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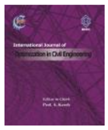

PREDICTION OF LOAD DEFLECTION BEHAVIOUR OF TWO WAY RC SLAB USING NEURAL NETWORK APPROACH

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ABSTRACT

Reinforced concrete (RC) slabs exhibit complexities in their structural behavior under load due to the composite nature of the material and the multitude and variety of factors that affect such behavior. Current methods for determining the load-deflection behavior of reinforced concrete slabs are limited in scope and are mostly dependable on the results of experimental tests. In this study, an alternative approach using Artificial Neural Network (ANN) model is produced to predict the load-deflection behavior of a two-way RC slab. In the study, 30 sets of RC slab specimens of sizes 700mm x 600mm x 75mm were cast, cured for 28days using the sprinkling method of curing and tested for deflection experimentally by applying loads ranging from 10kN to 155kN at intervals of 5kN. ANN model was then developed using the neural network toolbox of ANN in MATLAB version R2015a using back propagation algorithm. About 54% of the RC specimens were used for the training of the network while 23% of the sets were used for validation leaving the remaining 23 % for testing the network. The experimental test results show that the higher the applied load on the slab, the higher the deflection. The result of the ANN model shows a good correlation between the experimental test and the predicted results with training, validation and test correlation coefficients of 0.99692, 0.98921 and 0.99611 respectively. It was also found that ANN model is quite efficient in determining the deflection of 2-way RC slab. The predicted accuracy of performance value for the load-deflection set falls at 96.67% of the experimental load-deflection with a 0.31% minimum error using the Microsoft spreadsheet model. As such the comprehensive spreadsheet tool created to incorporate the optimum neural network. The spreadsheet model uses the Microsoft version 2013 excel tool software and can be used by structural engineers for instantaneous access to the prediction if any aspect of a concrete slab behavior given minimal data to describe the slab and the loading condition.

Keywords: reinforced concrete, 2- way slab, load- deflection, artificial neural network and prediction model.

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1. INTRODUCTION

Among the major structural elements, two-way slab forms a unique part of reinforced concrete floor. It is an efficient, economical, and widely used floor structural system. It is supported on all four sides and the length is less than twice the width. The slab will deflect in two directions according to Park [1], and the loads on the slab are transferred to all supports. Reinforced concrete slabs exhibit a level of complexity which is due to the composite nature of the material and the multitude and variety of factors in its behavior. These factors are equally responsible for the difficult nature of load- deflection calculations of two-way slabs. Traditionally, mathematical models, finite element (FE) analysis, and experimental testing are used in the practical study of load-deflection behavior. Neural networks can be used as preliminary alternatives to mathematical models or experimental testing for quick prediction of the load- deflection behavior of a two-way reinforced concrete slab. The neural network has the ability to simulate the behavior of systems with limited modeling effort and provide speedy and reasonably accurate solutions in complex, uncertainties and subjective situations as reported by previous researchers [2, 3]. Such prediction could be useful to a structural engineer on a preliminary basis to determine the initial suitability of a particular slab design

Over the past ten years, extensive research on the structura1 behavior of concrete slabs has been conducted including a number of experimental tests on full-scale reinforced concrete slabs. The research has been documented in several publications. Marzouk and Hussein [4] studied the behavior of seventeen normal and high strength concrete slabs subjected to concentrated loads applied axially through a stub column. Jiang [5] conducted supplemental tests on seven high strength concrete slabs which studied the effects of shear reinforcement on the slabs' behavior. Emam [6] had conducted an additional test on fourteen reinforced concrete slabs and column connections subjected to not only axial load but also bending moment. One common denominator in the earlier work lies on the fact of using mathematical models or testing load deflection characteristics of real life Rc slab systems. Developing mathematical models to predict concrete behavior under different loading conditions focus generally upon determining the behavior of individual structural elements. This requires the calculation of several equations to arrive at predictions for more than one parameter. The case of lengthy analytical solutions for structural designs and experimental determination of load-defection behavior in structural elements suggest the need for reliable alternative prediction. Garrett [7] stated that modeling with neural networks is much simpler because, although a neural network captures the mathematical relationships in its collection of interconnections between its nodes, no formal mathematical or formulae are used or observable within the model. Kaveh and Khalegi [8] reported that the artificial neural network can be used to predict concrete strength with less error less than 10%.

Garrett [9] further explained that for mathematical models, several iterations of the following procedure were necessary:

i. A material was tested and its behavior observed;
ii. Some mathematical relationship was postulated to explain its observed behavior,
iii. This mathematical model was used to predict yet untested concrete design and was checked against results from experiments; and

iv. The mathematical mode1 was then modified to account for behaviors observed but unexplained by the model.

These procedures may be limited to the application of ANN with an antecedent gain in time and cost.

1.1 Artificial neural networks (ANNs)

Beale, (2011) stated that Neural networks (NNs) offer an approach to computation that is different from conventional analytic methods; learn from experience and abstract essential characteristics from inputs containing irrelevant data. According to Elazouni, Ali [10] neural networks are a series of interconnected processing elements (artificial neurons) in a number of layers. NNs are trained using available data to understand the underlying pattern. During training, both the inputs (representing problem parameters) and outputs (representing the solutions) are presented to the network normally for thousands of cycles. At the end of each cycle, or iteration, the network evaluates the error between the desired output and actual output. Demuth, Beale [11] opined that the output of any layer provides the input to the subsequent layer and the strength of the output is determined by the connection weights between the neurons of two adjacent layers.

MATLAB (R2015a) provides NN toolbox functions and applications for modeling complex nonlinear systems that are not easily modeled with a closed-form equation. Principe, Lefebvre [12] added that these functions can take many forms: Linear, Logistic, and tangent. Most commonly used are threshold function (Hard limit), a sigmoid function, tanh function, and Bias function. Jiang [5] stated that there are many types of neural networks, but all have three things in common. A neural network can be described in terms of its individual neurons, the connections between them (topology), and it's learning rule as shown in Fig. 1.

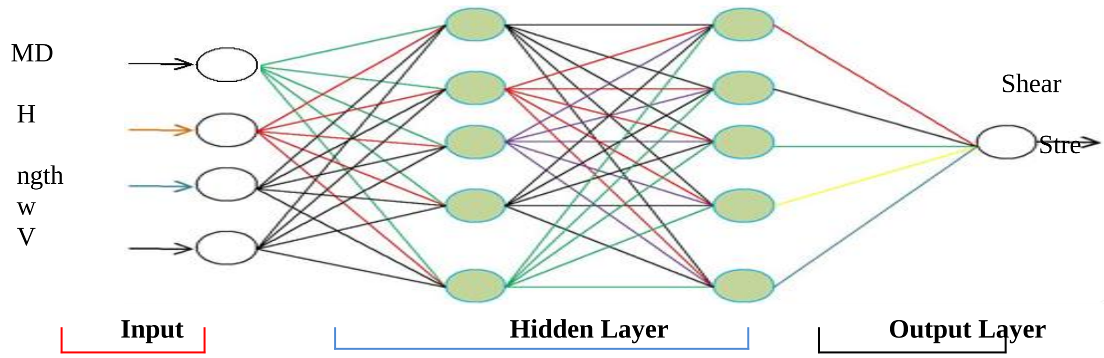


Figure 1. Network configuration with 4-5-5-1 for shear load and deflection prediction
*MD –Major diameter (mm), H –Height (mm), W –Weight (g), V –Volume (mL)

Different ANN methods has been used for design and design of several types of civil engineering structures these includes; design and analysis of large-scale structure [13], analysis design of double layer grid spanning up to 75 m using backpropagation algorithm [14, 15], analysis, design and predicting displacement of domes using backpropagation and radial basis functions neural network [16].

2. METHODOLOGY

The problem was evaluated by reviewing the theory and current practice in both ANN and strength behavior prediction of simply supported two-way RC slab. The structural behavior of the slab was examined by idealizing the slabs under loading and selecting appropriate ANN software. Then, conduct a preliminary investigation on the load- deflection neural network to determine the suitability of the NN technique for the problem, experimenting and training to achieve the optimum results which, is incorporated into a single spreadsheet tool to summarize the research objective.

2.1 Slab design procedure

A flat slab 700mm x 600mm 75mm panel divided into column strip and middle strips without drops were considered. The design moments obtained from the analysis was divided into the strips in the apportioned proportions of negative and positive moments as stated in the code BS 8110 (1997).

$$\text{Negative moment; } M = 0.04Fl \tag{1}$$
$$\text{Positive moment; } M = 0.083Fl \tag{2}$$

F is the total design ultimate load on the strip of the slab
L is the effective span

$$\text{Total design ultimate load (F)} = 1.4gk+1.6qk\ (kN) \tag{3}$$
$$\text{Area of reinforcement, (As) } K = \frac{m}{bd^2 fcu} \tag{4}$$

fcu = compressive strength of concrete, m = moment, d = effective depth of slab

$$La = 0.5 \pm \sqrt{0.25 - \frac{K}{0.9}}z < 0.95d \tag{5}$$
$$As = \frac{m}{0.95fyz} \qquad (mm^2/m) \tag{6}$$

As = Area of steel provided, Fy = compressive strength of steel
Deflection checking
Deflection is safe if,

$$(L/d)_{actual} < (L/d)_{allowable} \tag{7}$$
$$(L/d)_{allowable} = (L/d)_{basic} \times m.f.t.r \times m.f.c.r \tag{8}$$

$(L/d)_{basic}$ from Table 3.9 BS8110: Part 1:1997.
m.f.t.r = modification factor for tension reinforcement
m.f.c.r= modification factor for compression reinforcement
$(L/d)_{allowable}$= allowable span/effective depth ratio

$$\mathrm{m.f.t.r} = 0.55 + \frac{(477 - fs)}{\{120\left(0{,}9 + \frac{\mathrm{m}}{bd^2}\right)\}} \leq 2.0 \tag{9}$$

$$fs = \frac{5}{8} fy \frac{\mathrm{Asreq}}{\mathrm{Asprov}} \tag{10}$$

As_{req} = area of tension reinforcement required, Asprov = area of tension reinforcement provided

fs = service stress.

2.2 Experimentation

In BS 8110 (1997) [17] approach for a load-deflection study on a two-way RC slab, The slabs produced in this study measuring 700mm x 600mm x75mm were subjected to vertical loading over a Gibson MTK-500-(2224KkN) compression testing machine as shown in Fig. 2. The slab was supported on its four edges. Compression load was applied gradually until deflection occurs. Deflection at the slab center was measured using linear variable dial gauge placed under the compression setup at mid-span of the slab. Cracks were marked during loading and the final deflection pattern was observed. This was repeated on 29 other slabs of the same geometry, with different load intensities to deflect and were recorded accordingly. During the load distribution, the dial gauges were connected and deflection reading was observed and recorded.

Figure 2. Experimental setups for Load-Deflection test on 700x600mm slab

On the other hand, the NN study was developed using MATLAB (R2015a) package. The load-deflection test results for the thirty small scale RC slabs produced in this work were formulated into the appropriate input and output format. 3 - Column matrix containing the input parameter (Load (kN), Stress (kN/m^2) and deflection (mm) as the output parameter) were fed into the workspace. These automatically made the input neurons in the input layer to be three (3). The number of neurons in the hidden layer for optimum convergence was found to be two (2). Since the output parameter is one (1) (deflection), the numbers of neurons in the output layer were found to be one (1). Thus the values of parameters used in this work are as follows:

Numbers of input layers units = 3
Numbers of hidden layer = 2
Numbers of output layer unit = 1
Learning Cycle = 16

The linear tan-sigmoid function for concrete modeling was used as the transfer function in the hidden layer. In order to develop the NN model, the available data were divided into three subsets: the training set to construct the NN model, Validation set and test set to estimate the model accuracy performance. The data division ratio of 53.30% for training, 23.35% for validation and 23.35% for testing was used thus among the 30 data set: 16 randomly collected data were used in the training stage, 7 for validation and the remaining 7 data set were used in testing the network accordingly. The spreadsheet was developed as a Microsoft Excel v13 (2013) Workbook which interfaces with the MATLAB neural network toolbox software for predictions. The spreadsheet considers the slab geometry, constituent material properties, loading and boundary conditions in the model prediction as captured in Fig. 3.

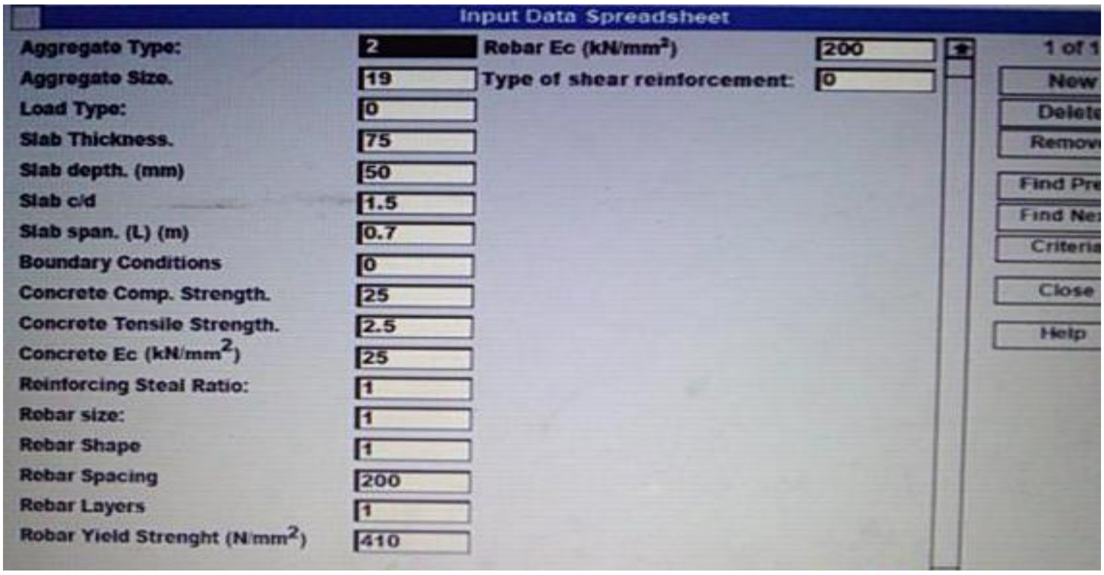


Figure 3. Input data spreadsheet

3. RESULTS AND DISCUSSIONS

The result of the load-deflection experimental study for the 2-way RC slab (700mm x 600mm) is presented in Table 1 and Fig. 4.

Table 1: Load-deflection results for two- way simply supported RC slab

S/No	Load(kN)	Stress (kN/m^2)	Deflection (mm)
1	10	23.81	0.03
2	15	35.71	0.07
3	20	47.62	0.12
4	25	59.52	0.17
5	30	71.43	0.19
6	35	83.33	0.23
7	40	95.24	0.27
8	45	107.14	0.39
9	50	119.05	0.55
10	55	130.95	0.73
11	60	142.86	1.28
12	65	154.76	1.44
13	70	166.67	1.67
14	75	178.57	2.31
15	80	190.48	2.79
16	85	202.38	3.35
17	90	214.29	3.92
18	95	226.19	4.42
19	100	238.10	4.85
20	105	250.00	5.38
21	110	261.90	5.93
22	115	273.81	6.16
23	120	285.71	6.38
24	125	297.62	6.47
25	130	309.52	6.65
26	135	321.43	6.71
27	140	333.33	6.79
28	145	345.24	6.83
29	150	357.14	6.84
30	155	369.05	6.97

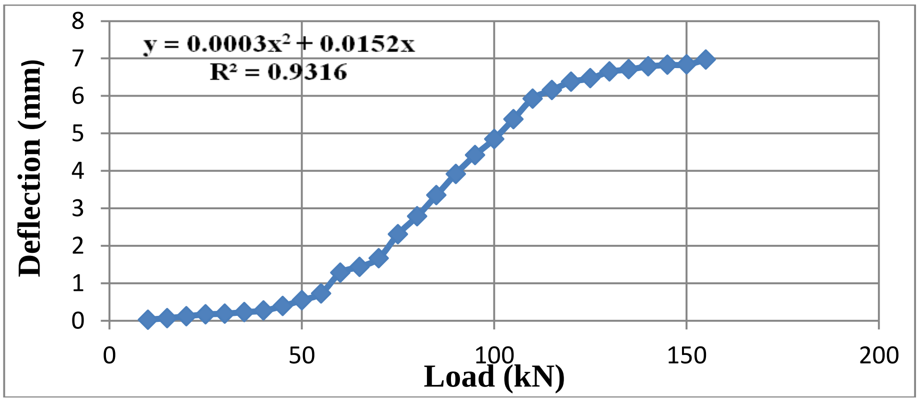


Figure 4. Load-Deflection Curve for two-way simply supported RC slab

From Table 1 and Fig. 4, it is evident that the stress increases with increase in load. Also, maximum deflection occurs at a load of 155kN or stresses 369.05kN/m^2. The regression analysis show that R^2 = 0.9316 with a curve equation of $y = 0.0003x^2 + 0.0152x$. This confirms that the relationship between load-deflection is nonlinear. Table 2 and Fig. 5 represent the load-deflection training, revalidation and testing using Artificial Neural Network. The results which predicted the deflection errors of the slab at thirty different load increments with experimental loads and deflections compares the weighted errors resulting from the training with those produced by the test error. The results of training, validation, and testing presented in Table 3 and Fig. 6 show that the models have excellent performance. It gives an average agreement between the actual and predicted values of the slabs with correlation factors of 0.834, 0.956 and 0.799 respectively. The accuracy of the best model developed by back-propagation network appears very favorable with data based on test set

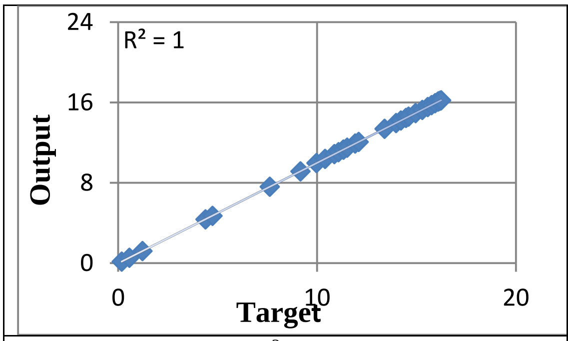
Table 2: ANN load deflection training result for two- way simply supported RC slab

s/No	Load (kN)	Load (kN/m2)	Deflection (mm)	Training Mean Error (%)	Test Mean Error (%)	Validation Error (%)	Weighted Error (%)	Deflection Error (%)
1	10	23.81	0.03	1.22	1.07	0.0078	0.90	0.00
2	15	35.71	0.07	0.18	1.21	0.019	0.38	0.00
3	20	47.62	0.12	0.56	1.52	0.033	0.66	0.00
4	25	59.52	0.17	4.39	2.10	0.047	2.84	0.01
5	30	71.43	0.19	4.74	2.37	0.056	3.09	0.01
6	35	83.33	0.23	7.62	2.43	0.075	4.65	0.01
7	40	95.24	0.27	9.17	2.64	0.083	5.52	0.01
8	45	107.14	0.39	9.97	2.82	0.090	5.99	0.01
9	50	119.05	0.55	10.41	3.39	0.093	6.36	0.02
10	55	130.95	0.73	10.87	3.72	0.097	6.69	0.02
11	60	142.86	1.28	11.08	3.97	0.11	6.86	0.04
12	65	154.76	1.44	11.32	4.21	0.13	7.05	0.05
13	70	166.67	1.67	11.33	4.67	0.17	7.17	0.06
14	75	178.57	2.31	11.52	5.33	0.52	7.51	0.08
15	80	190.48	2.79	11.92	5.46	0.78	7.81	0.09
16	85	202.38	3.35	12.10	6.16	0.94	8.11	0.11
17	90	214.29	3.92	13.39	6.27	1.032	8.85	0.13
18	95	226.19	4.42	13.97	6.42	1.072	9.20	0.15
19	100	238.10	4.85	14.22	6.67	1.17	9.41	0.16
20	105	250.00	5.38	14.47	7.32	1.12	9.69	0.18
21	110	261.90	5.92	14.61	9.76	1.086	10.33	0.20
22	115	273.81	6.16	14.95	10.11	1.067	10.58	0.21
23	120	285.71	6.38	15.29	10.32	1.054	10.81	0.21
24	125	297.62	6.47	15.56	10.53	1.048	11.00	0.22
25	130	309.52	6.65	15.76	11.65	1.031	11.37	0.22
26	135	321.43	6.71	15.94	11.89	1.027	11.52	0.22
27	140	333.33	6.79	16.09	12.03	1.022	11.63	0.23
28	145	345.24	6.83	16.12	12.22	1.020	11.69	0.23
29	150	357.14	6.84	16.19	12.29	1.018	11.74	0.23
30	155	369.05	6.97	16.24	12.54	1.014	11.83	0.23

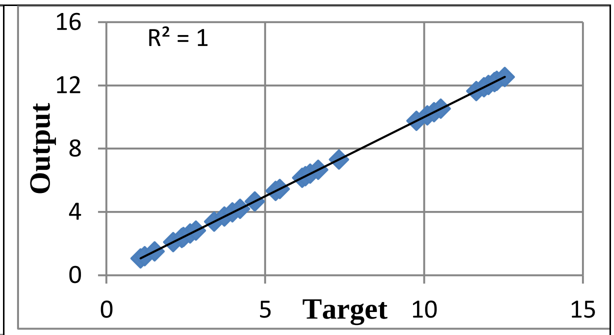
Figure 5. NN Load-Deflection Validation Performance curve for the trained network

Table 3: Summarized Result of Analyzed NN Load Deflection Performance measurement for model

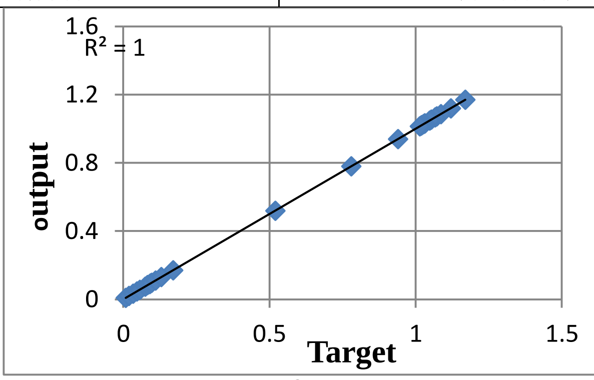
	Data Set	Mean Error	Weighted mean error (%)	Correlation Factor (R)	Mean Absolute Error (%)	Mean Absolute performance Error (%)	Accuracy performance (%)
Back propagation model	**Training set**	11.373	0.0492	0.99692	3.410	3.333	96.67
	Test set	6.436	0.0278	0.99611	1.931	3.334	96.67
	Validation set	0.601	0.00260	0.98921	0.180	3.327	96.67



Train: R^2 =0.99692



Validation: R^2 =0.98921



Testing: R^2 = 0.99611

Figure 6. Analyzed NN load deflection performance after training

The result shows that the at 155kN applied load on the slab, with a deflection of 6.97mm, a mean absolute performance error of 3.33% was measured for the test set, giving an average predicted error 0f 0.31% at 96.67 accuracy performance. Also, an average agreement between the actual and predicted values of the slabs, with a correlation factor of 0.99692, 0.99611 and 0.98921respectively, were obtained as it tends to 100% of the entire set.

Table 4: Results for optimum load-deflection neural network

Load (kN)	**Deflection (mm)**	**NN Deflection (mm)**	**Deflection Error (%)**
10	0.03	0.03	0.00
15	0.07	0.07	0.00
20	0.12	0.12	0.00
25	0.17	0.16	0.01
30	0.19	0.18	0.01
35	0.23	0.22	0.01
40	0.27	0.26	0.01
45	0.39	0.38	0.01
50	0.55	0.53	0.02
55	0.73	0.71	0.02
60	1.28	1.24	0.04
65	1.44	1.39	0.05
70	1.67	1.61	0.06
75	2.31	2.23	0.08
80	2.79	2.70	0.09
85	3.35	3.24	0.11
90	3.92	3.79	0.13
95	4.42	4.27	0.15
100	4.85	4.69	0.16
105	5.38	5.20	0.18
110	5.93	5.73	0.20
115	6.16	5.95	0.21
120	6.38	6.17	0.21
125	6.47	6.25	0.22
130	6.65	6.43	0.22
135	6.71	6.49	0.22
140	6.79	6.56	0.23
145	6.83	6.60	0.23
150	6.84	6.61	0.23
155	6.97	6.74	0.23

Comparing the experiment load-deflection results obtained with those of the optimum NN load-deflection results, Table 4 shows a maximum NN deflection of 6.74mm at 96.67% of the corresponding actual deflection of 6.97mm for a maximum load of 155kN. Also at the lowest actual deflection of 0.03mm, a corresponding lowest NN deflection of 0.03mm was obtained with a deflection error of 0.0%. Fig. 7 gave a regression line (R^2) of 0.9316 similar to that from Fig. 4 of the load-deflection curve for two-way simply supported slab with NN model equation of $y = 0.0002x^2 + 0.0147x$. The results suggest that the spreadsheet model performs well with 96.67% accuracy when presented with increasing number of slabs within the domain used to train the NN for the spreadsheet.

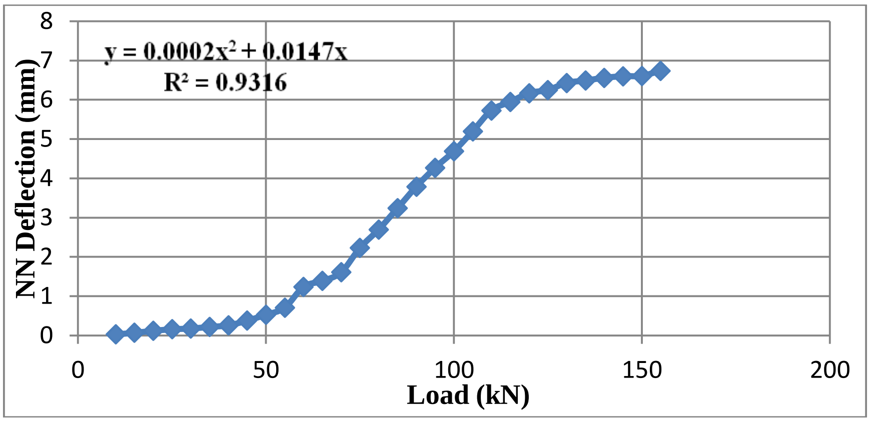


Figure 7. NN load-deflection curve

4. CONCLUSIONS

1. The deflection behavior of the two-way RC slab was found to increase with a corresponding increase in load.
2. Neural network performs best when a minimal number of outputs are predicted by the model. In this study, an average accuracy performance of 96.67% NN prediction with a minimum deflection error of 0.31% was obtained.
3. Neural network model predicted results with the minimum errors when presented with test cases within the domain of the training cases, especially when a minimal number of cases were used to train the model.
4. The load-deflection curves produced by the neural network models closely matched those produced during experimental testing. The NN load-deflection curve produced a model equation of $y = 0.0002x^2 + 0.0147x$ while the experimental load-deflection curve produced $y = 0.0003x^2 + 0.0152x$, both with correlation $R^2 = 0.9316$.
5. The spreadsheet helped to summarize the input parameters of the factors that govern the properties of a slab. It is a powerful tool that can be used to illustrate the vast amount of data.

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