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Full Length Research Paper

A new approach to analysis plastic shrinkage cracks in reinforced concrete slabs by using ann

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The moister of plastic concrete is reduced by evaporation, formwork absorption, and seeping. The result of moisture loss caused increase of negative capillary pressure in concrete that increase tensile stress. Summary when it crosses the limit of tensile strength of concrete, it cracks. The tensile stress will cause cracking in early age concrete that is called plastic shrinkage cracking (PSC). PSC remains a serious concern, particularly in large surface area placements like slabs. Learning about crack analysis before rehabilitation and strength of reinforced concrete (RC) slab is important. In this paper, RC slab analysis has been done by using Artificial Neural Networks (ANNs). Feed-forward Back- propagation Neural Network (FBNN) was the selected network to generate prediction system with the minimum error and maximum squared correlation coefficient.

Keywords: PSC, RC, ANNs, FBNN

INTRODUCTION

Plastic shrinkage cracking (PSC) appears on the surface of early age concrete after concreting and while it is not still hard. These cracks appear mostly on horizontal surfaces. They are usually parallel to each other on the order of 300 to 900 mm apart, relatively shallow, and generally do not intersect the perimeter of the slab. PSC will be occurred when high evaporation rates caused the surface of concrete to be dry before it has been set (ACI). High evaporation rate, high water-cement ratio, and chemical reaction in cement paste cause plastic shrinkage in early age concrete. Plastic shrinkage causes forces and tensile stresses in the concrete slabs. The cracks are the end result of these forces when tensile stress crosses the limit of tensile strength. When flexural members are also restrained at the supports, shrinkage causes a build-up of axial tension in the member (Gilbert, 1992). In the shrinkage development of the fully-restrained slab, the restraining force gradually increases until the first crack occurs usually within two weeks from the commencement of drying (Gilbert, 2001). During the recent years, some valuable researches are done in case of the crack behaviours in different concrete structures. Shi et al (2001; 2003) established a numerical study for recognizing the crack behaviours in dams. In this analysis, he emphasizes on the reasons inducing cracks on concrete dams or multiple cracks. Hadidi (2005) have also studied some case of the cracking occurred in concrete bridges. He has studied the transverse cracks in the bridge deck due to the volume change in concrete. Richard et al (2005) have studied in concrete for crack thresholds, crack paths, and growth rates. Chen and Baker (2004) have delivered an analytical model for predicting the crack in concrete surfacing. This analytical model is a combination of two close cracks and an elastic bar. By changing the length of the elastic bar, he studied the effect of tensile strength on cracks. He achieved the minimum and maximum distance between cracks by changing the length of elastic bar. For many years, artificial neural networks (ANNs) have been used as analytical method in different branch of civil engineering.

ANN consisted of many neurons and their interior power conntableection that have been used for solution of special problems. The input information has been taken from another neuron and after apply to shift function will be sent to another layer of neuron. Power connection in neural network layers called the memory

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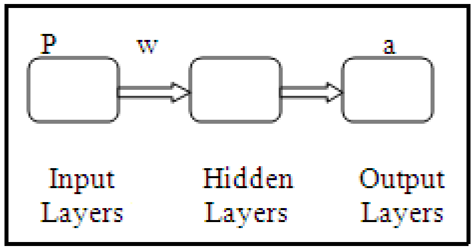

Figure1. A three layer of multi input layer

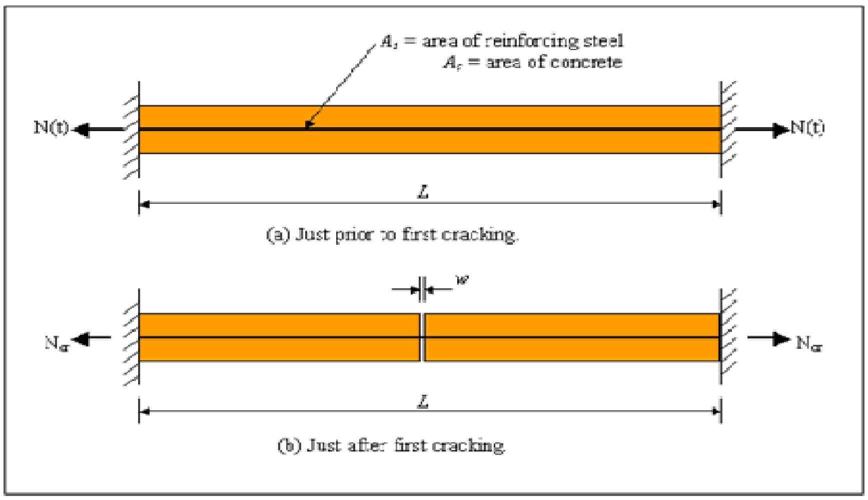

Figure2. The RC slab before and after cracking (Gilbert, 2001)
After first cracking

of elements and the effect of an interior connection called the weight of interior connection that ANN uses it to select random amounts. In teaching consequence, this neuron is proved to teach input-output functions. The structure and the equation of a neural network have been shown in figure 1 and formulas 1a and 1b.

$$n = \sum_{i=1}^{R} P_i W(1,i) + b = WP + b \quad \text{(1a)}$$

$$a = f(WP + b) \quad \text{(1b)}$$

Where W = weight or the effect of interior connection
n= the conclusion of input layer that is defined pure input
ANN showed as power and accurate analytical method for reinforced concrete (RC) structures and used for prediction of the different RC members. (Fairbairn, 2000, Chen, 2004, Maru, 2004, Umesh, 2007). Thomas Most and Christian Bucher (2007) have proposed an algorithm for the probabilistic analysis of RC structures which considers material uncertainties and failure due to cracking. Reda et al (2003) have carried out a study about a multilayer ANN for predicting creep performance of masonry structures. They have proved that the ANN is able to predict the creep performance with an excellent level of accuracy compared with that of conventional models. In current research reinforced concrete slabs analysed by using ANNs. Plastic shrinkage crack analysis in slab after the first crack have been studied and the ANNs is used to predicted the stress in concrete and steel and support force in the one way reinforced concrete slabs.

GILBERT'S EQUATIONS

The outside restrains in adjacent structures cause shrinkage stress in the elements. The restraining force N(t) due to shrinkage will be increased until the first crack occurs while:

$$N\,(t) = A_c\, f_t$$

Where: A_c = The cross-sectional area of the member
f_t = Tensile strength of the concrete. Figure 2.

- N(t) reduced to N_{cr}
- Stress in concrete away from crack is less than f_t.
- At the crack, the steel carries the entire force N_{cr}

and the stress in the concrete is obviously zero. The

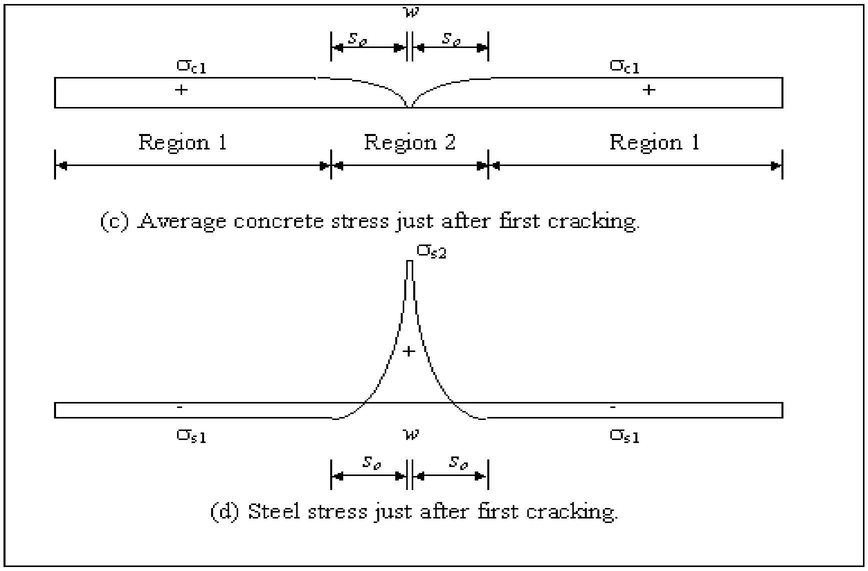

Figure3. Compressive and tensile stress diagram (Gilbert, 2001)

- stress in bar is in equation 2.

$$\sigma_{s2} = \frac{N_{cr}}{A_s} \qquad (2)$$

- In Region1 (figure3), the concrete and steel stresses are σ_{c1} (tensile stress) and σ_{s1} (compressive stress), respectively that are shown in equation 3.

$$\sigma_{c1} = \frac{N_{cr} - \sigma_{s1} A_s}{A_c} = \frac{N_{cr}(1+C_1)}{A_c} \qquad (3a)$$

$$\sigma_{s1} = \frac{2\, s_o}{3\, L - 2\, s_o} \frac{N_{cr}}{A_s} = -\, C_1 \frac{N_{cr}}{A_s} \qquad (3b)$$

Where: $C_1 = 2\, s_o / (3L - 2\, s_o)$.

$$N_{cr} = \frac{n\, \rho\, f_t\, A_c}{C_1 + n\, \rho\, (1 + C_1)}$$

$n = E_s / E_c$

In region 2 and in s_o distance, compressive strength of concrete has changed between 0 to maximum amount that Gilbert has used Favre et al (1983) formula (equation 4).

$$s_o = d_b / 10\, \rho \qquad (4)$$

Where: d_b= the bar diameter

ρ = the reinforcement ratio A_s / A_c

METHODOLOGY

The most important steps, concerned to develop an ANN to model different problems, are data gathering and neural network creation. Data gathering consist of data specification, organization, and analysis. Neural networks are fitted to apply a computerizing methodology due to learning from examples from prior understanding of the nature. The second step of neural network creation engages definition of a primary net, selecting a package of input properties, arrange the model, and try to find the best net architecture during the training process. If the generated neural network does not present an acceptable minimum error, the program loop back to adjust the net data in pre-processing step to improve the training data

Data Gathering

In current research, the using data in network generation has extracted from Gilbert's formulation. The structure of assumed sample is shown in Figure 4. Some of the slab characteristics assumed as constant data and some as variable data. The supposed constant and variable data are tabulated in table 1 and 2 respectively.

Artificial Neural Networks

The selection of network type is the first and important part of modelling by artificial neural network. After that the input parameters, adequate to output data, will be

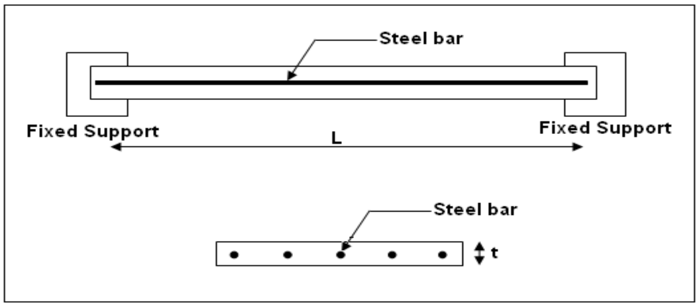

Figure 4. Purposed reinforced concrete slab for shrinkage crack analysis

Table1. The fix data

Yielding strength, f_y	400 N/mm2
Compressive St ,fc	30 N/mm2
Tensile St ,ft	3.5 N/mm2
Elasticity Module of Steel, E_s	200000 N/mm2
Elasticity Module of Concrete, E_c	20000 N/mm2

Table 3. The properties and modelling information of the generated network

Training function	TRAINBR
Adaption learning function	LEARNGD
Performance function	SSE
Number of Neurons in Hidden layer	20
Transfer function in Hidden layer	LOGSIG
Training Algorithms	Back Propagation
Function	LOGSIG
Network Architecture	4-20-4
Training	29data
verifying	4 data
Testing	3 data
Input	Slab length, thickness & steel bar and d_b / 10 ρ in Gilbert's Equation
Output	Support force, Stress in concrete, Stress in steel bar in the crack region and out of the crack region

selected. Then the network architecture means the number of layers, neurons in each layer and their connection together, the kind of transfer function for neurons, and the network training and learning function will be determined. After determining network type and net architecture, some data gathering need to generate network. The gathered data for network generation must be divided in three following phases (Ripley, 1996):

Training phase

Using all training data set for network learning to fit the weight of the classifier.

Validation phase

A set of data to adjust the parameters of a classifier,

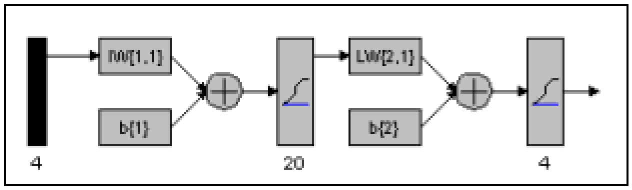

Figure 4. Network Architecture

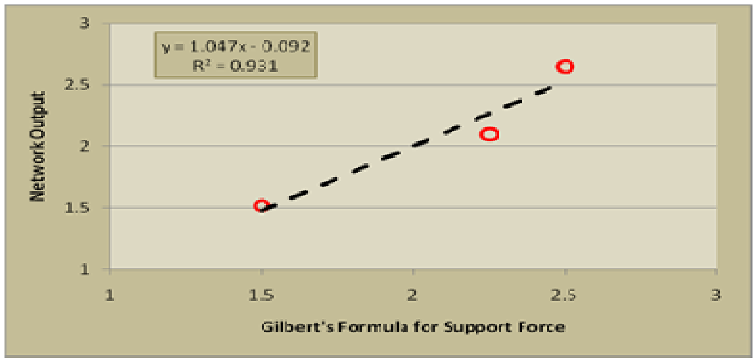

Figure 5. The ANN response for the support force

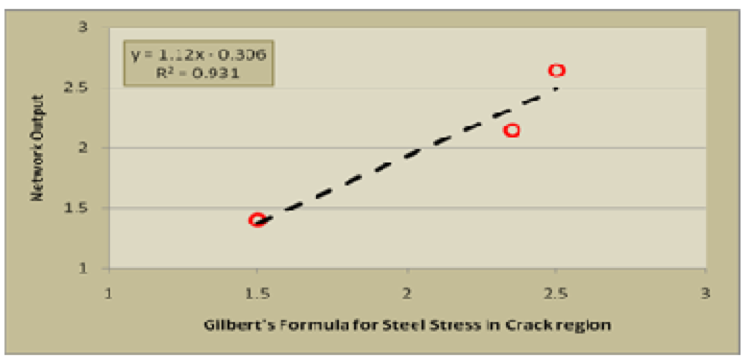

Figure 6. The ANN response for the steel stress in crack region

such as the number of hidden layer and neurons in each hidden layer. Actually, in this phase determine the necessary training iteration to avoid of overtraining.

Test phase

A set of data for fully assessment of the network performance.

Feed-forward Back-propagation Neural Network (FBNN) is the first and perhaps simplest artificial neural network which is used in current research. The other properties and modelling information of the generated network are presented in table 3. The architecture of the selected network is shown in figure 5.

RESULTS AND DISCUSSION

The mean square error (MSE) has used to estimate of different value among an estimator and the actual value of the estimated amount.

The best network was selected based on the following two conditions:

1. The minimum error between data in training process.
2. The maximum squared correlation coefficient between data in testing process

The properties and modelling of the generated network is selected base on minimum error between data in training stage of network generation. The minimum error equal to 3.17e-5 was the best result in training

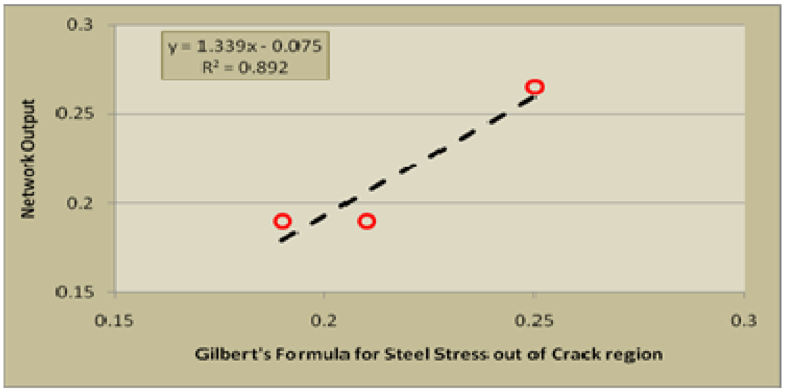

Figure 7. The ANN response for the steel stress out of crack region

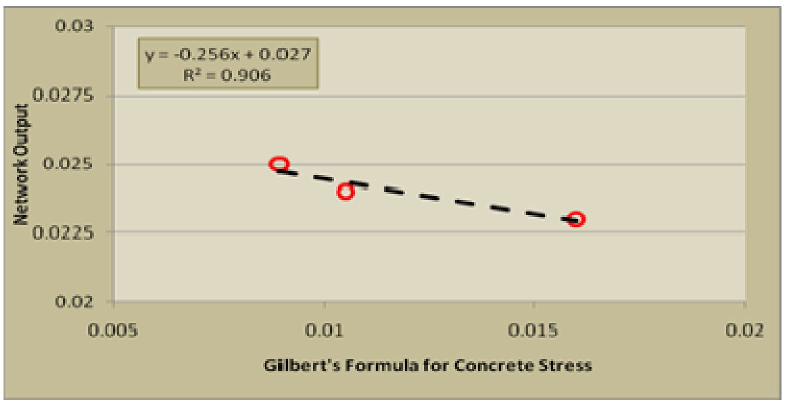

Figure 8. The ANN response for the concrete stress

process.

The squared correlation coefficient in testing process between real data and ANN's output for the support force, steel stress in crack region, steel stress out of crack region, and stress in concrete are shown in Figures 5, 6, 7, & 8 respectively. The comparison between ANN outputs and Gilbert's formula results are shown maximum squared correlation coefficient equal to 0.996, 0.993, 0.892, and 0.906 for the support force, steel stress in crack region, steel stress out of crack region, and stress in concrete respectively.

CONCLUSION

In this research, ANNs have been used as alternative method to theoretical formula for shrinkage crack analysis in RC slab. The following results showed the outputs of ANNs in good agreement with theoretical equations.

- The generated FBNN predicted the created shrinkage stress in RC slab with minimum error equal to 3.17e-5 in network training.
- The maximum squared correlation coefficient for the support force, steel stress in crack region, steel stress out of crack region, and stress in concrete were 0.996, 0.993, 0.892, and 0.906 respectively.

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