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Prediction of short- and long-term deflections of reinforced concrete flat plates using artificial neural network

Tahsin Reza Hossain[1], Salah Uddin Ahmed[2] and Md. Saiful Alam Siddiquee[3]

[1]Department of Civil Engineering
Bangladesh University of Engineering and Technology, Dhaka 1000, Bangladesh
[2]Structural Engineer
Binirman Design Studio, Dhaka, Bangladesh
[3]Application Engineer -Geotechnical
Bentley Systems Inc., USA

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Abstract

For a structure to serve its purpose properly, members need to be proportioned so that they will have adequate strength against failure and at the same time must possess sufficient stiffness to ensure serviceability. ACI, BNBC and other building codes suggest minimum thickness for flat plate slabs so that the deflections are not excessive. It also permits thinner slabs if calculated deflections are found tolerable. The procedure given in ACI and BNBC codes for deflection estimation is reasonably straightforward in compare to other codes. They use Branson's equation to take cracking along with tension stiffening into account for short-term deflection calculation. This calculation approach, suitably incorporated in a finite element (FE) package, had been used to estimate instantaneous deflections of two-way slabs. As for long-term deflection, a simplified multiplier approach is proposed in ACI/BNBC code which is easier to use. However, use of this finite element package is neither easy to use in the design office nor it is available to everybody. An attempt has been made in this paper to train a customized Artificial Neural Network (ANN) program using the results of the FE package and use the trained network to readily predict the deflection of flat plates. ANN is particularly suitable for predicting output parameters which depend upon a large number of input parameter like span, aspect ratio, DL, LL, fc', fy etc. An example demonstrates some simple steps in calculating short- and long-term deflections.

Keywords: Concrete slab, deflection, slab thickness, serviceability, neural network.

1. Introduction

In strength design, the structural members are so proportioned that will have a prescribed safety margin against failure under an overload state. It is also important that the member performance in normal service condition be satisfactory. This performance, termed as serviceability, is not ensured simply by providing adequate strength. Service load deflections under full load may be excessively large, or long-term deflections due to sustained load may cause damage to partition walls. There are other serviceability related problems like visually disturbing wide tension cracks, vibrations causing discomfort etc. which may hinder the performance of the structure.

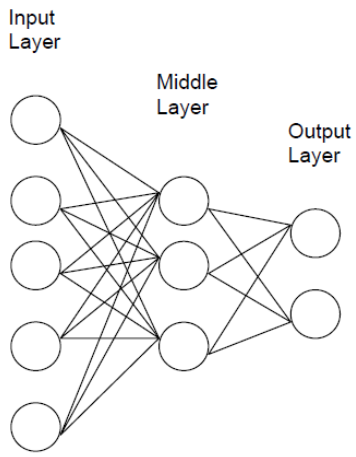

Fig. 1. Basic structure of a neural network.

In the past, questions of serviceability were dealt indirectly by limiting the working stresses in concrete and steel at service loads to some rather conservative values that resulted in satisfactory performance. Now, with strength design methods in general use that allow more slender members through more accurate assessment of capacity, such indirect methods of working stress design method will no longer do. Use of high strength materials further contributes toward this trend of smaller member sizes. ACI Code (2014) and BNBC (2017) provisions are identical in proposing minimum slab thickness to ensure serviceability and at the same time allows thinner slabs if deflection calculation permits so. ACI and BNBC codes also provide same deflection calculation procedure which is rather straightforward. A general-purpose finite element package, suitably adopted to take into consideration the effect of cracking according to ACI/BNBC Code, has been proved reasonable to predict deflection in several previous studies Hossain (1999), Hossain et. al (2005), Hossain and Alam (2004), Hossain and Alam (2003). However, use of this nonlinear finite element package is neither easy to use in the design office nor it is available to everybody. As deflection depends on a number of parameters, it is possible to employ an Artificial Neural Network program which can establish a relation between a large number of input and output by learning from known values. Hossain et al. (2007) carried out a study to train a neural network for edge-supported slab. In the current work, a customized ANN computer program of Siddiquee (2007) has been trained using the nonlinear FE results (Ahmed, 2007) so that it can be used to predict deflections as an alternative to performing time-consuming explicit FE analysis.

2. Description of the FE model and validation

A program module based on global plate stiffness approach has been developed by Hossain (1999) to incorporate the different short- and long-term models for predicting deflection of reinforced concrete slabs. The module acts as an integral part of the FE package FE77 (1999) and calculates modified elastic properties to represent cracking, creep and shrinkage for each element, on the basis of stresses of FE solution, which are then fed back into the assembly module of the FE package. Hossain and Vollum (2002) found good correlation in analysis of the real full scale 7 storied building at Cardington using this FE module employing EC2

(1992) and CEB-FIP Model Code 1990 MC-90 (1990) where creep and shrinkage deflections are dealt with more rigorously along with the effect of construction load. Deflection estimation procedure in ACI Code (2014) and BNBC (2017)is simpler than these codes where long-term deflections are calculated from instantaneous deflection using multiplier. Branson’s crack model (1977) is adopted in these codes to calculate instantaneous deflection and has been used in the current work.

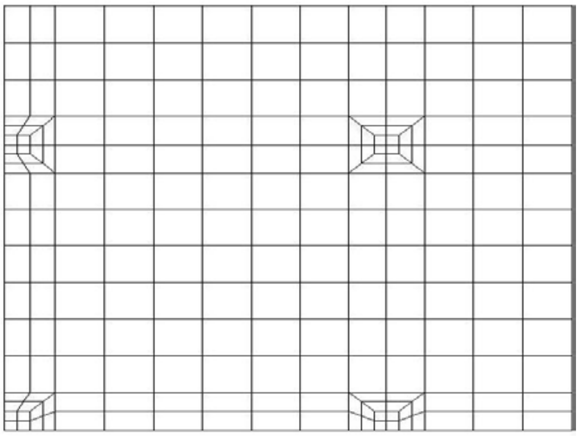

Fig. 2. The finite element mesh for 3x3 panel (1/4th slab).

In the current work, within the FE program, elastic moments in two principal directions for each element are calculated in the first run which are then used to calculate the effective moment of inertia in two principal directions using Branson’s (1977) equation:

$$I_{e1} = \left(\frac{M_{cr}}{M_1}\right)^3 I_g + \left[1 - \left(\frac{M_{cr}}{M_1}\right)^3\right] I_{cr1} \tag{1}$$

$$I_{e2} = \left(\frac{M_{cr}}{M_2}\right)^3 I_g + \left[1 - \left(\frac{M_{cr}}{M_2}\right)^3\right] I_{cr2} \tag{2}$$

where, I_g and I_{cr} are gross and cracked moment of inertia of slab element. M_{cr} is the moment at which cracks occur and M_1 and M_2 are the principal moments. Modification factors α_n and α_t for major and minor principal directions are calculated using:

$$\alpha_n = \frac{I_{e1}}{I_g} \tag{3}$$

$$\alpha_t = \frac{I_{e2}}{I_g} \tag{4}$$

The constitutive matrix [E′]is modified in the principal directions as follows for each element:

$$[E'] = \begin{bmatrix} \frac{\alpha_n E_c}{(1-\nu^2\alpha_n\alpha_t)} & \frac{\nu\alpha_n\alpha_t E_c}{(1-\nu^2\alpha_n\alpha_t)} & 0 \\ \frac{\nu\alpha_n\alpha_t E_c}{(1-\nu^2\alpha_n\alpha_t)} & \frac{\alpha_t E_c}{(1-\nu^2\alpha_n\alpha_t)} & 0 \\ 0 & 0 & \frac{E_c\sqrt{\alpha_n\alpha_t}}{2(1+\nu\sqrt{\alpha_n\alpha_t})} \end{bmatrix} \tag{5}$$

This [E′] matrix for each element is then transformed into global directions and fed back into the assembly module of the FE package. The analysis is repeated with the modified stiffness and the deflections obtained are therefore deflections considering cracking and tension stiffening. In reality, there would be stress redistribution due to cracking. However, earlier studies Polak (1996), Hossain (1999) indicate that effect of stress redistribution is not significant. Hossain et. al. (2011) successfully used Branson's equation as given in ACI/BNBC Code to model stiffness reduction due to cracking considering tension stiffening and used long-term multipliers to calculate long-term deflections of the full-scale Cardington building.

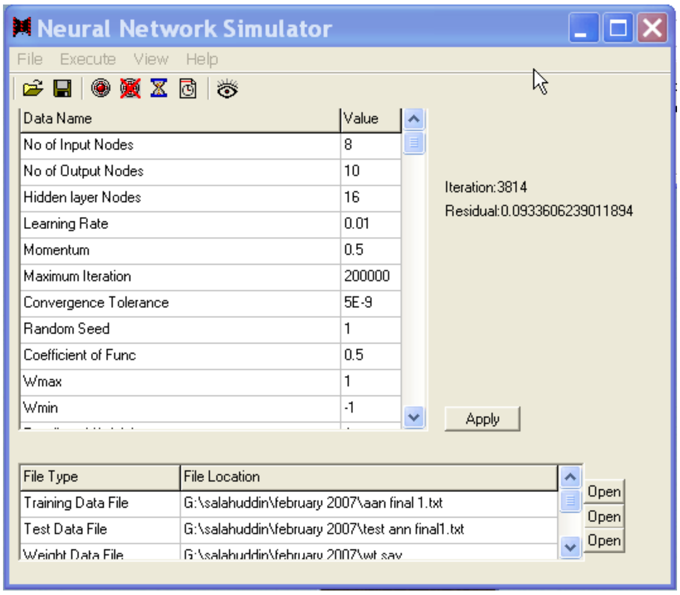

Fig. 3. The Neural network being trained for flat plate slab deflections.

3. Artificial neural network

3.1 ANN: from brain to mathematical prediction tool

Artificial Intelligence (AI) is a very versatile and potential prediction tool in the field of computer technology, which enables computer users in various fields to solve problems for which algorithmic approach cannot be formulated and which normally requires human intelligence and expertise. Expert Systems (ESs) and Artificial Neural Networks (ANNs), the best known manifestations of AI, have today gained immense credibility and acceptance in many professional fields. ANN approaches have successfully been used in wide range Civil Engineering problems where conventional approaches based on engineering mechanics proved difficult to establish an explicit relationship between causes and effects. These include a wide range of problems in the fields of structural engineering, construction engineering and management, environmental and water resources engineering, traffic engineering, highway engineering, and geotechnical engineering Jeng et al (2003), Flood (2001), Adeli (2001), Kartam (1997), Flood and Kartam (1994), Goh(1994).

Artificial neural networks are biologically inspired in the sense that neural network configurations and algorithms are usually developed with the natural counterpart in mind. The tremendous processing power of human brain is basically the result of the massively parallel processing units called neurons. A human brain functions with hundreds of thousands of such biological neurons, which are interconnected by a highly complex network. Every neuron consists of a cell body, axon and dendrites. Dendrites extend from the cell body to the other neurons where they receive signals at a connection point called the synapse. These inputs are communicated to cell body where all such inputs are essentially summed up. If the resulting sum exceeds a specified threshold value, the cell fires and a signal is sent down the axon.

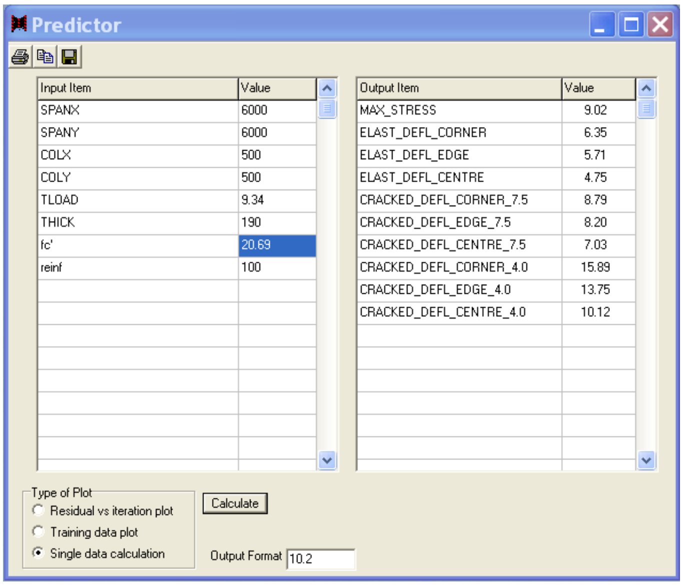

Fig. 4. The neural network predictor to predict deflection and stress.

An artificial neural network, also called a simulated neural network (SNN) or commonly just neural network (NN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionistic approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network. In more practical terms neural networks are nonlinear statistical data modelling or decision making tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data.Use of Artificial Neutral Network (ANN) techniques is advantageous as it is not necessary to define relationship beforehand between causal input vectors and corresponding output vectors.

3.2 Back-propagation and training the network

Here in this paper a general purpose ANN program (Siddiquee, 2007) is used which is basically a back propagation type of neural network. In this network a set of input parameters are connected to a set of output parameters through a set of weights and hidden or middle layers as shown in the Figure 1. The network is trained to recognise the correct input-output pattern by adjusting the weight values of the interconnecting weight matrix. The adjustment follows an error-correcting method called "error back-propagation", from where the name of the method is developed. After sufficient number of training when the error becomes gradually diminished, the network becomes capable of predicting any new data within the trained range of input data or any data outside the range. Number of any hidden layers actually represents the number of the data input-output relationship. The number of hidden layers is determined by gradually increasing its number and checking the error-norm of the trained data set. The best number of hidden layers is the number for which the error-norm is the lowest. In this paper best number of hidden layers was found out to be 16.

4. Database development for training the ANN for flat plate

In order to train the neural network successfully to predict deflections, a large number of flat plate slabs with 3X3 panels with varying geometric, material and loading parameters were analyzed using the nonlinear FE analyses using Hossain's (1999) module employing

Branson's crack model. The FE mesh of the 1/4th 3x3 panel slab is shown in Figure 2. The varying parameters are span lengths in both directions, column sizes in directions, load, slab thickness, concrete strength and steel area. They are presented in the following sections.

4.1 Span length

The panel sizes used in analysis for 3 x 3 panel flat plate are
8400 mm x 8400 mm, 8400 mm x 6900 mm,8400 mm x 5400 mm, 8400 mm x 4200 mm, 6900 mm x 6900 mm, 6900 mm x 5400 mm, 6900 mm x 4200 mm, 5400 mm x 5400 mm, 5400 mm x 4200 mm, 4200 mm x 4200 mm.

4.2 Column size

Column size used in the analysis varies from 300 mm to 600 mm with an interval of 100 mm in size. The column sizes are 600mm by 600mm, 500mm by 500 mm, 400 mm by 400 mm and 300 mm by 300 mm. The columns supporting the slab have same cross sectional area for exterior and interior panel of the flat plate slab.

4.3 Slab thickness

In the current work, slab thickness was calculated as per ACI code (2014) and BNBC (2017). Minimum thickness was restricted to 125mm (5 inch). Thicknesses were also used in the analysis for the value of 0.8t, 1.1t and 1.2t, where t is the ACI slab thickness.

4.4 Loading

The slabs are designed by USD method and dead load and live load have been considered in this analysis. The self-weight of slab and 1.0 kN/m^2 of floor finish load are treated as total dead load. Total 2.4 kN/m^2 load is considered as random partitioned wall. The live load varied from 1.9 kN/$m^2$to 4.79 kN/m^2 for design and analysis. For FE analysis, the total load includes constant floor finish and partition wall load as mentioned above. FE analysis has been performed using total un-factored load.

4.5 Reinforcement

Calculations for required slab reinforcement have followed by Equivalent Frame Method. The minimum reinforcement has been taken equal to *0.002bt* in which b = width of slab and t = slab thickness. Reinforcement was also increased up to 10% and 20% of that required from strength design.

4.6 Material properties

The material properties that have been varied in the analyses are concrete strength f'_c, modulus of elasticity of concrete E_c, modulus of rupture of concrete f_r, yield strength of steel f_y, Poisson's ratio ν and modular ratio n. The material properties used in the analyses are as follows:

- Modulus of elasticity of concrete E_c= $4733\sqrt{f'_c}$ MPa.
- Poisson's ratio ν = 0.18
- Modulus of elasticity of steel E_s = 200000 MPa.
- According to ACI Code (2014) modulus of rupture of concrete is taken $f_r = 0.62\sqrt{f'_c}$ N/mm^2 and $f_r = 0.33\sqrt{f'_c}$ N/mm^2. The lower value indicates tensile strength reduced due to effect of restrained shrinkages.
- Yield strength of steel f_y = 413.7 N/mm^2

- Concrete cylinder strength f'_c = 17.24 N/mm^2, 20.7 N/mm^2, 24.14 N/mm^2, 27.69 N/mm^2
- Modular ratio $n = E_s / E_c$

5. Training, validation and use of ANN

Using the results of these FE analyses, the ANN was trained as shown in Figure 3. The program builds a weight matrix and continuously updates it in a back-propagation technique where it tries to minimise the error in prediction by adjusting the matrix components. Once the amount of error i.e. the residual becomes very small, the network is ready for prediction with the weight matrix being saved for future use. The use of this ANN is shown in Figure 4 where input parameter like span, loading and material properties were given as inputs to predict maximum stress, elastic and cracked deflections. To check if the program is properly trained and is capable of predicting the original FE results, some randomly selected FE results are compared with the predicted results in Table 1.

The ANN prediction values are very close to the original FE results with the maximum difference being 6.27%. Earlier studies also found Ahmed (2007), Hossain et.al. (2007) that these predictions are reasonably accurate in comparison with the FE analysis for both flat plate and edge supported slabs.

6. Deflection calculation: ACI/BNBC provisions

ACI Code (2014) and BNBC (2017) permit slab thickness less than that those given in code if it can be shown by computation that deflections will not exceed the prescribed limit values. Calculation of slab deflection is complicated due to presence of cracking even in service loads and also there are time-dependent deformations due to concrete creep and shrinkage. ACI/BNBC Code incorporates Branson’s equation (Equations 1 and 2) for calculating short-term deflection considering cracking. As for long-term deflection calculation, unlike EC2 (1992) and MC90 (1990), ACI/BNBC Code adopted a simplified multiplier approach. Darwin et.al.(2016) explained that precise deflection calculations are not justified due to presence of uncertainties regarding material properties, effect of cracking and load history. The calculated deflections must satisfy the maximum permissible deflection tabulated in the Code to ensure serviceability.

6.1 Long-term deflection multiplier

On the basis of empirical studies, ACI/BNBC Code specifies that additional long-term deflection due to combined effects of creep and shrinkage shall be calculated by multiplying the immediate deflection by the factor:

$$\lambda = \frac{\xi}{1 + 50\rho'} \tag{8}$$

where, ξ= a time-dependant coefficient, ACI/BNBC Code suggested a five-year value of ξ=2.0, and $\rho'=A_s'/bd$, is usually zero for slabs as compression steels are seldom used.

7. Example: Long-term deflection calculation

The calculation of long-term deflection has been performed using sustained load of 30% live load and ξ = 2.0 as proposed by the ACI/BNBC Code. An earlier study Hossain et.al (2005) demonstrated a deflection calculation procedure with ξ=3.0 as proposed by Branson for slabs. A 10 storied office building of 3x3 panel with flat plate floor system (no edge beam, dropped panel or column capital) having span length of 6000 mm in both direction and the column size is 500 mm by 500 mm for all columns. The loads considered are 1 kN/m^2 for floor finish,

Table 1
Comparison of FE results and ANN prediction along with percent variation

Input								Output results										
Span		column size		Total load (kN/m^2)	Slab thickness (mm)	Concrete strength (N/mm^2)	Reinforcement	Predictions	Stress (N/mm^2)	Deflection								
										Elastic			Craked with $f_r = 0.62\sqrt{f'_c}$			Craked with $f_r = 0.33\sqrt{f'_c}$		
x direction (mm)	y direction (mm)	x direction (mm)	y direction (mm)							Corner (mm)	Edge (mm)	Center (mm)	Corner (mm)	Edge (mm)	Center (mm)	Corner (mm)	Edge (mm)	Center (mm)
8400	8400	600	600	12.45	265	20.69	100	ANN	13.119	12.689	11.015	9.037	21.963	17.784	13.481	34.262	28.226	21.000
								FE	13.147	12.684	11.026	9.031	21.931	17.761	13.404	34.416	28.279	20.988
								Difference	-0.21%	0.04%	-0.10%	0.07%	0.15%	0.13%	0.57%	-0.45%	-0.19%	0.06%
8400	8400	300	300	12.45	265	20.69	100	ANN	22.093	18.713	13.924	7.316	35.191	24.128	9.492	47.229	33.464	15.413
								FE	21.801	18.737	13.961	7.298	35.185	24.119	9.462	47.017	33.509	15.381
								Difference	1.32%	-0.13%	-0.27%	0.25%	0.02%	0.04%	0.32%	0.45%	-0.13%	0.21%
8400	6900	500	500	12.45	265	20.69	100	ANN	12.141	9.903	9.100	6.576	16.515	15.852	9.934	27.642	24.598	16.776
								FE	12.253	9.869	9.089	6.501	16.786	15.930	9.765	27.598	24.676	16.706
								Difference	-0.92%	0.34%	0.12%	1.14%	-1.64%	-0.49%	1.70%	0.16%	-0.32%	0.42%
6900	6900	600	600	11.49	215	20.69	120	ANN	10.932	8.987	8.017	6.922	13.787	11.979	10.088	23.150	19.587	15.600
								FE	10.938	8.948	8.011	6.966	13.793	11.811	10.038	23.251	19.672	15.409
								Difference	-0.05%	0.43%	0.07%	-0.64%	-0.04%	1.40%	0.50%	-0.44%	-0.43%	1.22%
6900	5400	600	600	13.40	215	20.69	100	ANN	10.204	6.869	6.589	5.518	11.420	11.311	8.239	20.501	16.809	15.828
								FE	10.179	6.832	6.620	5.490	11.315	11.179	8.341	19.720	17.861	15.414
								Difference	0.25%	0.54%	-0.47%	0.51%	0.92%	1.17%	-1.24%	3.81%	-6.26%	2.62%
5400	4200	600	600	10.05	165	27.69	100	ANN	8.145	4.847	4.447	4.019	6.370	5.943	5.430	11.472	9.998	8.288
								FE	8.259	4.843	4.458	4.015	6.234	6.029	5.295	11.701	9.798	8.133
								Difference	-1.40%	0.08%	-0.25%	0.10%	2.14%	-1.45%	2.49%	-2.00%	2.00%	1.87%
5400	4200	300	300	10.05	165	20.69	100	ANN	10.604	5.559	5.165	3.403	8.022	7.973	5.404	14.258	13.779	8.226
								FE	10.578	5.507	5.103	3.378	8.073	8.144	5.398	14.221	13.796	8.177
								Difference	0.25%	0.94%	1.20%	0.73%	-0.64%	-2.14%	0.10%	0.26%	-0.12%	0.60%
4200	4200	300	300	9.33	125	20.69	100	ANN	11.405	5.688	4.899	3.907	8.334	7.312	6.004	14.210	11.651	8.379
								FE	11.371	5.722	4.952	3.926	8.399	7.198	5.999	14.251	11.518	8.498
								Difference	0.30%	-0.60%	-1.08%	-0.49%	-0.78%	1.56%	0.08%	-0.29%	1.14%	-1.42%

1.44 kN/m^{2}for random partition wall and 2.4 kN/m^2 for live load. Materials strength used are f_y = 414 MPa, f'_c = 20.69 MPa. For long-term deflection calculation, the long-term multiplier ξ = 2 will be used as per ACI Code (2014).

7.1 Calculation of slab thickness

Clear span = 6000- 500 = 5500 mm
Slab thickness = 5500/30 = 183 mm ≈ 190 mm (according to ACI/BNBC Code)
Self weight = 4.5 kN/m^2
Floor finish = 1 kN/m^2
Random partition wall = 1.44 kN/m^2
Live load = 2.4 kN/m^2
Total un-factored load = 4.5+1+1.44+2.4 =9.34 kN/m^2

Immediate deflection for dead load and live load predicted using the ANN as shown in Figure 4: $\Delta_{d+l} = 8.79\,\text{mm}$
Assuming 50% of creep due to self-weight occurs before the finishing of the building starts. The time-dependent portion of dead load deflection is

$$\Delta_d = 8.79 \times \frac{4.5}{9.34} \times 1 + 8.79 \times \frac{2.44}{9.34} \times 2 = 4.24 + 4.59 = 8.83\,\text{mm}$$

The long-term deflection due to sustained portion of the live load is

$$\Delta_{0.3L} = 8.79 \times \frac{2.40}{9.34} \times 0.3 \times 3 = 2.03\,\text{mm}$$

The instantaneous deflection due to application of short-term portion of the live load is

$$\Delta_{0.7L} = 8.79 \times \frac{2.40}{9.34} \times 0.7 = 1.58\,\text{mm}$$

The total incremental deflection is $\Delta = 8.83 + 2.03 + 1.58 = 12.44\,\text{mm}$

The ACI Code limitation of incremental deflection is *span/480* = 12.5 mm
Thus, the calculated incremental deflection marginally satisfies the tolerable limit.
The total deflection is

$$\Delta_{total} = 8.79 \times \frac{4.5}{9.34} \times 3 + 8.79 \times \frac{1.0}{9.34} \times 3 + 8.79 \times \frac{1.44}{9.34} \times 3 + 2.03 + 1.58 = 23.20\,\text{mm}$$

The ACI Code limitation of total deflection is *span/240* = 25.0 mm
From calculation, slab thickness is found to be adequate from total deflection consideration.

8. Conclusion

Earlier studies Vollum et. al. (2002), Vollum and Hossain (2002) show that in many cases the thickness provided by the ACI/BNBC Code result in flat plate deflections exceeding the permissible limits. This is particularly true for longer spans, heavy service load and construction load that result in higher level of cracking. The thicknesses are proved to be adequate when the slabs are mostly uncracked or slightly cracked.ACI/BNBC Code allows slab thickness less than the specified value if calculated values are within code-specified limits. On the contrary, for excessive construction or live load and larger panels, which generates high level of cracking in slab, providing ACI/BNBC Code minimum thickness may not be adequate. In such conditions, deflection calculations should be mandatory to decide a higher thickness. A quick estimation of slab deflection as demonstrated in the current paper using the trained ANN software which is capable of producing results as good as the nonlinear FE analysis, should indicate if ACI/BNBC minimum thickness is appropriate to use.

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