International Journal of Civil Engineering (IJCE)
ISSN(P): 2278-9987; ISSN(E): 2278-9995
Vol. 3, Issue 3, May 2014, 55-62


International Academy of Science, Engineering and Technology
Connecting Researchers; Nurturing Innovations

# PREDICTION OF DEFLECTION IN POST-TENSIONED SLABS AT CONCEPTUAL STAGE OF DESIGN BY APPLYING RESUBSTITUTION VALIDATION TECHNIQUE

**GAURAV SANCHETI, RAVINDRA NAGAR & VINAY AGRAWAL**

Department of Civil Engineering, Malaviya National Institute of Technology, Jaipur, Rajasthan, India

## ABSTRACT

An attempt has been made in this paper to develop an artificial neural network model capable of determining the deflection in post tensioned slabs at conceptual stage of design. A three span continuous post tensioned slab system with drop panels is generated using standard design software. The results of deflection at the mid span have been recorded for various slab configurations. Both single layered and doubled layered neural networks are developed and compared for their performance. Back propagation algorithm is employed for making the network learn. The results of deflection so obtained are used as a database for training the developed neural network. Re substitution validation technique is utilized for validating the selected network. Training, validation and testing of data is done using MAT Lab software. The outputs given by the artificial neural networks proved the success of this attempt in determining the deflection in post tensioned slabs.

**KEYWORDS:** Artificial Intelligence, Artificial Neural Networks, Deflection, Leven Berg-Marquardt Back Propagation, Post Tensioned Slabs, Resilient Back Propagation, Resubstitution, Training Function, Transfer/Activation Function, Validation

## INTRODUCTION

Post-tensioned concrete flat slabs are widely used for multi-story structures of commercial and residential buildings of all types [12]. Although, the post tensioning system and methodology is not quite easy but still in the last two decades more and more construction activities had adopted the post tensioning systems. This is due to certain concrete benefits arising out of this technique, such as having longer spans and thin sections as compares to RCC structures. In RCC structures, the load is transferred to the reinforcing bars only after certain particular limit of load is reached. In case of post tensioned structural members, the strands begin to take stresses as soon as the load is applied. Consideration of serviceability criteria, particularly deflection, is becoming more and more important due to utilization of modern analysis procedures and the use of high strength materials, which result in slender members that are more susceptible to large deflections [5]. Post-tensioning enables minimum slab depth with good control of deflections; it also keeps the slab weight low and building height down to a minimum [12]. Apart from these advantages of post tensioned slabs, due to the increased span length of the structures, deflection is a matter of concern. As deflection is directly proportional to the serviceability of the structure, it is required to be predicted carefully and it must be under the prescribed limits. In this paper deflection has been estimated at the mid span for various slab configurations using standard design software for the post tensioned slabs.

## ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are a part of the Artificial Intelligence (AI) techniques. The basic aim of AI is to develop such soft computing tools that are capable of taking their own intelligent decision. Out of many such tools of AI, one most promising one is the ANNs. They may be considered as the networks with small computational units. These units, which are also known as neurons or nodes, make a web of highly interconnected nodes. These networks are influenced by the structure and working of the biological neural networks in the human brain. The structure of the biological neural network is shown in Figure 1(a). In a live neuron, nucleus in a cell body or the soma receives the signals from the dendrites through the synaptic terminals of some other neurons. When these signals pass a certain threshold value, the neuron is said to be activated. In this activated state, a signal is fired from the neuron which is carried through the axon to the synapse.

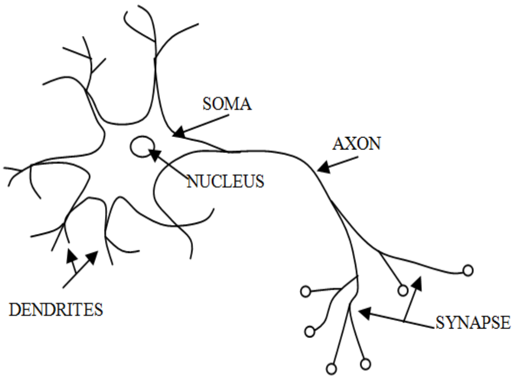


**Figure 1: (a) Biological Neural Network**

Now, these signals at the synapse become the incoming signals for the dendrites of some other neuron. This process continues and several neurons are activated for performing a particular task or for making a decision. The same concept is utilized in the working of ANNs. The various artificial neurons are connected to each other through the links referred to as weights. At one end, the network receives signals in form of the inputs. With the received inputs some weights are associated and then these inputs are passed through the hidden layer which consists of the artificial neurons or nodes. When these signals pass a threshold value then only they are transferred to the output layer through weighted links. A general structure of an artificial neural network has been shown in Figure 1(b).

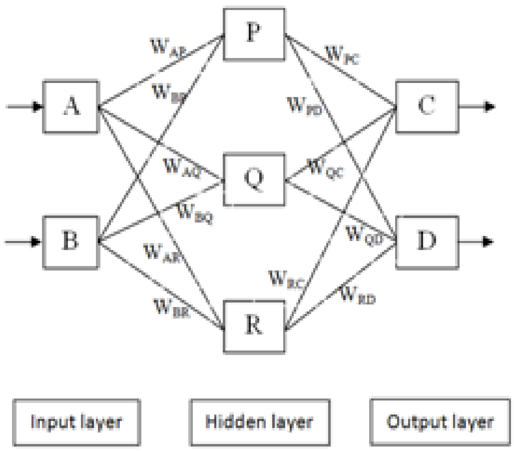


**Figure 1: (b) Artificial Neural Network**

The information is stored and processed through this network only. One of the most important characteristic of ANNs is their ability to learn from examples. They are capable of approximating a relationship between the input and the target values. These neural networks works well even when the data is incomplete or if the data contains some noise. Feed forward artificial neural networks (ANNs) are currently being used in a variety of applications with great success [2].

ANNs, till now, have been applied to several different types of problems related to Civil and Structural Engineering. These include the determination of free lime content in cement clinker [9], conceptual design of communication towers [1], for predicting the shear strength of reinforced circular concrete columns [4], determining the chloride diffusion inside the reinforced concrete member [17], estimation of bond between steel and concrete [6], for predicting the compressive strength of a silica fume concrete [7], for identification of damage intensities of joints of a truss bridge structure [13], for the determination of flow resistance in smooth open channels [3], to estimate the shear strength of concrete beams devoid of shear reinforcement [11], for the analysis of non-linear structures under dynamic loading [10], building-related symptoms prevailing in individuals [16], investigations for designing reinforced concrete beam [15], determining the deformation capacity of rectangular reinforced concrete columns [8], replacement of cement by flyash and silica fumes to study the variation in strength of concrete [14], with many more complex problems related to civil engineering. Thus successful applications of ANNs in civil engineering field will open doors for several other analytical methods that will not only provide a reliable database of results but will also save time and labour.

## EXPERIMENTAL PROGRAM

In this study, a three span continuous flat plate with drop panels have been analysed for deflection under the specified loading. The deflection has been evaluated at the mid span using the trial version of structural design software for design of post tensioned slabs; ADAPT-PT. The result obtained by this software has been verified by designing the prestressed flat plate manually. Several slab configurations has been developed and analysed for different span lengths by considering the major design parameters. In the design database, some of the slab configurations which were failing in design have been separated out. The variation of these design parameters are as shown in the Table 1.

**Table 1: Design Parameters in PT-Slab**

| Inputs | Parameters | Units |
|---|---|---|
| **Span** | 7, 8, 9, 10, 11 and 12 | m |
| **Depth** | 170, 190, 210, 230 & 250 | mm |
| **Live load** | 3, 4 and 5 | kN/mm$^2$ |
| **Column** | 450x450, 600x600 & 750x750 | mm$^2$ |
| **Concrete** | M35, M40 and M45 | |

A number of networks are developed for the determination of deflection for the post tensioned slabs. Neural network toolbox in MATLAB software has been employed for generating the various artificial neural network architectures. The networks developed are having single hidden layer as well as double hidden layer. As there are no fixed guidelines for selecting the network model for a particular type of problem, so a large number of networks with different architectures are employed to the stated problem.

The number of neurons in the hidden layer of the single layered networks is taken as 5, 10, 15 and 20. On the other hand, in case of double layered networks the number of hidden layer neurons are taken as 5, 5; 7,7 and 9,9 in both the layers. Total of five inputs are considered as the span of slab, the depth of slab, live load, column size and grade of concrete.

The output is the deflection of the selected slab system. Total of 799 data units are provided to the network. Since re substitution validation technique have been employed for validating the network, so the entire database of 799 data units are used for training, validating and testing the network performance. The entire database has been normalized in the range of -1 to +1. Each network is trained for a maximum cycle of 1000 epochs. Back propagation learning algorithm has been employed for training the network. Resilient back propagation (Train RP) and Leven berg-Marquardt back propagation (Train LM) have been compared for performance. Log-sigmoid (Log_ sig) and tan-sigmoid (Tan_sig) algorithms have been employed for activating various neural network models. The variation of training and activation function along with other design parameters are done, as a part of trial method, for achieving the best network.

**Table 2: Validation and Testing MSE of Single Layered Networks**

| S.No | Network Model | No. of Layers | No. of Neurons | Validation MSE at 1000 Epoches | Testing MSE |
|---|---|---|---|---|---|
| Deflection of PT Slabs | | | | | |
| Single Layer Networks | | | | | |
| 1 | NET1: 1L_RP_Tan | 1 | 20 | 0.1269696 | 0.12487 |
| 2 | NET2: 1L_RP_Log | 1 | 20 | 0.0945598 | 0.09499 |
| 3 | NET3: 1L_LM_Tan | 1 | 20 | 0.0261074 | 0.02620 |
| 4 | NET4: 1L_LM_Log | 1 | 20 | **0.0245480** | **0.02484** |

## RESULTS AND DISCUSSIONS

Various results obtained as the output from the selected neural networks have been shown below in the graphs. The results obtained are quite encouraging and proves the suitability of using ANNs in problems relating to civil and structural engineering field. In Figure 2, total of four single layered networks, NET1 to NET4, have been compared. Here the variation of MSE deflection with the number of epochs is shown. Networks NET1 and NET2 start off from the range between 1.1 and 0.9 and merges towards the mark of 0.1 MSE. It can be seen from Figure 2 that the variation of networks NET3 and NET4 is representing a straight line when compared to NET1 and NET2. It implies that the performance of NET3 and NET4 are far better than the performance of NET1 and NET2.

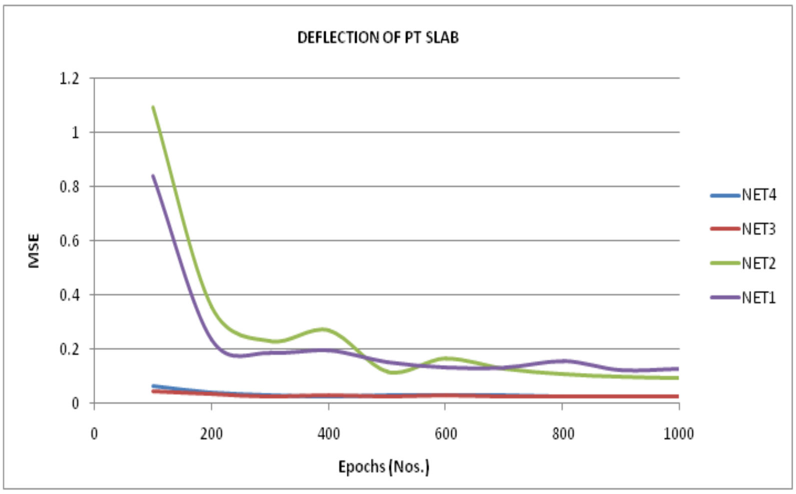


**Figure 2: Deflection Models for Single Layered Networks 1 to 4**

The validation and testing MSE of all the four single layered networks is tabulated in Table 2. From this Table it is evident that the network NET4 gives the best performance for single layer networks. The two networks, NET3 and NET4, have been plotted in Figure 3 for better comparison. On an average network NET3 shows a constant MSE from epochs 300 to 1000 as evident in Figure 3. Network NET4, however, starts off with a higher MSE near 0.07, shows some undulations in between 400 to 800 epochs and finally sets to a lower MSE from epochs 800 to 1000. There is not much difference in the performance of these two networks.

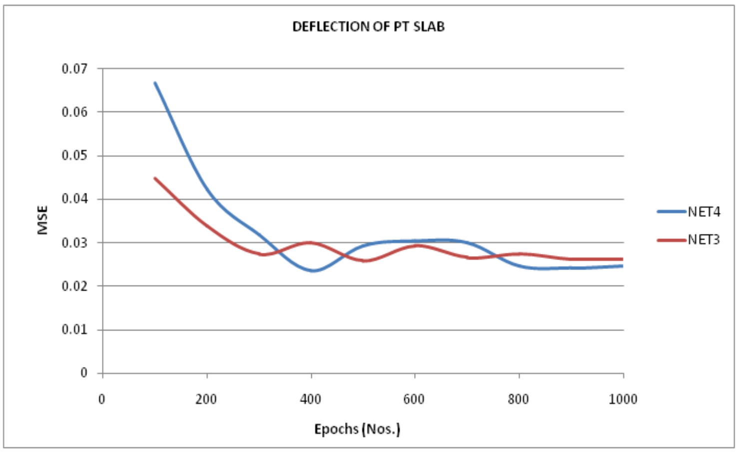


**Figure 3: Deflection Models for Single Layered Networks 3 and 4**

Performance of double layer networks has been shown in Figure 4. Eight such networks, NET5 to NET12 have been plotted to study the variation of deflection MSE against the number of epochs. It is seen that networks NET5 to NET8 shows much better convergence of error when compared with single layered networks NET1 to NET4. Here networks NET9 to NET12 tends to merge towards the mark of 0.1 MSE with more or less same level of performance. Networks NET5 to NET8 perform very well and seen as a straight line when compared to the other double layer networks. When these four networks, NET5 to NET8 are plotted separately, Figure 5, all the networks seem to converge to the same mark of 0.02 MSE. From the results of the performance of double layer networks as been tabulated in Table 3, it can be seen that the network NET7, with Levenberg-Marquardt training algorithm and having activation function as tan-sigmoid in first layer and log-sigmoid in second layer gives the best performance. The maximum epochs considered are 1000. This network consisted of nine neurons in each hidden layer.

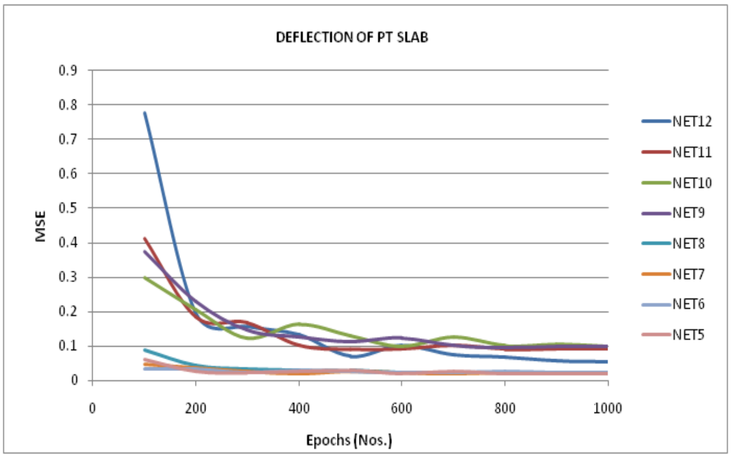


**Figure 4: Deflection Models for Double Layered Networks 5 to 12**

All the 12 neural networks models shown in the table 2 and table 3 have been referred as per their architecture. For example, network net2:1l_rp_log indicates to a network with single layer, using trainrp as the training function and log-sigmoid as the activation function.

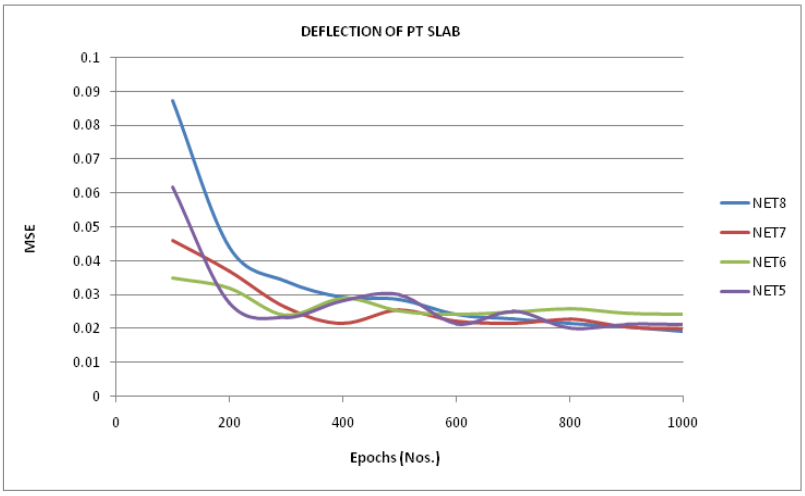


**Figure 5: Deflection Models for Double Layered Networks 5 to 8**

The performance of single layer network is somewhat less as compared to the performance of double layer network. Also there is a difference in the number of hidden layer neurons. The number of hidden layer neurons in single layered network is taken as 20 whereas it is 9 in double layer network. It implies that networks with double layer perform well when compared to single layered networks.

**Table 3: Validation and Testing MSE of Double Layered Networks**

| S.No | Network Model | No. of Layers | No. of Neurons | Validation MSE at 1000 Epoches | Testing MSE |
|---|---|---|---|---|---|
| Deflection of PT Slabs | | | | | |
| Double Layer Networks | | | | | |
| 5 | NET5: 2L_LM_Tan_Tan | 2 | 9,9 | 0.0212347 | 0.02100 |
| 6 | NET6: 2L_LM_Log_Log | 2 | 9,9 | 0.0243439 | 0.02421 |
| 7 | NET7: 2L_LM_Tan_Log | 2 | 9,9 | **0.0200615** | **0.01998** |
| 8 | NET8: 2L_LM_Log_Tan | 2 | 9,9 | 0.0192428 | 0.02008 |
| 9 | NET9: 2L_RP_Tan_Tan | 2 | 9,9 | 0.0998318 | 0.09755 |
| 10 | NET10: 2L_RP_Log_Log | 2 | 9,9 | 0.0976033 | 0.09522 |
| 11 | NET11: 2L_RP_Tan_Log | 2 | 9,9 | 0.0929758 | 0.09115 |
| 12 | NET12: 2L_RP_Log_Tan | 2 | 9,9 | 0.0540056 | 0.05355 |

## CONCLUSIONS

The results obtained by various configurations of artificial neural networks have been tabulated in Table 2 and Table 3, showing the variation of validation MSE and testing MSE. Main inferences which we can draw out of this are:

- The double layer networks in all the cases performs better than single layer networks. Single layer networks consisted of 20 neurons in the hidden layer whereas double layer networks consisted of only 9 neurons in each of its hidden layer. It implies that with increased number of network layers, the number of neurons is decreased and better network performance is achieved.

- Two different types of training functions were used in the development of the neural networks. First algorithm was the train RP and the other one was the train LM. It is very clear from the results obtained that the performance of the network with train LM algorithm is far better than achieved by train RP.

- In this particular problem the different activation functions i.e., log-sigmoid and the tan-sigmoid, does not affected the network performance very much.
- The final selected neural network model NET7 performed the best out of all other network models.

## ACKNOWLEDGEMENTS

I thank the Director, Malaviya National Institute of Technology Jaipur (MNIT), Rajasthan, India for providing such wonderful working facilities in the institute and the entire faculty members of Civil Engineering department for their constant support.

## REFERENCES

1. Agrawal V., Nagar R., and Sancheti G. (2011),“ Application of Artificial Neural Network in Conceptual Design of Communication Towers”, Proceedings of the International Conference on Electrical, Electronics and Civil Engineering (ICEECE'2011), Planetary Scientific Research Centre Conferences, Pattaya, Thailand.
2. Benardos P. G., and Vosniakos G. C. (2007), “Optimizing feed-forward artificial neural network architecture” Engineering Applications of Artificial Intelligence, 20, 365-382.
3. Bilgil A. and Altun H. (2008), “Knowledge-based prediction of shear strength of concrete beams without shear reinforcement”, Flow Measurement and Instrumentation, Vol. 19, pp. 404 - 408.
4. Caglar N. (2009), “Neural network based approach for determining the shear strength of circular reinforced concrete columns”, Construction and Building Materials, Vol.23, pp. 3225–3232.
5. Chouman M., (2003), “Initial and Long Term Deflection of Partially Prestressed Concrete”, Proceedings of the Fourth International Symposium on Uncertainty Modeling and Analysis (ISUMA’03).
6. Dahou Z., Sbartaï M.Z., Castel A., and Ghomarid F. (2009), “Artificial neural network model for steel-concrete bond prediction”, Engineering Structures, Vol.31, pp. 1724_1733.
7. Özcan F., Atis C.D., Karahan O., Uncuoglu E. and Tanyildizi H. (2009), “Comparison of artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete”, Advances in Engineering Software, Vol.40, pp. 856–863.
8. Inel M. (2007), “Modeling ultimate deformation capacity of RC columns using artificial neural networks”, Engineering Structures, Vol.29, pp. 329–335.
9. Jingling Y., Luo Z., Hongfu D. and Haizheng T. (2012), “Prediction of Free Lime Content in Cement Clinker Based on RBF Neural Network”, Journal of Wuhan University of Technology, 27, No.1, 187-190.
10. Joghataie A. and Farrokh M. (2008), “Dynamic Analysis of Nonlinear Frames by Prandtl Neural Networks”, Journal of Engineering Mechanics, Vol.134, No.11, pp. 961–969.
11. Jung S. and Kim K.S. (2008), “Investigation of flow resistance in smooth open channels using artificial neural networks”, Engineering Structures, Vol. 30, pp. 1515–1525.
12. Marinkovic S.B. and Alendar V.H., (2008), “Punching failure mechanism at edge columns of post-tensioned lift slabs”, Engineering Structures, 30, 2752-2761.

13. Mehrjoo M., Khaji N., Moharrami H., and Bahreininejad A. (2008), "Damage detection of truss bridge joints using Artificial Neural Networks", Expert Systems with Applications, Vol.35, pp. 1122–1131.

14. Pala M., Ozbay E., Oztas A. and Yuce M.I., (2007), "Appraisal of long-term effects of fly ash and silica fume on compressive strength of concrete by neural networks", Construction and Building Materials, Vol.21, pp. 384–394.

15. Rao H.S. and Babu B.R. (2007), "Hybrid neural network model for the design of beam subjected to bending and shear", Sadhana, Vol.32, Part 5, pp. 577–586.

16. Sofuoglu S.C. (2008),"Application of artificial neural networks to predict prevalence of building-related symptoms in office buildings", Building and Environment, Vol.43, No.2, pp. 1121–1126.

17. Song H.W. and Kwon S.J. (2009), "Evaluation of chloride penetration in high performance concrete using neural network algorithm and micro pore structure", Cement and Concrete Research, Vol.39, pp. 814–824.