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Predicting the Long Term Deflection of Flexural Members Using Artificial Neural Networks

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Abstract: A long term deflection response of reinforced concrete flexural members is influenced by many factors like compression reinforcement, creep coefficient, shrinkage strain, total time of experiment (years) and the ultimate compressive strength. A statistical approach artificial neural network for the predicting of long term deflection of reinforced concrete beams or slabs is proposed in this study. The artificial neural network predicted approach from this study was compared with (ACI-318) code equation. Results of artificial neural network was discussed and compared with the experimental data obtained from conducted studies. It showed a good agreement. However, the predicted approach was found to be too simplified to assess the increment of the long-term deflection.

Key words: Long term deflection, concrete, artificial neural networks, flexural members, increment, beams

INTRODUCTION

Reinforced concrete beams or slabs should be designed to compensate strength, deflections and cracking at different loading conditions (serviceability requirements). Numerous experimental investigations on long term deflection have been made, since, 1907 until now. The authoritative investigation which contains obvious information about the dimensions of the beam or slab, reinforcement details, the initial deflection, the total time of experiment, the total deflection, the ultimate compressive strength and the compression reinforcement. Espion (1988), documented and reconsidered the variability of researched depend on the method submitted by ACI-318 to evaluate the long term deflection of simply supported beams. Espion (1988), documented almost the published research data, since, 1907-1988 which concerned or study experimentally long term deflection. Espion (1988) covered 45 different researches and the kept research was 29 different researches which give clearly the dimensions of the beam or slab, reinforcement details, the initial deflection, the total time of experiment and the last recorded deflection at the end of experiment. For the present study 28 researches accredited, the ultimate compressive strength for all the 28 researches ranging between 9.9 and 45.7 Mpa, the duration of experiments ranging between 88-3123 days while the compression reinforcement ρ' ranging between 0-0.016696. Paulson, *et al.* (1991) studied the influence of the ultimate compressive strength and compression reinforcement ρ' on the creep coefficient and deflection. The experiment carried out on 9 simply supported beams for a duration of 360 days. The ultimate compressive strength ranged between 37-90 MPa while the compression reinforcement ρ' ranged between 0-0.014998. Lieping *et al.* (2011), conducted a study to investigate experimentally beams reinforced with glass fiber and steel bars. The experiment carried out on 2 simply supported beams reinforced with steel bar for 360 days. The values of creep coefficient, shrinkage strain and the ratio between initial and time-dependent deflection were presented. The ultimate compressive strength of concrete is 56 MPa while ρ' is 0. Gudonis *et al.* studied short and long-term deflection for duration of 315 days for four reinforced concrete beams whereas the ultimate compressive strength for concrete is 33.5 MPa while ρ' is zero. Al-Numan (2007), proposed an analytical sample to calculate the long-term deflection for different types of reinforced concrete slabs. Muhaisin (2012) proposed an analytical model to calculate the long term deflection for reinforced concrete beams. This study included the effect of many factors such as compressive strength, compression reinforcement, dimensions of beam and span length. Shallal (2013), studied experimentally and theoretically the long term deflection of existing reinforced concrete beam. Proposing a model take into account the effects of construction loads, effects of cracking on the long-term deflection.

Most of the previous researches used the code equation for the determination of long term deflection, hence there is a lack in the literature for evaluating absolute theoretical equation to evaluate the influential factors in long term deflection like dimensions of beams or slabs, creep coefficient, shrinkage strain, reinforcement details, the initial deflection, the total time of experiment, the total deflection, the compressive strength and the compression reinforcement. Analytical equation developed in this study using the advance statistics neural network to evaluate the long term deflection of the flexural members influenced via. different parameters which are mentioned above.

The main objective of this research is to present a systematic approach to assess the benefit of Artificial Neural Networks (ANNs) for the calculation of long-term deflection in reinforced concrete beams or slabs. The following parameters are included in the proposed approach: compression reinforcement, creep coefficient, shrinkage strain, total time of experiment (days) and the ultimate compressive strength. Then the proposed approach is compared with the experimental data which found in literature as well as with the ACI Code equation to check the accuracy.

MATERIALS AND METHODS

Deflection control: Relatively slender members become commonly used due to the quality outline technique, together with the utilization of higher-quality cements and steels. As a conclusion, deflections have become severe problems recently. To avoid the overestimation of deflection in beams and slabs which may lead to damage the structure appearance, sagging slabs, poor fitting of doors and windows. One of the best methods to diminish redirections is by expanding part profundities. Reinforced concrete related international codes usually confine redirections by determining certain base profundities or maximum allowable processed avoidances.

In the ACI Code Table 9a, outlines the minimum required thicknesses for beams and one-way slabs, unless genuine redirection estimations alludes that the minimum thicknesses are permitted. The value of minimum thickness have been created based on experience of experts over decays, these values should be used only for shafts and segments which were unsupported or associated with parcels or different individuals prone to be harmed by diversions. Similar manner has adopted in ACI Code for the two-ways slabs throughout Table 9c and provision 9. If the originator picks not to meet the base thicknesses given in tables, the deflections must be calculated and the qualities decided may not surpass the qualities determined in Table 9b of the ACI Code. The diversion of RC individuals might likewise control by curvature. The individuals are worked in this shape to the point which they will acknowledge their hypothetical shape under some organization stacking condition.

The prediction of the moment of inertia which will be computed after cracking take place no matter how the deflection have been computed, it will be difficult due to the cracks amount and shape, McCormac and Russell (2014). The beam section have been assumed uncracked, when the cracking moment, M_{cr} is larger than the moment subjected to beam segment, so, the gross moment of inertia I_g assumed to be equal to the moment of inertia. At the point when the moment is more noteworthy than M_{cr}, the tractable splits that create will bring about the pillar segment to be lessened and the moment of inertia might be expected to square with the changed esteem, I_{cr}, cracking moment of inertia. It is genuine that at areas where pressure breaks are precisely found, the first moment of area near the changed I_{cr}, however, in the middle of splits, it is might be closer to I_g. In addition, slanting strain splits may exist in zone of high shear, bringing on different varieties. Thus, it is hard to choose what estimation of moment of inertia should be used. It is easy to say that an accurate strategy for registering diversions must take these variations into account, Leet (1997). The ACI Code (9.5.2.3) area characterizes the moment of inertia expression which will conduct for evasion estimations. Such value gives a transitional incentive amongst I_g and I_{cr} that depends on the level of splitting brought on by connected burdens. The effective moment of inertia alluded to as Branson and Metz (1963) which is depend on the assessment of the likely measure of cracking created by the varying moment all through the traverse.

Adequate I_e with the suitable deflection term, immediate or beginning avoidances are gotten. Long-term or sustained loads be that as it may, cause huge increments in these deflections on account of shrinkage and creep. The variables influencing deflection increments incorporate moistness, temperature, healing conditions, compression reinforcement, proportion of stress to strength and the concrete age at the time of stacking. On the off chance that solid is stacked during early age, its long haul redirections will be fundamentally extended. Intemperate avoidances in strengthened solid structures can all the time be taken after to the early usage of burdens. After around 5 years the creep strain (the creep effect is irrelevant) the initial strain may be raised to four to 5 times when subjected to initial load which usually connected after 7-10 days of the setting of concrete, if the initial loading take place after 3 or 4

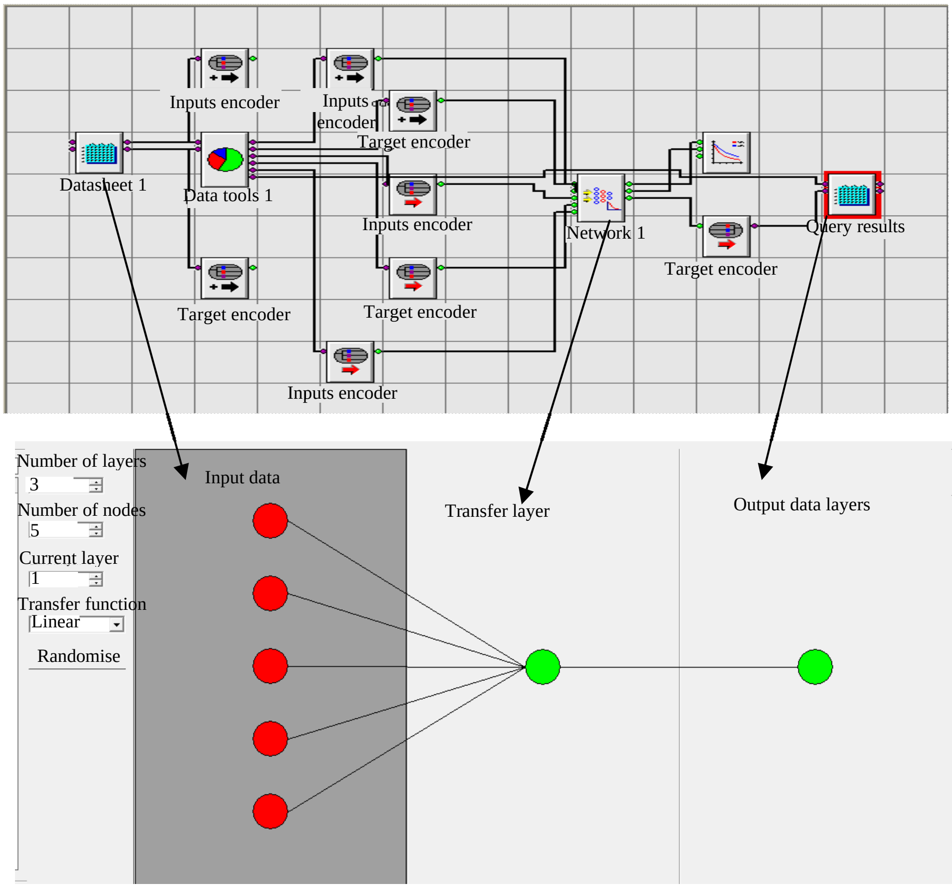

Fig. 1: Graphing component of Neufram V.4 program and structure of the ANNs optimal model (D-1)

months of concrete placement the ratio will be very little. The ACI Code (9.5.2.5) states that to evaluate the development in redirection in view of these causes, the piece of the incite avoidance that is a result of supported burdens may be increased by the exactly inferred Fig. 1 λ, Branson (1971) (as showed up in Eq. 1 which is ACI Eq. 9-11) and the result added to the immediate diversion:

$$\lambda = \frac{\xi}{1+50\rho'} \quad (1)$$

In this condition which is considerable to use for both customary and lightweight cement, ξ is a period subordinate component that may be found from code arrangement 9.5.2.5. The effect of pressure steel on long haul diversions is considered in this condition with the term ρ′. The full dead load of a structure can be named as a supported load, however, the kind of inhabitance will choose the rate of live load that can be called maintained. A review by the ACI Code demonstrates that for the controlled research office environments, 90% from the test cases had avoidances something close to 20% below and 30% over the qualities figured by the technique portrayed above, ACI Committee 435 (1972). Regardless that field conditions don't recreate the lab environments and redirections in genuine structures will change extensively more than those incident in the lab examples. In aversion of using arrangements and details and field examination, it is troublesome to control hands on work sufficiently. Generally, advancement staff may increase the water content for concrete to produce more workability. Typically, development staff might add some water to the solid for more workability together with the happen of voids and honeycomb. Eventually, the structures probably cleared from molds before the full maturation of concrete. Assuming this is the case, the modulus of burst and flexibility will underneath and extraordinary parts may occur in columns that would not have happened if the solid had been more grounded. These components can realize strengthened solid structures to avoid apparently more than is shown by the typical calculations.

ANN Model variables: The purpose of research estimation is to predict or estimate the long term deflection from known or assumed values of other variables related to it.

The data collection method used in this study based on the direct data gathering from 32 published papers which contain 201 experiment results. The model input variables are consisting of five objective variables (i.e., ρ′, ε, creep coefficient, time "years" and fc′) which might affect the estimation of long term deflection the output variables are λ_{ACI} and λ_{Exp}. The selection of input variables for the model which had significant effect on the model efficiency is an important step in developing ANN Models. Introducing as substantial various info factors as conceivable to ANN Models for the most part expands organize estimate, bringing about a diminishing in handling speed and a decrease in the productivity of the system, Shahin, (2003).

The 5 parameters had the extreme considerable effect on the deflection and therefore used as the ANN Model inputs.

The following stage to improve the models of ANN is the division of the obtained data to them subsets, training, testing and validation sets. Trail-and-error process was used to choose the optimum allocation by using Neuframe, (Version 4) software program that is easy to use, transparent and customary to many practitioners in construction (Fig. 1).

Scaling of data: At the beginning the selected data should be separated to their subsets, the pre-processing of input and output variables by scaling them to exclude their dimension and to assure equal solicitude for all variables throughout training. The scaling in the hidden and output layers is required to proportional to the limitation of the transfer functions (i.e., -1.0-1.0 for tanh transfer function and 0.0-1.0 for sigmoid transfer function). For scaling the neural networks, the simple linear mapping of the variables was adopted for the extremes used for scaling because it's the most commonly used method, Shahin (2003). The scaled value X_n calculated according to Eq. 2 which is a function of this system each variable X had a minimum and maximum values of X_{min} and X_{max}, respectively (Eq. 2):

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

RESULTS AND DISCUSSION

Model architecture, optimization and stopping criteria: The determination of model architecture task had a great importance and difficulty for development of ANN Models (i.e., the hidden layer node's number and connectivity). The best network which performs with respect to the lowest testing error followed by

Table 1: Effect of data division on performance of ANNs

Data division					
Training (%)	Testing (%)	Querying (%)	Training error (%)	Testing error (%)	Coefficient correlation (r) (%)
80	**15**	**5**	**11**	**10.3**	**73.5**
70	10	20	10.4	07.9	65
68	12	20	09.9	11.3	64.4
66	14	20	10.3	10.5	65.6
65	15	20	11.2	10.5	64.1
65	20	15	10.9	12.1	68.8
60	20	20	10.6	10.4	64.6
60	25	15	10.6	11.5	70.3
60	30	10	10.8	10.9	65.1
55	30	15	10.6	10.5	68.4
55	25	20	10.1	11.1	66.1
55	20	25	09.5	11	52.5
50	30	20	11	11.6	64.4

*The highlighted cells represented the chosen division of data that effect on the performance of ANNs

training error and high correlation coefficient of validation set was retrained with different combinations of momentum terms, learning rates and transfer functions to develop the model rendering. Consequently, the ANN Model that has the optimum momentum term, learning rate and transfer function was retrained several times with different initial weights until no additional amelioration occurred, Alzwainy (2015) which was shown through Table 1-6.

The optimum network of the selected model is set to one hidden layer with learning rate equals to 0.2 and momentum term equals to 0.8 and the sigmoid transfer function was utilized for hidden and output layers whose include the lowest training error of 11.1% and testing error of 7.2% with the highest correlation coefficient of 96.6%, hence, it is used in this research.

Artificial neural network model formula: The small number of association weights acquired by Neuframe for the ideal ANNs Model empowers the network to be converted into moderately basic formula. To exhibit this, the the ANNs Model structure is appeared in Fig. 1 while as association weights and threshold levels (bias) are likewise outlined in Table 7.

Utilizing the connection weights and the threshold levels illustrated in Table 7, the predication of long-term deflection could be expressed as follows Eq. 3:

$$\lambda_{ANN} = \frac{1}{1+e^{(-0.752+5.8932\tanh x_1)}} \quad (3)$$

Where, Eq. 4:

$$X_1 = \begin{Bmatrix} \theta_6 + (w_{6\text{-}1} \times V_1) + (w_{6\text{-}2} \times V_2) + \\ (w_{6\text{-}2} \times V_2)(w_{6\text{-}4} \times V_4) + (w_{6\text{-}5} \times V_5) \end{Bmatrix} \quad (4)$$

Before using Eq. 3 and 4, a step should be done, all the input variables (i.e., $V_{1\text{-}5}$), should be scaled between 0.0 and 1.0 using Eq. 2 according to Table 8 were the data ranges in the ANN Model training shown.

Table 2: Effects of method division on ANNs performance

Data division (%)						
Training	Testing	Querying	Choices of division	Training error (%)	Testing error (%)	Coefficient correlation (r) (%)
80	15	5	Striped	11	10.3	73.5
80	15	5	Blocked	9	11.6	16.8
80	15	5	Random	11.1	07.2	96.6

Table 3: Effects no. of nodes on ANNs performance

Model no.	No. of nodes	Training error (%)	Testing error (%)	Coefficient correlation (r) (%)	Parameters effect
1	**1**	**11.1**	**07.2**	**96.6**00	choices of division
2	2	10.8	10.4	71.400	(Random)
3	3	11.1	09.2	75.400	Learning rate
4	4	10	12.5	77.500	(0.2)
5	5	10.5	10.1	78.209	Momentum term
6	6	11.3	11.1	63.800	(0.8)
7	7	10.8	09.6	80.500	Transfer function in hidden layer
8	8	10.3	10.7	69.400	(Sigmoid)
9	9	10.7	09.5	69.500	Transfer function in output layer
10	10	11.7	10	86.900	(Sigmoid)
11	11	11.4	14.6	54.500	-
12	12	10.3	08.3	59.600	-
13	13	09.9	12.4	65.100	-

*The highlighted cells represented the chosen division of data that effect on the performance of ANNs

Table 4: Effects momentum term on ANNs performance (Model 1)

Momentum Term	Training error (%)	Testing error (%)	Coefficient correlation (r) (%)	Parameters effect
0.01	10.3	13.1	67.4	Model no.(1)
0.05	11.7	10.2	72	Choices of division
0.1	11	11.8	72.9	(Random)
0.2	10.7	10.1	67.7	Learning rate
0.3	11.1	12.3	66.2	(0.2)
0.4	11	11.7	66.7	No. of nodes
0.5	11	11.1	68.5	(1)
0.55	11.1	10.4	68.2	Transfer function in hidden layer
0.6	10.6	11	54.4	(Sigmoid)
0.7	10.7	09	65	Transfer function in output layer
0.8	**11.1**	**07.2**	**96.6**	(Sigmoid)
0.9	10	10.7	75.2	-
0.95	10.7	11.4	64.2	-

*The highlighted cells represented the chosen division of data that effect on the performance of ANNs

Table 5:Effects learning rate on ANNs performance (Model 1)

Parameters effect	Learning rate	Training error (%)	Testing error (%)	Coefficient correlation (r) (%)
0.02	10.3	12.5	70.9	Model No.(1)
0.05	10	14	77.1	Choices of division
0.1	10.6	10.6	65.3	(Random)
0.15	10.5	10.8	80.7	Momentum term
0.2	**11.1**	**7.2**	**96.6**	(0.8)
0.3	12.1	8.9	59.7	No. of nodes
0.4	10.3	11.1	54.7	(1)
0.5	11.7	9	66.5	Transfer function in hidden layer
0.55	11.6	10	59.4	(Sigmoid)
0.6	12.5	10.2	67.1	Transfer function in output layer
0.7	10.8	12.2	63	(Sigmoid)
0.8	11.2	10.3	68	-

*The highlighted cells represented the chosen division of data that effect on the performance of ANNs

Table 6: Effects of transfer function on ANNs performance (Model 1)

Transfer function					
Hidden layer	Output layer	Training error (%)	Testing error (%)	Coefficient correlation (r) (%)	Parameters effect
Sigmoid	**Sigmoid**	**11.1**	**7.2**	**96.6**	Model no.(1)
Sigmoid	Tanh	11.6	9.6	75	Choices of division (Random)
Tanh	Sigmoid	11	7.1	70.9	No. of nodes (1)
Tanh	Tanh	12.4	10.5	50.5	Momentum term (0.8), Learning rate (0.2)

*The highlighted cells represented the chosen division of data that effect on the performance of ANNs

It should also be noted that the predicted value of long-term deflection obtained from Eq. 4 and 5 is scaled between 0.0 and 1.0 and in order to obtain the actual value of long-term deflection. It has to be re-scaled using Eq. 2 and the data from Table 8. The procedure for scaling and substituting the values of the weights and

Table 7: Weights and threshold levels for the ANNs optimal model (Model 1)

	w_{ji} (weight from node i in the input layer to node j in the hidden layer)					
Hidden layer nodes	i = 1	i = 2	i = 3	i = 4	i = 5	Hidden layer threshold θ_j
j = 6	1.27735	-0.85767	-0.393090	-4.2911	1.91919	-1.05576
	w_{ji} (weight from node i in the hidden layer to node j in the output layer)					
Output layer nodes	i = 6	-	-	-	-	Output layer threshold θ_j
j = 7	-5.8932	-	-	-	-	0.75156

Table 8: Input and output statistics for the ANNs (Model 1)

Parameters	ρ (%)	ε	Creep coefficient	Time year	fc´ kN/m^2	Output
Max	1.666253	0.00019	1.7	5.069	34.6	2.681529
Min	0	0.00016	1.4	0.4722	18.8	0.494163
Rang	1.666253	0.00003	0.3	4.597	15.8	2.187365

threshold levels is shown in Table 7. The predicted of long-term deflection can be expressed as follows (Eq. 5):

$$\lambda_{ANN} = \frac{2.187365}{1+e^{(-0.752+5.893\tanh x_1)}}+0.494163 \quad (5)$$

And Eq. 6:

$$x_1 = 0.77\rho' - 2.86\varepsilon + 1.31cc - 0.933t + 0.121fc' + 3.511 \quad (6)$$

Validity of the ANN Model: The statistical measures used to understand the performance of the optimum ANN Models:

Mean Absolute Percentage Error (MAPE) Eq. 7:

$$MAPE = \left(\sum_{i=1}^{n}\frac{|A-E|}{A}*100\%\right)\Big/n \quad (7)$$

Where:
A = Experimental value
E = Predicted value
n = Number of trails

Average Accuracy percentage (AA %)

$$AA\% = 100\% - MAPE \quad (8)$$

- The Coefficient of Correlation (R)
- The Coefficient of Determination (R^2)

The coefficient of determination standardizes how well the model outputs qualified the objective esteem. The MAPE and percentage RMSE are control of the average error.

The statistical values of checking the ANN Model validity are given in Table 9. (i.e., the MAPE and average accuracy percentage created by ANN Model were observed to be 3 and 97%, respectively). In this way, it can be presumed that ANN demonstrates a good agreement with the real measurements.

Table 9: Results of the comparative study

Description	ANN for Model 1 (%)
MAPE	2.43
AA %	97.5
R	96.6
R^2	93.36

Table 10: Error categorization (%), Schexnaydr and Mayo (2003)

MAPE		
Good	Fair	Poor
<25	25-50	>50

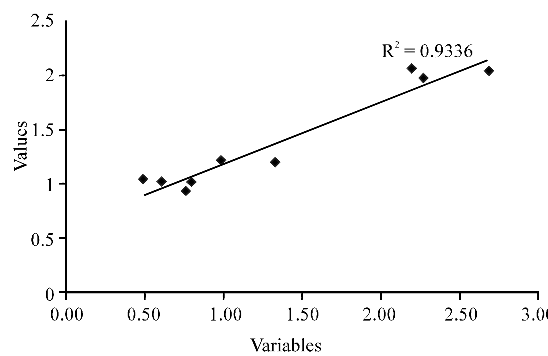

Fig. 2: Comparison of predicted and observed deflections for validation data

Numerous trails were performed to produce the statistical values as illustrated in Table 9 while the error categorization was set up to conceptual estimate. Schexnayder and Mayo (2003) proposed the error of estimation was approximately between ±25%. According to this study, MAPE of Model 1 was good 3%.

To assess the accuracy of the ANNs Model for predicting the long term deflection. Predicted values of long-term deflection are plotted against measured values as illustrated in Fig. 2 and summarized in Table 10 and 11. It is clear from Fig. 2 that the coefficient of determination (R^2) is 93.36%, so, ANNs Model indicates great concurrence with the experimental results.

Table 11: Results of the comparative study

Input data					Output data		
ρ' (%)	Shrinkage *0.001 mm/m (ε)	Creep coefficient	Time years	fc' MPa	ACI (λ)	Exp. (λ)	ANN equation (λ)
0	0.00019	1.7	5.06944444	28.8	2.00	2.19	2.678155
1.666253	0.00019	1.7	2.575	20.3	0.94	0.99	0.507534
0	0.00016	1.4	4.95277778	19.8	1.99	2.68	2.627996
0	0.00016	1.4	0.81944444	34.6	1.33	0.80	0.506729
0	0.00016	1.4	0.81944444	34.6	1.33	0.49	0.506729
0	0.00016	1.4	1.55833333	30	1.56	1.33	0.506791
1.241935	0.00016	1.4	2.22222222	32	1.03	0.76	0.506745
0	0.00019	1.7	5.06944444	18.8	2.00	2.26	2.673041
1.428217	0.00019	1.7	0.47222222	34.1	0.69	0.62	0.506724

CONCLUSION

In this research, ANN technique used for the prediction of long term deflection of reinforced concrete flexural members. A multilayer feed-forward neural network with back-propagation algorithm was applied. The results show that ANN Model is able to learn the cause-effect relationships between input and output, during the training stage, the proposed model is capable of predicting with reasonable accuracy the long-term deflection of flexural members in compare with the experimental data. Obtained average accuracy percentage is 97.5% and the coefficient of correlation is 96.6%.

This model takes into consideration the influence of compression reinforcement, creep coefficient, shrinkage strain, total time of experiment and the ultimate compressive strength.

The agreement between the proposed model of long term deflection and the ACI (2011) is good with coefficient of correlation of 86.6%.

REFERENCES

ACI, 2011. Building Code Requirements for Structural Concrete (ACI 318M-11). American Concrete Institute, Farmington Hills, MI48331, USA., Pages: 509.

Al-Numan, B.S., 2007. Analytical model for estimating long-term deflectionsof two-way reinforced concrete slabs. J. Eng. Dev., 11: 1-12.

Alzwainy, F.M.S., A.R.H. Suhaily and Z.M. Saco, 2015. Project Management and Artificial Neural Networks: Fundamental and Application. Lambert Academic, Germany, Pages: 288..

Branson, D.E. and G.A. Metz, 1963. Instantaneous and time-dependent deflections of simple and continuous reinforced concrete beams. Master Thesis, Department of Civil Engineering, Auburn University, Auburn, Alabama.

Branson, D.E., 1971. Compression steel effect on long-time deflections. J. ACI., 68: 555-559.

Espion, B., 1988. Long-term sustained loading tests on reinforced concrete beams: A selected data base. Master Thesis, Université libre de Bruxelles, Brussels, Belgium.

Leet, K., 1997. Reinforced Concrete Design. 3rd Edn., McGraw-Hill, New York, USA., Pages: 155.

Lieping, Y., F. Peng and Y. Qingrui, 2011. Experimental Time-Dependent Deflections of Concrete Beams Reinforced with GFRP Bars. In: Advances in FRPþ Compsites in Civil Engineering, Mias, C., L. Torres, A. Turon and C. Barris (Eds.). Springer, Berlin, Germany, ISBN:9783642174865, pp: 352-355.

McCormac, J.C. and H.B. Russell, 2014. Design of Reinforced Concrete. 9th Edition, John Wiley & Sons, Hoboken, New Jersey, USA.,.

Meyers, B.L., J.R. Benjamin, G.M. Sabnis, W.C. Alsmeyer and D. Branson *et al*., 1972. Variability of deflections of simply supported reinforced concrete beams. J. Amer. Concr. Inst., 69: 29-35.

Muhaisin, H.M., 2012. Long-term deflection for normal and high strength reinforced cocrete beams. J. Babylon Univ. Eng. Sci., 20: 46-62.

Paulson, K.A., A.H. Nilson and K.C. Hover, 1991. Long-term deflection of high-strength concrete beams. Mater. J., 88: 197-206.

Schexnayder, C.J. and R.E. Mayo, 2003. Construction Management Fundamentals. McGraw-Hill, Boston, Massachusetts,.

Shahin, M.A., 2003. Use of artificial neural networks for predicting settlement of shallow foundations on cohesionless soils. Ph.D Thesis, Department of Civil and Environmental Engineering, University of Adelaide, Adelaide, South Australia.

Shallal, M.A., 2013. Prediction of long-term deflection of reinforced concrete beams suitable for Iraqi conditions. J. Babylon Univ. Eng. Sci., 21: 1328-1347.