IJE TRANSACTIONS A: Basics Vol. 32, No. 7, (July 2019) 908-914

International Journal of Engineering

Journal Homepage: www.ije.ir

Estimation of Punching Shear Capacity of Concrete Slabs Using Data Mining Techniques

Y. Aggarwal, P. Aggarwal*, P. Sihag, M. Pal, A. Kumar

Department of Civil Engineering, National Institute of Technology, Kurukshetra, Haryana, India

PAPER INFO

Paper history:
Received 02 August 2018
Received in revised form 26 March 2019
Accepted 03 May 2019

Keywords:
Adaptive Neuro-fuzzy Inference System
Artificial Neural Network
Coefficient of Correlation
Generalized Neural Network
Punching Load

ABSTRACT

Punching shear capacity is a key factor for governing the collapsed form of slabs. This fragile failure that occurs at the slab-column connection is called punching shear failure and has been of concern for the engineers. The most common practice in evaluating the punching strength of the concrete slabs is to use the empirical expressions available in different building design codes. The estimation of punching loads involves experimental setup which is time-consuming, uneconomical and also, more manpower and materials are required. The present study demonstrates the use of data mining techniques as a substitute of former to predict the punching loads on the variation of various parameters. In this study, various type of data mining techniques including Adaptive Neuro-fuzzy Inference System (ANFIS), Artificial Neural Network (ANN) and Generalized Neural Network (GRNN) were applied to model and estimate the punching load of reinforced concrete slab–column connections. For the study, a data set consisting of 89 observations from available literature was analysed and randomly selected 62 observations were used for model development whereas the rest 27 were used to test the developed models. While the outcomes of ANN and GRNN model provides suitable estimation performance, the Gaussian membership based ANFIS model performed best in the determination of coefficient of correlation (C_c). Sensitivity study indicates that the parameter effective depth of slab (d) is the most influencing one for the estimation of punching load of reinforced concrete slab–column connections for this data set.

***doi**: 10.5829/ije.2019.32.07a.02*

1. INTRODUCTION

Punching shear capacity is an important factor for governing the collapsed form of slabs. In the link of slab-column, high shear stresses are the main reason for punching shear failure. The failure mode of punching is fragile in nature and diagonal cracks chase the surface of a truncated cone around the column. The failure that occurs at the connection between the slab and the column, called punching shear failure has been of concern for the designers and engineers [1, 2]. The most common practice in evaluating the punching strength of the concrete slabs is to use the empirical expressions available in different building design codes for calculating punching loads. The empirical expressions given in design codes are based on experimental results on specimens of a column and a portion of the slab [3]. The estimation of punching loads involves experimental setup which is time-consuming and also, a lot of labor and materials are required. The experimental part is also not economical and can be easily substituted by using data mining techniques to predict the punching loads on the variation of various parameters. Some of the parameters influencing the punching strength of slabs are: the cylinder strength of concrete (f_c), yield strength of steel (f_y), effective depth of slab (d), radius of a column or loaded area (r_o) and geometrical ratio of reinforcement (ρ) can be considered for the development of the model. The present treatments of codes of practices (e.g. ACI [4], BS8110 [5]) for the problem of punching shear in reinforced concrete slabs consist mainly of empirical formulations derived from tests on specimens of a column and a portion of slab within the elastic line of contra flexure. Existing theoretical approaches by

*Corresponding Author Email: *paratibha@rediffmail.com* (P. Aggarwal)

Please cite this article as: Y. Aggarwal, P. Aggarwal, P. Sihag, M. Pal, A. Kumar, Estimation of Punching Shear Capacity of Concrete Slabs Using Data Mining Techniques, International Journal of Engineering (IJE), IJE TRANSACTIONS A: Basics Vol. 32, No. 7, (July 2019) 908-914

Kinnunen and Nylander [6, 7], Nielsen et al. [8] and Andra [9] for punching are still complicated and have features making their acceptance difficult.

A more realistic rational model was previously proposed by Shehta [10] and Shehta and Regan [11]. It involves a more detailed analysis of the slab as a whole and of the concrete under stress concentration near the column face. This model gives a good account of both slab behaviour and the parameters affecting the punching strength, but in its present state it is considered to be too complicated to be handled by designers and adopted by current codes. Reinforced concrete flat slabs are widely employed in structural systems. The location of the slab-column connection is the most sensitive part of the flat slab [12]. Although, several theoretical models are proposed in the literature to compute the punching strength of the reinforced concrete slabs [13] and only a few research projects have been conducted on the punching shear strength of concrete slabs. Theoretical approaches proposed by few researchers [6, 8] are quite complicated. Different approaches like Truss Analogy [14], Fracture Analysis [15], Finite Element Analysis [16, 17] and the modified mechanical model [18] have also been proposed. Easier methods were proposed [19, 20] for calculating the punching resistance of simple and high strength concrete slabs respectively.

Conventional modeling techniques are based on empirical relationships developed from the experimental data. Within last few year, researchers have explored the capabilities of artificial intelligence techniques such as ANN [20–25], Support Vector Machines (SVM), Fuzzy Logic, M5 model tree, GRNN, ANFIS [25–33] for various problems in the field of civil engineering. A need to derive a simpler method to compete with the simplicity of empirical formula can be use of data mining techniques. The use of data mining technique can very well reduce the formulations and calculations required with best model to estimate the punching shear capacity of the slab-column connections, with optimum parameters. The modelling techniques are used where failure of classical and empirical equations occurs to predict the punching shear capacity. The modelling techniques, if properly optimised with various parameters, can estimate the strength very close to actual strengths and thus, can be used for the simulation of results, instead of time consuming experimental processes or may be finite element simulations. Most of the studies are focussing only on Artificial Neural Network (ANN), with few studies on use of Adaptive Neuro-fuzzy Inference System (ANFIS), and Generalized Neural Network (GRNN) and their comparison here forth. The objective of the paper is to examine the capability of ANN, GRNN, and ANFIS for estimating punching shear capacity of slab-column connections, so as to reduce the experimental work in the laboratory and onsite; also the cost of casting of specimens.

2. MODELING APPROACHES

2. 1. Generalized Regression Neural Network (GRNN)

The GRNN was proposed by Specht [36], to perform linear and non-linear regressions. The GRNN structure contains four layers: the input units are in the initial layer, the second layer has the pattern units, the outcomes of these layers are passed on to the summation units in the third layer, and the last layer covers the target units. The initial layer is linked to the second layer, where each unit represents a training pattern and its target is to measure the distance of the input from the stored patterns. The optimal value of a primary parameter called spread (s) is found experimentally. For more information about GRNN readers are referred to Specht [34] and Wasserman [35].

2. 2. Artificial Neural Networks (ANN)

The ANN is an artificial intelligence based approach generally used for the exact forecast of civil engineering problems [36, 37]. ANN is a parallel knowledge processing system containing a set of layered neurons. It contains an input layer, hidden layer and at last a target layer. The target layer is the ultimate processing part. The neurons are linked by a weight in each layer to the neurons in a successive layer during the learning process. For further information, readers are referred to Haykin [38]. In the current study, one hidden layer with 9 neurons is used in ANN model.

2. 3. Adaptive Neuro-fuzzy Inference System (ANFIS)

The ANFIS is a combination of Sugeno fuzzy inference model with ANN. ANFIS approach is based on adaptive and non-adaptive nodes in different layers. Figure 1 shows the structure of ANFIS model (first-order Sugeno fuzzy model) having 2 inputs (a and b), 4 rules and one target (c). The first order Sugeno type is implemented to develop two if-then rules as follows:

i. Rule 1 If a is X1 and b is Y1, then c1 = m1 a + n1 b + p1,
ii. Rule 2 If a is X2 and b is Y2, then c2 = m2 a + n2 b + p2,

The structure of ANFIS model has five layers. Every layer executes special role; explained as following in Figure 1.

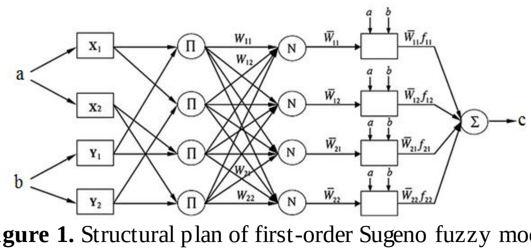


Figure 1. Structural plan of first-order Sugeno fuzzy model

Sugeno type ANFIS model is used in this paper to model the punching load of slabs. Four types of Membership functions (MFs) named trapezoidal, triangular, generalized bell-shaped and Gaussian functions are used in this paper.

3. MODEL PERFORMANCE EVALUATION CRITERIA

Estimating the performance of various techniques in estimation of the punching load of slab, various performance evaluation parameters were selected such as Coefficient Of Correlation (Cc), Bias, Mean Square Error (MSE), Root Mean Square Error (RMSE) and Nash-Sutcliffe Model Efficiency(NSE).

$$C_c = \frac{n\sum X1X2-(\sum [\![X1]\!] \sum [\![X2]\!])}{\sqrt{n(\sum [\![X1^2]\!]-\sum [\![X1]\!]^2)}\sqrt{n(\sum [\![X2^2]\!]-\sum [\![X2]\!]^2)}} \quad (1)$$

$$\sum_{i=1}^{n}(X1-X2) \quad (2)$$

$$\sum_{i=1}^{n}(X1-X2)^2 \quad (3)$$

$$\frac{1}{n(\sum_{i=1}^{n}(X1-X2)^2)} \quad (4)$$

$$NSE = 1-\frac{\sum_{i=1}^{n}(X1-X2)^2}{\sum_{i=1}^{n}(X1-\overline{X1})^2} \quad (5)$$

where,
X1 = observed values
X2 = predicted values
$\overline{X1}$ *= mean of observed values*
n = number of observations

4. DATA SET

The data set for ANFIS, GRNN, and ANN was collected from published journal (Shehata, 1990). Data were collected for the cylinder strength of concrete (f_c), yield strength of steel (f_y), ratio of effective span to the effective depth of slab (d), radius of a column or loaded area (r_0), the geometrical ratio of reinforcement (ρ), the effective depth of slab (d), and column diameter (D). The total dataset consists of 89 observations in which randomly selected 70% observations were implemented for the learning model and rest 30% were selected to validate the models. Punching shear load (P) was considered as a target for this study. Table 1 gives the features of the training and testing data set.

5. MODEL DEVELOPMENT

Preparation of ANN, GRNN, and ANFIS include choosing the primary number such as the number of neurons, number and shape of MFs, hidden layers, and spreads. In the starting of the design process, a small number of primary parameters are considered. Then the model is trained and developed. The outcomes of the model are assessed. If the outcomes are not found satisfactory, increase the number of primary parameters successively. For assessing the model accuracy, the outcomes of the model are compared with the actual data.

6. RESULTS AND DISCUSSIONS

6. 1. Result of GRNN Model Developing the GRNN

TABLE 1. Features of the data set

Variables	Units	Min.	Max.	Mean	St Dev.	Kurtosis	Skewness
Training Data							
fc	N/mm^2	9.500	50.600	28.182	7.780	1.042	0.063
fy	N/mm^2	322.000	725.000	471.000	116.847	-0.284	0.587
d	mm	47.000	201.000	114.194	37.193	1.010	0.605
ro	mm	40.000	227.000	122.339	51.311	-0.975	0.115
ρ	%	0.340	3.700	1.222	0.823	2.653	1.770
P	KN	45.000	825.000	344.306	175.254	-0.322	0.360
Testing Data							
fc	N/mm^2	20.300	44.000	28.796	5.213	1.493	0.972
fy	N/mm^2	322.000	720.000	450.296	119.084	0.705	1.005
d	mm	54.000	201.000	109.778	27.055	4.766	0.737
ro	mm	40.000	227.000	123.926	47.237	-0.852	-0.115
ρ	%	0.350	3.700	1.246	0.849	3.810	1.972
P	KN	63.000	581.000	344.111	146.721	-0.820	-0.206

model is a trial and error method. Development of GRNN is also based on the data set listed in Table 1 which was divided into two parts of learning and testing.The selection of learning and testing datasets were based on randomization. For developing GRNN model, spread (s) need to be selected. In this study, the optimum value of spread was achieved at 0.2. During the GRNN training, obtained Cc was 1.0, RMSE was 31.887 and NSE was 0.966 and when testing the model, Cc was 0.868; RMSE was 71.887 and NSE was 0.751. Figure 2 shows the aggrement plot using GRNN model during testing stage.

6. 2. Result of ANN Model ANN model development is also trial and error process such as GRNN model development. The ANN model consists only single hidden layer. Hidden layer contains nine neurons with iteration =1500, momentum =0.2, and learning rate = 0.1. As revealed from Table 2 and Figure 3, the precision of the ANN model is more than GRNN based model for prediction of Punching Shear load.

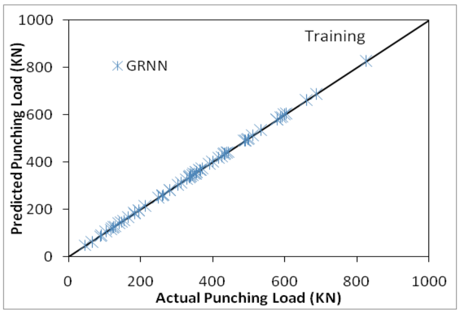


Figure 2. Evaluation of GRNN model

TABLE 2. Performance evaluation Parameters

Approaches	Cc	Bias	MSE	RMSE	NSE
Training Data set					
GRNN	1.000	0.002	1016.796	31.887	0.966
ANN	0.951	-10.249	2989.138	54.673	0.901
ANFIS_trimf	0.983	0.002	994.651	31.538	0.967
ANFIS_trap	0.592	0.001	18500.380	136.016	0.388
ANFIS_gbell_mf	0.981	-0.003	18298.881	135.273	0.395
ANFIS_gaussian	0.983	-0.001	58.866	7.672	0.998
Testing Dataset					
GRNN	0.868	3.678	5167.779	71.887	0.751
ANN	0.936	-14.446	5038.999	70.986	0.757
ANFIS_trimf	**0.960**	**12.542**	**1769.297**	**42.063**	**0.915**
ANFIS_trap	0.649	-12.103	10204.225	101.016	0.508
ANFIS_gbell_mf	0.956	12.223	9260.653	96.232	0.553
ANFIS_gaussian	0.963	1.104	126.377	11.242	0.994

* Highlighted values shows the best performance model

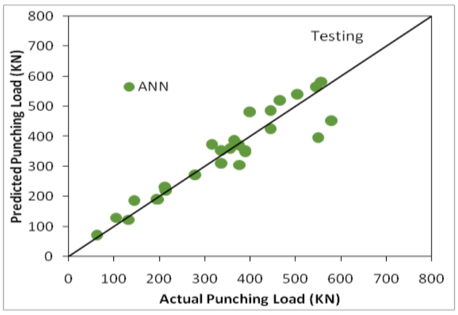


Figure 3. Evaluation of ANN model

6. 3. Result of ANFIS Model Developing the Sugeno fuzzy rule-based ANFIS models is as similar as ANN and GRNN process. Designing of ANFIS model includes defining the number of hidden layer(s), Neurons, number and shape of member functions. Four shapes (Triangular, Gaussian, Trapezoidal and Generalized bell) of the membership functions were chosen for developing the models. Results of the ANFIS model to predict the Punching load is shown in Figure 4. From Table 2, it can be inferred that Gaussian-based ANFIS model works better as compared to triangular, trapezoidal and generalized bell shape MFs based ANFIS models with CC=0.963, and RMSE = 11.242. Overall, as shown in Figure 4, the Gaussian MFs based ANFIS model is most suitable for predicting the values of punching load for the slab.

Comparison of data mining techniques based models (Table 2 and Figure 5) indicates that Gaussian based ANFIS models work better than GRNN and ANN based models. To evaluate the estimating capability of ANFIS, GRNN and ANN models, agreement, were plotted in Figure 5 for both training and testing stages. It is incidental from the plots that the predicted values produced by Gaussian MF based ANFIS are extremely close to the actual punching load values.

6. 4. Sensitivity Analysis A sensitivity study was performed to find the significant input parameter in the estimation of punching load in the concrete slab. The most effective parameters for estimation of Punching

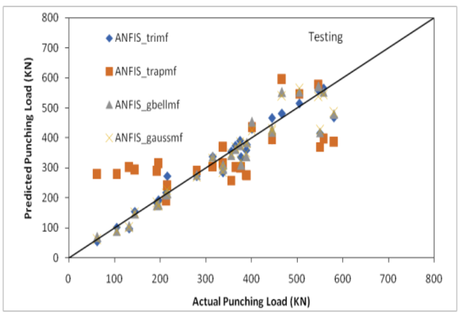
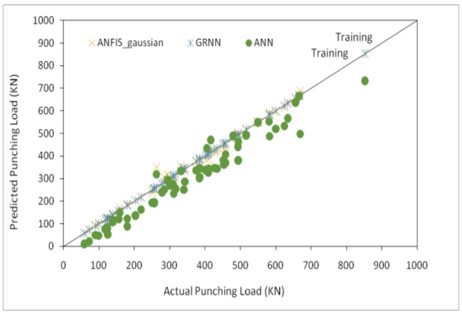


Figure 4. Evaluation of ANFIS model



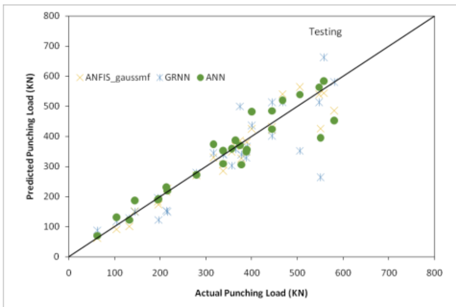


Figure 5. Assessment of the performance of ANFIS, GRNN and ANN models

Shear load by ANFIS are defined by a Gaussian MF based ANFIS modeling method. This method explains the consequences of every constraint in the model to estimate the Punching Shear load. At first, all the parameters regard to the Table 1 except P were considered as inputs for ANFIS gauss_mf and then single input parameter is eliminated. Further the model was reconstructed with the same configuration. After adjusting the model structure, the sensitivity analysis of the models began in order to define the most effective parameters. Eliminating one of the input variables caused a change in model performance. The performance of the models in the deficiency of every input parameter was examined using the estimation of indices containing Cc, Bias, MSE, RMSE, and NSE. The outcome of sensitivity analysis of ANFIS gauss_mf is shown in Table 3. As evident from Table 3, the effective depth of slab (d) is the most effective parameter in the estimation of punching shear load.

TABLE 3. Performance of parameters for sensitivity analysis

Input Parameters	Removed Parameters	ANFIS Gaussian Member Functions				
		C_c	Bias	MSE	RMSE	NSE
fc, fy, d, r_o, ρ		0.963	1.104	126.377	11.242	0.994
fy, d, r_o, ρ	fc	0.950	21.172	2615.143	51.139	0.874
fc, d, r_o, ρ	fy	0.954	12.733	2080.144	45.609	0.899
fc, fy, r_o, ρ	d	0.563	20.136	19312.265	138.969	0.068
fc, fy, d, ρ	ro	0.944	12.102	2433.769	49.333	0.883
fc, fy, d, r_o	ρ	0.929	17.191	3263.917	57.131	0.843

7. CONCLUSION

Based on obtained results, the ANFIS model with the Gaussian membership functions has a suitable capability to estimate the Punching shear load. The ANFIS model also provides better performance than the ANN and GRNN models. Another major conclusion was that ANN model works better than GRNN model. Sensitivity results suggest that the effective depth of slab (d) is the most significant factor when ANFIS Gaussian membership function based model is implemented for the forecast of punching shear strength. Sensitivity investigation concludes that effective depth of slab (d) is the most effective parameter in the estimation of punching load for this data set.

8. REFERENCES

1. Muttoni, A., "Punching shear strength of reinforced concrete slabs without transverse reinforcement", ***ACI Structural Journal***, Vol. 105, No. 4, (2008), 440–450.
2. Metwally, I.M., "Prediction of punching shear capacities of two-way concrete slabs reinforced with FRP bars", ***HBRC Journal***, Vol. 9, No. 2, (2013), 125–133.
3. Dilger, W., "Flat slab-column connections", ***Progress in Structural Engineering and Materials***, Vol. 2, No. 3, (2000), 386–399.
4. ACI Committee Ommittee 318, Building Code Requirements for Structural Concrete and Commentary, American Concrete Institute, Detroit, USA, (1995).
5. BS 1881, Part 116, Method for Determination of Compressive Strength of Concrete Cubes, British Standards Institution, London, (1985).
6. Kinnunen, S. and Nylander, H., Punching of concrete slabs without shear reinforcement, Elanders Boktryckeri Aktiebolag, Stockholm, (1960).
7. Kinnunen, S., Punching of concrete slabs with two-way reinforcement, Elanders Boktryckeri Aktiebolag, Stockholm, (1963).
8. Nielsen, M.P., Braestrup, M.W., Jensen, B.C., and Bach, F., Concrete plasticity—beam shear—punching shear—shear in joints, Danish Society for Structural Science and Engineering, Copenhagen, (1978).
9. Andrä, H.P., Zum Tragverhalten des Auflagerbereichs von Flachdecken, Dissertation Technische Hochschule Stuttgart, Institut für Baustatik, (1982).
10. Shehata, I.A.E.M., Theory of punching in concrete slabs, Doctoral Thesis, University of Westminster, University of Westminste, London, United Kingdom, (1985).
11. Shehata, I.A.E.M. and Regan, P.E., "Punching in R.C. Slabs", ***Journal of Structural Engineering***, Vol. 115, No. 7, (1989), 1726–1740.
12. Abdollahi, S.M., Ranjbar, M.M., and Ilbegyan, S., "Shear Capacity of Reinforced Concrete Flat Slabs Made with High-strength Concrete: A Numerical Study of the Effect of Size, Location, and Shape of the Opening (TECHNICAL NOTE)", ***International Journal of Engineering - Transactions B: Applications***, Vol. 30, No. 2, (2017), 162–171.
13. Regan, P.E. and Braestrup, M.W., Punching shear in reinforced concrete: A state of art report, Volume 168 of Bulletin

d'information: Euro-International Committee for Concrete, Secretariat Permanent, (1985).

14. Alexander, S.B. and Simmonds, S.H., "Ultimate strength of slab-column connections", ***Structural Journal***, Vol. 84, No. 3, (1987), 255–261.
15. Bažant, Z.P. and Cao, Z., "Size effect in punching shear failure of slabs", ***ACI Structural Journal***, Vol. 84, No. 1, (1987), 44–53.
16. Vidosa, F.G., Kotsovos, M.L.D., and Pavlovic, M.N., "Symmetrical punching of reinforced concrete slabs: an analytical investigation based on nonlinear finite element modeling", ***Structural Journal***, Vol. 85, No. 3, (1988), 241–250.
17. Sagaseta, J., Tassinari, L., Ruiz, M.F., and Muttoni, A., "Punching of flat slabs supported on rectangular columns", ***Engineering Structures***, Vol. 77, (2014), 17–33.
18. Hallgren, M., Punching shear capacity of reinforced high-strength concrete slabs, Doctoral dissertation, Kungliga Tekniska Hogskolan, Royal Institute of Technology, Sweden, (1998).
19. Shehata, I.A.E.M., "Simplified model for estimating the punching resistance of reinforced corete slabs", ***Materials and Structures***, Vol. 23, No. 5, (1990), 364–371.
20. Goel, A., "ANN Based Modeling for Prediction of Evaporation in Reservoirs (RESEARCH NOTE)", ***International Journal of Engineering - Transactions A: Basics***, Vol. 22, No. 4, (2009), 351–358.
21. Poursina, M., Khalili, M., and Golestanian, H., "Experimental and Neural Network Prediction of Elongation and Spread after First Stage of Fullering", ***International Journal of Engineering - Transactions B: Applications***, Vol. 23, No. 3&4, (2010), 233–242.
22. Kamalloo, A., Ganjkhanlou, Y., Aboutalebi, S.H., and Nouranian, H., "Modeling of Compressive Strength of Metakaolin Based Geopolymers by The Use of Artificial Neural Network (RESEARCH NOTE)", ***International Journal of Engineering - Transactions A: Basics***, Vol. 23, No. 2, (2010), 145–152.
23. Sheikh Khozani, Z., Bonakdari, H., and Zaji, A.H., "Comparison of Three Soft Computing Methods in Estimating Apparent Shear Stress in Compound Channels", ***International Journal of Engineering - Transactions C: Aspects***, Vol. 29, No. 9, (2016), 1219–1226.
24. Theodorakopoulos, D.D. and Swamy, R.N., "Ultimate punching shear strength analysis of slab–column connections", ***Cement and Concrete Composites***, Vol. 24, No. 6, (2002), 509–521.
25. Siddique, R., Aggarwal, P., Aggarwal, Y., and Gupta, S.M., "Modeling properties of self-compacting concrete: support vector machines approach", ***Computers and Concrete***, Vol. 5, No. 5, (2008), 461–473.
26. Aggarwal, P. and Aggarwal, Y., "Prediction of Compressive Strength of Self- Compacting Concrete with Fuzzy Logic", ***International Scholarly and Scientific Research & Innovation***, Vol. 5, No. 5, (2011), 774–781.
27. Aggarwal, P., Aggarwal, Y., Siddique, R., Gupta, S. and Garg, H., "Fuzzy logic modeling of compressive strength of high-strength concrete (HSC) with supplementary cementitious material", ***Journal of Sustainable Cement-Based Materials***, Vol. 2, No. 2, (2013), 128–143.
28. Sihag, P., "Prediction of unsaturated hydraulic conductivity using fuzzy logic and artificial neural network", ***Modeling Earth Systems and Environment***, Vol. 4, No. 1, (2018), 189–198.
29. Goharriz, M. and Marandi, S.M., "Assessment of Lateral Displacements using Neuro-Fuzzy Group Method of Data Handling Systems", ***International Journal of Engineering - Transactions B: Applications***, Vol. 28, No. 5, (2015), 677–685.
30. Javdanian, H., "The effect of geopolymerization on the unconfined compressive strength of stabilized fine-grained soils" ***International Journal of Engineering - Transactions B: Applications***, Vol. 30, No. 11, (2017), 1673-1680.
31. Maleki, E., Di Milano, P., Farrahi, G.H., Maleki, E., "Modelling of Conventional and Severe Shot Peening Influence on Properties of High Carbon Steel via Artificial Neural Network", ***International Journal of Engineering - Transactions B: Applications***, Vol. 30, No. 11, (2017), 382–393.
32. Tabatabaeian, Z. S. and Neshati, M.H., "Sensitivity Analysis of a Wideband Backward-wave Directional Coupler Using Neural Network and Monte Carlo Method (RESEARCH NOTE)", ***International Journal of Engineering - Transactions B: Applications***, Vol. 31, No. 5, (2018), 729–733.
33. Jadidi, A.M. and Jadidi, M., "An Algorithm based on Predicting the Interface in Phase Change Materials", ***International Journal of Engineering - Transactions B: Applications***, Vol. 31, No. 5, (2018), 799–804.
34. Specht, D.F., "A general regression neural network", ***IEEE Transactions on Neural Networks***, Vol. 2, No. 6, (1991), 568–576.
35. Wasserman, P., Advanced methods in neural computing, John Wiley & Sons, Inc., (1993).
36. Siddique, R., Aggarwal, P., and Aggarwal, Y., "Prediction of compressive strength of self-compacting concrete containing bottom ash using artificial neural networks", ***Advances in Engineering Software***, Vol. 42, No. 10, (2011), 780–786.
37. Singh Nain, S., Garg, D., and Kumar, S., "Prediction of the Performance Characteristics of WEDM on Udimet-L605 Using Different Modelling Techniques", ***Materials Today: Proceedings***, Vol. 4, No. 2, (2017), 546–556.
38. Haykin, S., Neural networks: A comprehensive foundation, Prentice Hall PTR, (1994).

Estimation of Punching Shear Capacity of Concrete Slabs Using Data Mining Techniques

Y. Aggarwal, P. Aggarwal, P. Sihag, M. Pal, A. Kumar

Department of Civil Engineering, National Institute of Technology, Kurukshetra, Haryana, India

PAPER INFO

Paper history:
Received 02 August 2018
Received in revised form 26 March 2019
Accepted 03 May 2019

Keywords:
Adaptive Neuro-fuzzy Inference System
Artificial Neural Network
Coefficient of Correlation
Generalized Neural Network
Punching Load

چکیده

ظرفیت برش پانچ یک عامل کلیدی برای کنترل شکل سقوط اسلب است. این تنش شکننده که در اتصال ستون اتفاق می افتد، برش پانچ نامیده می‌شود که برای مهندسان جای نگرانی دارد. شایع‌ترین روش در ارزیابی قدرت پانچینگ اسلب‌های بتنی، استفاده از اصطلاحات تجربی موجود در کدهای طراحی ساختمان‌های مختلف است. برآورد بارهای پانچ شامل راه اندازی تجربی است که وقت گیر، غیراقتصادی و همچنین نیاز به نیروی انسانی و مواد دیگر دارد. مطالعه حاضر، استفاده از تکنیک‌های داده‌کاوی را به عنوان جایگزین سابق برای پیش‌بینی بارهای پانچ در تنوع پارامترهای مختلف نشان می‌دهد. در این مطالعه به منظور مدل‌سازی و برآورد بار مشت زدن اتصالات ستون‌های بتونی بتن مسلح، از روش‌های مختلف استخراج اطلاعات از جمله سیستم استنتاج نوری فازی (ANFIS)، شبکه عصبی مصنوعی (ANN) و شبکه عصبی مصنوعی (GRNN) برای مطالعه، یک مجموعه داده شامل ۸۹ مشاهدات از ادبیات موجود مورد تجزیه و تحلیل قرار گرفته و به طور تصادفی انتخاب شده برای توسعه مدل ٦٢ مشاهدات استفاده گردید، در حالی که ۲۷ مورد برای آزمون مدل‌های توسعه یافته مورد استفاده قرار گرفت. در حالی که نتایج مدل ANN و GRNN عملکرد برآورد مناسب را فراهم می‌کند، مدل ANFIS بر اساس عضویت در گاوسی بهترین روش برای تعیین ضریب همبستگی (Cc) است. مطالعه حساسیت نشان می‌دهد که پارامتر عمق اسلب (d) تاثیر بیشتری برای برآورد بار مشت زدن اتصالات ستون‌های بتونی بتن مسلح برای این مجموعه داده دارد.

***doi**: 10.5829/ije.2019.32.07a.02*