.e. shear span depth ratio). In construct to slender beams, the response of deep beams is characterized by a significant direct load transfer from the point of loading to the supports, and a nonlinear strain distribution over the depth of the cross section (even in elastic stage).the deformations by shear are not negligible any more, compared to those caused by flexure .furthermore the large stiffness of this type of structures makes them highly sensitive to differences in support settlements [6].

The feed forward Artificial Neural Network (NN) modelling can be employed as a useful tool to precisely predict structural performance of concrete members if many reliable test results are provided as shown by several researches [7]. Goh and Sanad showed that shear strength of deep beams can be better predicted by multi-layered feed-forward NNs than other existing formulae. It should, however, be noted that ANNs are hardly capable of giving extrapolation for parameters outside the network training set as they can learn and generalize through only previous patterns [7,8,9]. It is therefore important to provide ANNs with more test data to find acceptable solutions to different situations.

In engineering problems, the most important property of ANNs is their capability of learning directly from examples. The other important properties of ANNs are their correct or nearly correct response to incomplete tasks, their extraction of information from noisy or poor data, and their production of generalized results from the novel cases. The above-mentioned capabilities make ANNs a very powerful tool in solving many engineering problems, particularly, where data may be complex or in an insufficient amount. Over the last decade, ANNs have successfully been performed in fracture mechanics of cement-based materials, prediction of fracture toughness of materials fatigue of materials and concrete technology [10, 11].

In the present study, multi-layered feed-forward ANNs trained with the back-propagation algorithm are developed to model the non-linear relationship between the deflection under ultimate strength of deep beams and different influencing parameters. An extensive dataset of continuous deep beams tested by different researchers is used to train, validate and test the developed ANN. Many researchers study different behavior of concrete deep beam such as Ashour [12], Asin [13], Rogowsky [14], Yang [15], and Subedi [16].

EXPERIMENTAL DATA SET

A total of 75 two-span top loaded reinforced concrete deep beams were compiled from different sources as given in Table 1. Thirty-six specimens were tested by Yang et al. 2007a,b ; and the rest were collected from Ashour et al. 1997 , Rogowsky et al.1986, Subedi 1998, and Asin 1999. The shear span-to-overall depth ratio of deep beams in the database ranged from 0.5 to 2.0. The test specimens were made of concrete having a very low compressive strength of 14.5 MPa and a high compressive strength of 68.2 MPa. Some test specimens had no web reinforcement, whereas others were reinforced with vertical and horizontal shear reinforcement. The range of load capacity of test specimens was 180 to 1483 KN. All beams were reported to fail in shear due to a major diagonal crack within interior shear spans, joining the edges of load and intermediate support plates.

The dataset deals with the ultimate strength of deep beams was influenced by geometrical conditions such as section width ,bw , and depth, h, longitudinal top, $\rho'= A'_s/$bw d , and bottom, rs $\rho= A_s/$bw d reinforcement ratios, vertical, $\rho_v= A_v/$bw S_v , and horizontal , $\rho_h= A_h/$bw S_h web reinforcement ratios, and shear span-to-overall depth ratio, a/h, and material properties such as concrete compressive strength, f_c', and yield strength, fy, of reinforcing bars, where A'_s and $A_s$are area of longitudinal top and bottom reinforcement, respectively, d is effective section depth, Av and Sv area and spacing of vertical web reinforcement, respectively,

Ah and Sh are area and spacing of horizontal web reinforcement, respectively and a is shear span for continuous deep beams, as shown in Figure 1.

LINEAR REGRESSION MODELLING

Modelling the Prediction of engineering properties is very popular using the regression equation. The form used for modeling simply can be represented as:

f = b0 + b1 X Eq.1

Where:

f: dependent engineering properties, such as compressive strength, deflection, or others.

X: independent variables, can represent w/c ratio, load, member geometry or others.

b0, b1: coefficients

The previous equation is the linear regression equation .The origin of this equation is called Abram's Law which relate compressive strength of concrete to the w/c ratio of the mix. Many researchers utilized this equation to develop many models for different engineering problems. Thereafter, according to Eq. 1, multiple regression equation was introduced to represent the problems of multi-variables which called multi-linear-regression modelling that deals with problems of various types of variables as below:

f = a0 + a1 X 1+ a2 X2 + ………+ an Xn Eq.2

This eq. called the multivariable linear regression formula, and in engineering, variables are often dependent on several independent variables, this functional dependency is best characterized by the equation mentioned earlier, and is said to give results that are more realistic too. In this study, the multivariable linear regression was used to predict the behavior of deep beam (deflection as a dependent variable). Factors affecting this engineering property were listed in the table in the appendix as an independent variables (X 1 to Xn) [17,18].

RESULTS AND DISCUSSION

In the present study, some of the samples were excluded from the ANN modelling due to the absence of some test results. All of other samples were introduced to the three stages of model development. Major part of the data set was used to train the network, the rest of data set was divided into two groups, one for validating the developed model, and the second for testing the final model.

Two approaches of ANN modelling were adopted, the first approach was to deal with the normal data set. Meanwhile the second approach was to use the smoothing of data set throughout the generating of approximated extra data by the function of interpolation depending on the leading column of the results as explained below:

```
function:[sorintpdata]=interandANN(data, numberofpoints,outxls,leadingcol)
```

The results of these two model were compared with the model generated throughout utilizing the nonlinear regression technique.

First ANN Approach: This modelling adapted the data set of 65 specimens. The information was feeding to the system directly utilizing the function of "newff" with three layers of 10, 15, and 10 neurons for each respectively. The number of epochs was 150 as shown below:

```
net = newff([a],T,[10 15 10],{'tansig' 'tansig' 'tansig'});
net.trainParam.epochs = 150;
net = train(net,P,T);
output=sim(net,P);
```

The algorithm used to train the system was Levenberg-Marquardt, and the performance was controlled by the Mean Square Error function, the data division was randomly selected. This system achieved the analysis and reached the excepted model within the 3rd epoch as shown in Figure 2-a, which plots the epoch number with mean square error for train, validation and testing results. The algorithm and the layers used was shown in Figure 2-b, which explain the three layers for outputs and one layer for the inputs and the other parameters for the model.

The analysis of the developed model was explained in Figure 3. The behavior of predicted results was gone through the data set closely to the observed data except the zones around the points 5, 12, 28, and 45 which show some divergence of the predicted results relative to observed data Figure 3-a. the correlation of the model was graduated very high to high through train, validate, test, and overall data set. The R was 97.27 % for the overall data set which reflect high correlation and good model behavior Figure 3-b, c, d, and e.

Second ANN Approach: This modelling adopted the function (*sorintpdata*) to extend the data set up to 200 points within the original specimens' results. This technique would keep the limits for each parameters but generate extra internal point to smooth the generated model and its predicted results. Other information regarding the algorithm and the layers were as for first approach. This system achieved the analysis and reached the excepted model within the eleventh epoch as shown in Figure 4, which plots the epoch number with mean square error for train, validation and testing results.

The analysis of the developed model was explained in Figure 3. The behavior of predicted results was gone through the data set closely to the observed data except the zones around the points 180 and 125 which show some divergence of the predicted results relative to observed data Figure 5-a. the correlation of the model was graduated very high to high through train, validate, test, and overall data set. The R was 99.13 % for the overall data set which reflect high correlation and good model behavior Figure 5-b, c, d, and e.

Multi-Linear Regression Modelling

To predict the model for the data set used in this study, the equation 2 that discussed earlier was adopted to predict the behavior of the tested samples. The model was modified to suit with our problem as explained in the following equation:

Model is: V11=a0+a1*V1+a2* V2 +………..+a10*V10.... eq. 3

Where: V1 is the dependent variable (deflection) and V1 to V10 are the independent variables as listed in the appendix of data set.

The properties of the modeling technique used was the loss function of least squares, and the level of confidence was 95.0% (alpha=0.050). The developed model was of the parameters in Table 1.

The correlation was good for the predicted data with the actual observations. The R-value was 81.16 % which reflect good correlation. Very few points were of high divergence especially for the specimens with deflection of more than 12 mm as shown in figure 6.

CONCLUSIONS

This research adopted the artificial neural network model (ANN) with Back Propagation algorithm (Levenberg-Marquardt). The aim was to compare the ANN results with the multi-linear regression modelling. These two approaches was developed to predict the behavior of deep beam by learning and training process.

Results show the neural network provides a high accuracy prediction of the deflection for the specimens depended on eleven independent variables of the data collected for 75 samples of previous research work. The correlation was 99.13% and 97.27% for the extended and the original data set using ANN modeling. Meanwhile, the multi-linear regression modeling was of correlation 81.16%. This reflect the high degree of the accuracy of neural network modeling.

These three modelling technique can be used with high degree of confidence to predict the behavior (deflection) of deep beam with a minimum error according to the correlation coefficient for each model.

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Appendix

Specimen	bw mm	h mm	fc' Mpa	a/h	L mm	ρb	ρt	ρv	ρh	REFERENCE	Pu	Δ
CDB1	120	625	30	1.09	1340	0.007	0.009	0.008	0.01	Ashour 1997	1078	1.95
CDB2	120	625	39.2	1.09	1340	0.007	0.009	0.004	0.005		931	2.35
CDB3	120	625	25	1.09	1340	0.007	0.009	0	0.005		559	0.8

CDB4	120	625	31.5	1.09	1340	0.007	0.009	0.004	0		867	1.85
CDB5	120	625	32	1.09	1340	0.003	0.003	0.004	0.005		803	2.98
CDB6	120	425	26.5	1.6	1340	0.008	0.008	0.005	0.003		485	1.6
CDB7	120	425	30.9	1.6	1340	0.008	0.008	0.002	0.001		436	2.9
CDB8	120	425	29.4	1.6	1340	0.005	0.005	0.002	0.001		377	2.4
1.0/1/1	150	1000	37.1	1.1	2300	0.003	0.004	0.005	0	Asin 1999	1600	2.9
1.0/1/2	150	1000	30.2	1.1	2300	0.003	0.004	0.004	0		1510	2.7
1.0/1/3	150	1000	30.4	1.1	2300	0.003	0.004	0.002	0		1190	2.05
1.0/2/1	150	1000	28.2	1.1	2300	0.004	0.003	0.005	0		1829	5.2
1.0/2/2	150	1000	34.3	1.1	2300	0.004	0.003	0.004	0		1487	2.5
1.0/2/3	150	1000	36.8	1.1	2300	0.004	0.003	0.002	0		1371	2.95
1.5/1/1	150	600	34.9	1.83	2300	0.007	0.009	0.005	0		1190	6.9
1.5/1/2	150	600	33.3	1.83	2300	0.007	0.009	0.004	0		1039	6.5
1.5/1/3	150	600	32.6	1.83	2300	0.007	0.009	0.002	0		797	4.4
1.5/2/1	150	600	33.2	1.83	2300	0.01	0.008	0.005	0		1161	6.1
1.5/2/2	150	600	33.2	1.83	2300	0.01	0.008	0.004	0		1070	6.8
1.5/2/3	150	600	34.4	1.83	2300	0.01	0.008	0.002	0		768	4.1
3/1.0	200	1000	28.9	1	2100	0.005	0.006	0.002	0	Rogowsky et al. 1986	2167	10.2
4/1.0	200	1000	28.5	1	2100	0.005	0.006	0	0.003		2165	7.2
5/1.0	200	1000	36.9	1	2100	0.005	0.006	0.006	0		2559	8.9
6/1.0	200	1000	35.8	1	2100	0.005	0.006	0	0.004		2190	5.5
7/1.0	200	1000	34.5	1	2100	0.005	0.006	0	0		1409	3.8
3/1.5	200	600	14.5	1.67	2100	0.009	0.011	0.002	0		799	4.1
4/1.5	200	600	32.5	1.67	2100	0.009	0.011	0	0.003		645	2.6
5/1.5	200	600	39.6	1.67	2100	0.009	0.011	0.006	0		1705	22.5
6/1.5	200	600	45	1.67	2100	0.009	0.011	0	0.004		806	2.1
7/1.5	200	600	30.4	1.67	2100	0.009	0.011	0	0		717	3
8/1.5	200	600	37.2	1.67	2100	0.009	0.011	0.002	0.003		1080	3.9
3/2.0	200	500	42.5	2	2100	0.011	0.011	0.002	0		847	7
4/2.0	200	500	38.3	2	2100	0.011	0.011	0	0.003		597	4.5
5/2.0	200	500	41.1	2	2100	0.011	0.011	0.006	0		1338	22
6/2.0	200	500	37.4	2	2100	0.011	0.011	0	0.004		596	3.5
7/2.0	200	500	46.8	2	2100	0.011	0.011	0	0		587	3.3
L5NN	160	600	32.4	0.5	600	0.01	0.01	0	0	Yang et al. 2007a,b	1635	1.23
L5NS	160	600	32.4	0.5	600	0.01	0.01	0.003	0		1710	
L5NT	160	600	32.4	0.5	600	0.01	0.01	0.006	0		1789	1.34
L5SN	160	600	32.4	0.5	600	0.01	0.01	0	0.003		1887	
L5SS	160	600	32.4	0.5	600	0.01	0.01	0.003	0.003		2117	1.66
L5TN	160	600	32.4	0.5	600	0.01	0.01	0	0.006		2317	1.75
L10NN	160	600	32.1	1	1200	0.01	0.01	0	0		880	1.32
L10NS	160	600	32.1	1	1200	0.01	0.01	0.003	0		1153	
L10NT	160	600	32.1	1	1200	0.01	0.01	0.006	0		1541	4
L10SN	160	600	32.1	1	1200	0.01	0.01	0	0.003		884	
L10SS	160	600	32.1	1	1200	0.01	0.01	0.003	0.003		1177	3.04
L10TN	160	600	32.1	1	1200	0.01	0.01	0	0.006		935	1.42
H6NN	160	600	65.1	0.6	720	0.01	0.01	0	0		2248	1.5
H6NS	160	600	65.1	0.6	720	0.01	0.01	0.003	0		2289	
H6NT	160	600	65.1	0.6	720	0.01	0.01	0.006	0		2625	1.85
H6SN	160	600	65.1	0.6	720	0.01	0.01	0	0.003		2427	
H6SS	160	600	65.1	0.6	720	0.01	0.01	0.003	0.003		2763	1.73
H6TN	160	600	65.1	0.6	720	0.01	0.01	0	0.006		2966	1.62
H10NN	160	600	68.2	1	1200	0.01	0.01	0	0		1276	1.6
H10NS	160	600	68.2	1	1200	0.01	0.01	0.003	0		1443	
H10NT	160	600	68.2	1	1200	0.01	0.01	0.006	0		2116	3.35
H10SN	160	600	68.2	1	1200	0.01	0.01	0	0.003		1309	
H10SS	160	600	68.2	1	1200	0.01	0.01	0.003	0.003		1575	2.3
H10TN	160	600	68.2	1	1200	0.01	0.01	0	0.006		1287	1.9
L5-40	160	400	32.4	0.5	400	0.01	0.01	0	0		1529	1.08
L5-72	160	720	32.4	0.5	720	0.011	0.011	0	0		1786	1.33
L10-42	160	400	32.4	1	800	0.01	0.01	0	0		717	1.27
L10-72	160	720	32.4	1	1440	0.011	0.011	0	0		1003	2.05
H6-40	160	400	65.1	0.6	480	0.01	0.01	0	0		2025	1.58
H6-72	160	720	65.1	0.6	864	0.011	0.011	0	0		2342	1.65

H10-42	160	400	65.1	1	800	0.01	0.01	0	0		1112	
H10-72	160	720	65.1	1	1440	0.011	0.011	0	0		1282	
L5SS-W	160	600	32.1	0.5	600	0.01	0.01	0.003	0.003		1635	1.18
L10SS-W	160	600	32.4	1	1200	0.01	0.01	0.003	0.003		880	1.62
H6SS-W	160	600	65.1	0.6	720	0.01	0.01	0.003	0.003		2248	1.5
H10SS-W	160	600	68.2	1	1200	0.01	0.01	0.003	0.003		1276	
1CB1	50	400	56.5	0.63	500	0.011	0.011	0.006	0.006	Subedi 1998	259	
1CB2	50	400	56.5	1.25	1000	0.011	0.011	0.006	0.006		175	
2CB4	75	600	44.7	1.4	1680	0.015	0.005	0.011	0.011		361	

Table 1: The parameters a_0 to a_{11} for the developed model.

	bw mm	h mm	fc' Mpa	a/h	L mm	ρb	ρt	ρv	ρh	Vu-max	Pu(KN)	Δ(mm)
a_0	**a1**	**a2**	**a3**	**a4**	**a5**	**a6**	**a7**	**a8**	**a9**	**a10**	**a11**	
-12.188	**0.054**	**0.002**	**-0.054**	**7.868**	**-0.004**	**12.966**	**-57.875**	**266.288**	**-159.5**	**0.066**	**-0.016**	

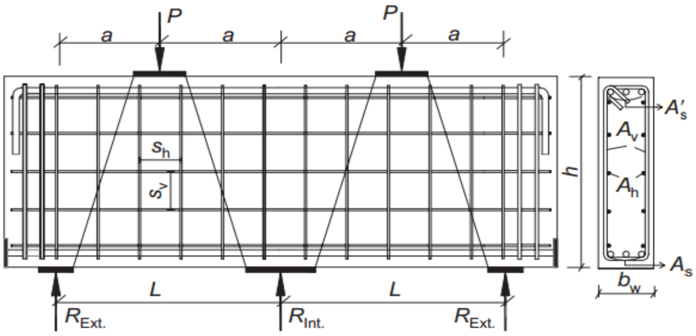
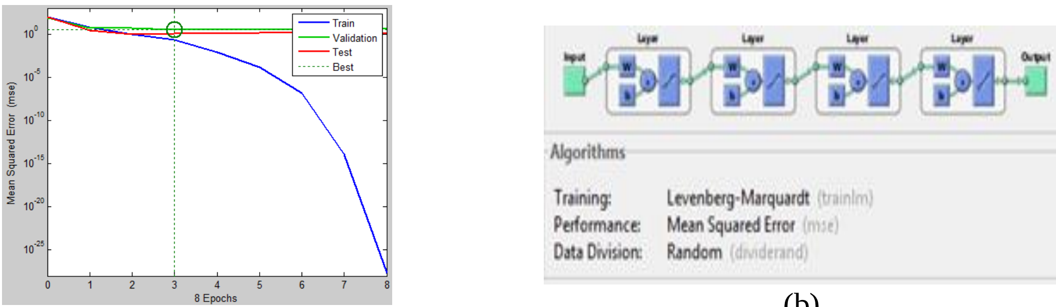


Figure 1. Symbolic identification for deep beams in the neural network model



(a) (b)

Figure 2: the performance of the ANN model (a), and the layers of the model (b)

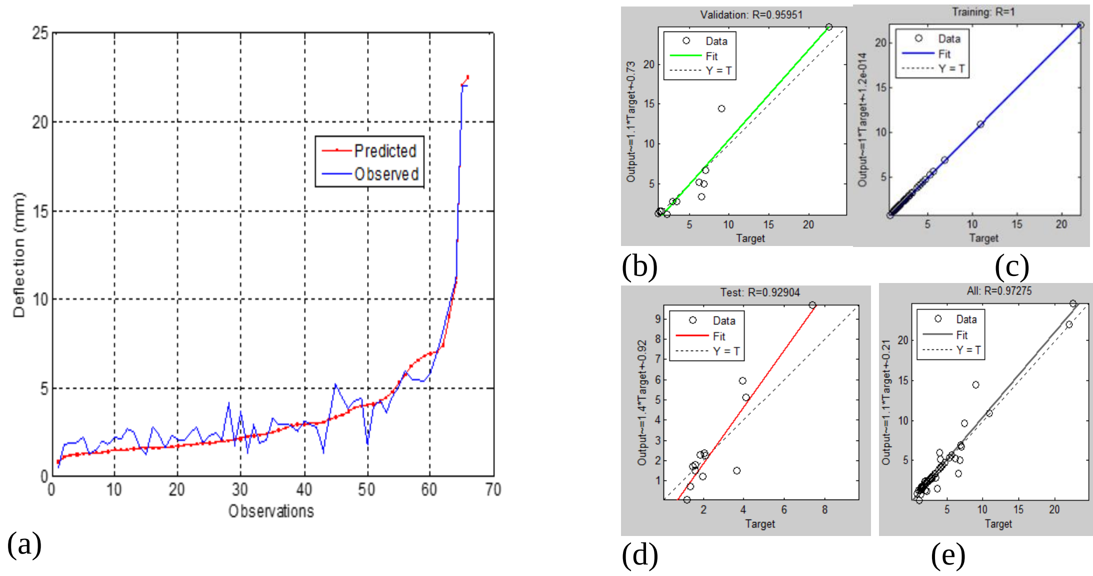


Figure 3: predicted vs. observed results of the ANN model (a), and the correlation of the model components (b, c, d, e) for original data set.

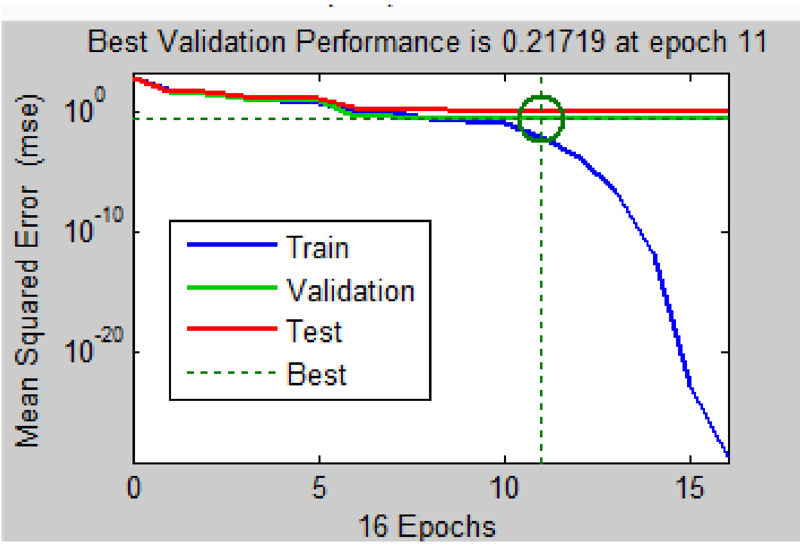


Figure 4: Plots of the epoch number with mean square error

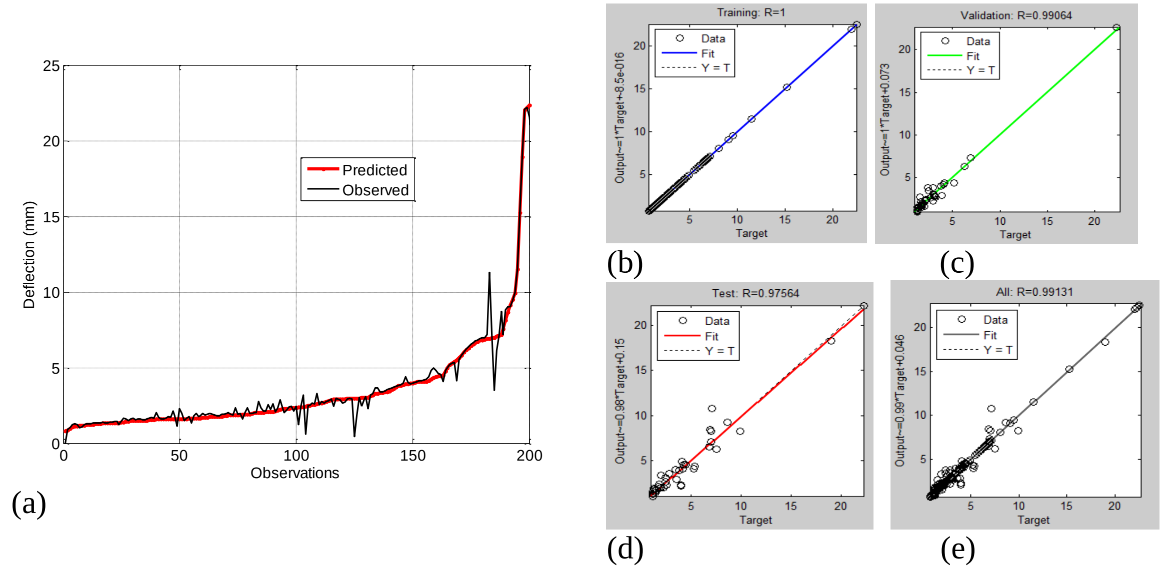


Figure 5: predicted vs. observed results of the ANN model (a), and the correlation of the model components (b, c, d, e) for the extended data set.

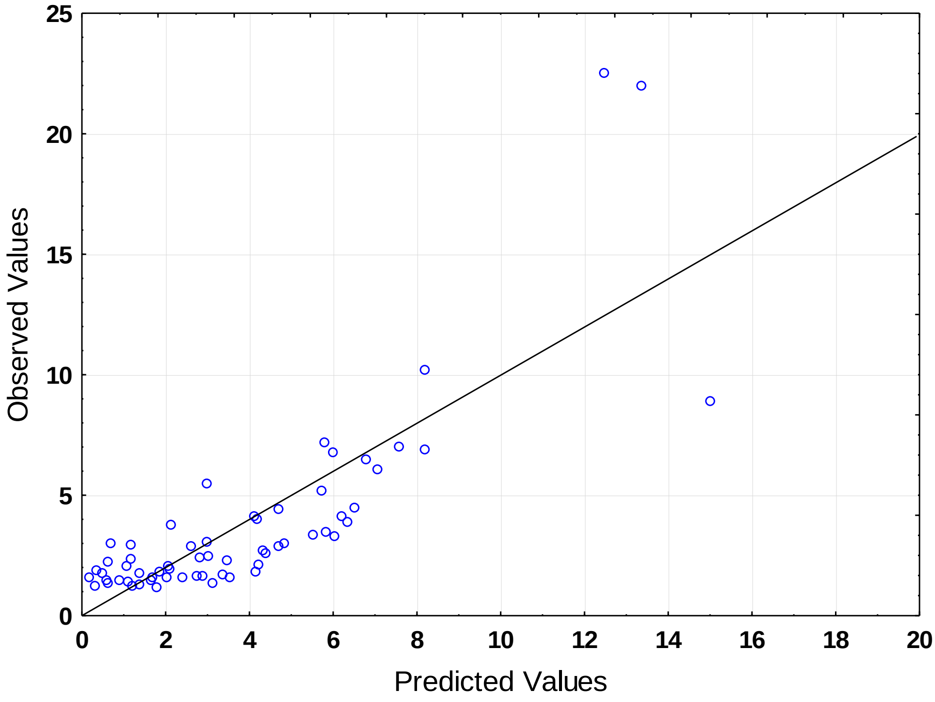


Figure 6. Correlation of the regression model

اعتماد الشبكات العصبية والنمذجة الاحصائية للتنبوء بمقدار التشوه للعتبات المسلحة العميقة المستمرة

الخلاصة:

تناولت دراسة المقارنة هذه اعتماد تقنية الشبكات العصبية الصناعية وتقنية الانحدار الخطي المتعدد للتنبؤ بمقدار التشوه تحت ظروف قوة التحميل القصوى للعتبات المسلحة المستمرة. تم جمع البيانات العملية من خلال مراجعة العديد من البحوث السابقة التي تغطي الحالة الدراسية. نوع التحميل كان باعتماد الحمل ثنائي التمركز المتناظر على فضاء العتبة بالتساوي. شملت البيانات العملية عدة مدخلات منها العمق الفعال، ونسبة الفضاء الى العمق، وطول الفضاء الواحد، وعرض المقطع، ونسبة التسليح، ومقاومة الانضغاط للخرسانة. في حين كان مقدار التشوة تحت قوة التحميل القصوى تمثل مخرجات البيانات. تم بناء الموديل بتقنية الشبكات العصبية واجراء التحقق والفحص ومن ثم مقارنة النتائج مع مخرجات تقنية الانحدار الخطي المتعدد. اظهرت النتائج تقاربا وارتباطا عاليا جدا لتقنية الشبكات العصبية وفق الطريقتين المتبعتين مع معامل ارتباط (99.13% و 97.27%) وكذلك ارتباطا جيدا بين نتائج التنبؤ ومخرجات البيانات العملية باعتماد الانحدار الخطي المتعدد مع معامل ارتباط (81.16%). اثبتت النتائج الموثوقية الجيدة لاستخدام النموذج المتبع في هذا البحث لغرض التنبؤ المستقبلي بتصرف العتبات الخرسانية باعتماد المتغيرات الواردة في البحث.