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Comparison of ANN and Finite Element Model for the Prediction of Ultimate Load of Thin-Walled Steel Perforated Sections in Compression

Zhi-Jun Lu, Qi Lu, Meng Wu, Qian Xiang, Jun Gu

***Abstract*—**The analysis of perforated steel members is a 3D problem in nature, therefore the traditional analytical expressions for the ultimate load of thin-walled steel sections cannot be used for the perforated steel member design. In this study, finite element method (FEM) and artificial neural network (ANN) were used to simulate the process of stub column tests based on specific codes. Results show that compared with those of the FEM model, the ultimate load predictions obtained from ANN technique were much closer to those obtained from the physical experiments. The ANN model for the solving the hard problem of complex steel perforated sections is very promising.

***Keywords*—**Artificial neural network, finite element method, perforated sections, thin-walled steel, ultimate load.

I. Introduction

THIN-WALLED steel are widely used in many fields of civil engineering, bridges, storage racks, car bodies, railway coaches, transmission towers, and various types of equipment. Unlike other industrial applications, the columns used in storage racks are usually thin-walled steel sections contain arrays of perforations along the length, enabling beams to be clipped by connectors at variable heights and the bracings to be bolted to form the frames (Fig. 1). Despite their light weight and considerable height, storage racks are able to carry very high loads. In addition, upright members with mono-symmetrical sections are usually subjected to axial compression and bending about both axes. Nowadays, the ultimate load calculations on thin-walled columns can be made with some specific computer programs such as: Thin-Wall [1] and CUFSM [2], based on the finite strip method (FSM); and GBTUL [3], based on the generalized beam theory (GBT). The use of these specific programs has made the direct strength method very quick and effective. At the moment, unfortunately, they cannot be applied to perforated members, since FSM and GBT are essentially 2D theories but the analysis of perforated members is a 3D problem [4]. The FEM can certainly be applied, but the computational cost is significantly higher. So even if in the last many years, numerous investigations [5]-[7] were devoted to the effects of holes and members' slenderness on the ultimate capacity of pallet rack uprights, it has not been achieved in generally accepted analytical design method for rack structures [8]. For this reason, the current design of these structures is mostly based on experimental tests prescribed by specific codes. The increasing security demands from the storage racks make clear the need to explore novel ways of prediction on design load of thin-walled steel perforated sections furthermore.

During the last few years, the use of ANNs has grown in popularity because neural networks represent a novel and modern approach that can provide solutions in problems for which conventional mathematics, algorithms, and methodologies are unable to find a satisfactory and acceptable solution [9]. In this paper, an attempt has been made to use ANN technology to overcome many of the difficulties associated with the design load of thin-walled steel perforated sections. Results have been compared with those of the traditional FEM. The relative experiments and research method are presented in detail.

II. Stub Column Tests

The stub column test can be used to synthetically evaluate the effective area accounting for perforations, cold forming processes, local and distortional buckling and their natural interactions. So, in accordance to AnnexA.2.1.2 (Alternative1) the stub column tests were performed in order to observe the influence of perforations and the effects of local buckling on the ultimate strength of these members. The length of specimens was taken to respect the code requirements, i.e.: (1) it shall include at least five pitches of the perforations, at the midway between two sets of perforations. The base and cap plates shall be bolted or welded to each end of the stub upright; (2) the length of specimens shall be three times the greatest flat width of the section (ignoring intermediate stiffeners). The end-devices, at both ends, consist of pressure pads 30 mm thick with an indentation of 5 mm and a ball bearing of 40 mm diameter. Details of the testing set-up and supporting system are presented in Fig. 2. Nine series of open cold-formed steel sections (Fig. 3) were selected as uprights in pallet racking have been tested and analyzed. Dimensions range of specimens is relatively wide: web of 45~120 mm, flange of 50~145 mm, and thickness of 1.8~2.5 mm. Two sections have intermediate and edge stiffener, five sections have only intermediate stiffener, and two sections have none. In order to build an ANN-based predictive model on thin-walled steel perforated sections, a total of 90 different data from stub columns compression experiments were collected from the shanghai Jingxing Logistic Equipment Engineering co., Ltd.

Zhi-jun Lu (Associate professor) is with the Donghua University, Shanghai, P. R. China. (corresponding author, phone: +86-021-67792583, fax: +86-021-67792583, e-mail: lvzj@dhu.edu.cn).

Qi Lu and Meng Wu (Graduate students) are with the Donghua University (e-mail: lu1995qi@163.com, freemeng1@163.com respectively).

Fig. 1 Arrays of perforations of columns

Fig. 2 The testing set-up and supporting system of EN15512 [10]

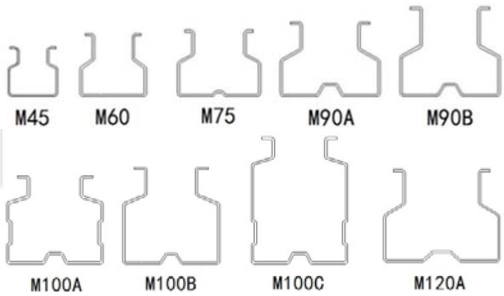

Fig. 3 Nine series of open cold-formed steel sections

III. ANN Model Design

The use of ANNs has grown in popularity during the last few years. The reason for this is that neural networks represent a novel and modern approach that can provide solutions in problems for which conventional mathematics, algorithms, and methodologies are unable to find a satisfactory and acceptable solution [10]. These problems are usually very complex and some of the mechanisms involved have not been fully understood by the researchers dealing with them. Considering some salient features of ANN, there was proposed ANN-based ultimate load prediction system on thin-walled steel perforated sections. The internal detailed architecture of ANN is shown in Fig. 4. In intelligent model, there were nine input neurons such as perforated sections parameters and one output neuron, ultimate load, all listed in Table I. All the data are normalized, and it is pre-processed to be converted in the range (−1,1) before being fed into ANN. The feed-forward neural network architecture is fully connected, that is, each neuron in the hidden layer is connected to all the neurons in the previous and next layer. Each neuron constitutes a learning unit. The neural network was trained for a different combination of hidden layer neurons and nine were found to be most suitable for this specific data set. The training function, "trainlm", had been transferred from the MATLAB ANN toolbox to realize the training of these models. The transformation function of hidden neuron was "tansig", and "purelin" was the output layer function, which were also obtained from the ANN toolbox of the MATLAB software. The learning rate η was set from 0.01 to 0.07, which can speed up the convergence of training function on the condition of accepted training precision (Fig. 5).

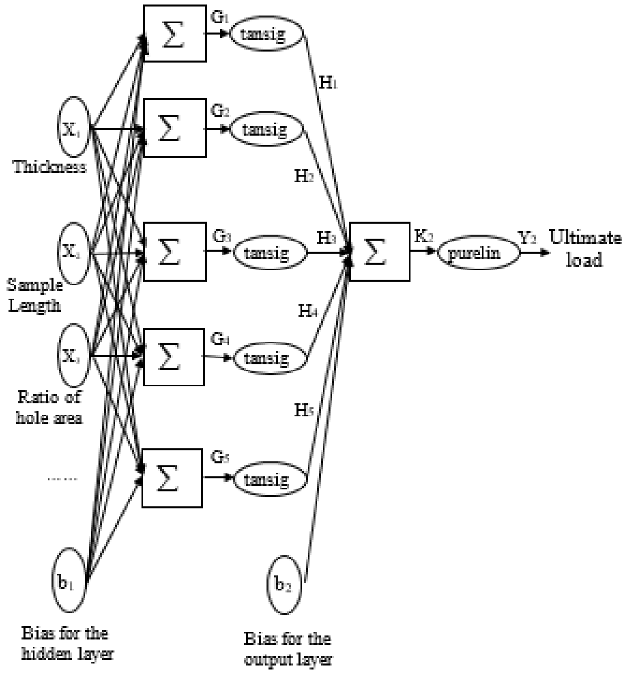

Fig. 4 ANN architecture

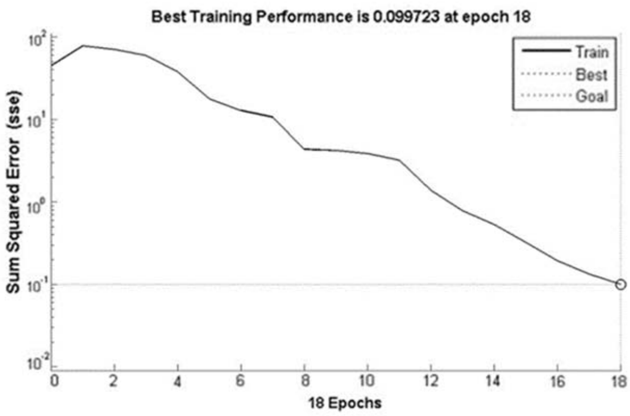

Fig. 5 The iterative process of predictive model

IV. Finite Element Model

The finite element (FE) method has proven to be a very effective and powerful tool for analysis of perforated members and predicting their strength and behavior [4], [5]. Referring to AnnexA.2.1.2 of EN15512, a parametric FE model has been created with the ANSYS code [11]. Element type SHELL 181 was selected to be used for the experiment simulations. The merit of this kind of four-node shell with six degrees of freedom per node lies in the linear and non-linear analysis, including large displacements and plasticity and rotations. In our model, all slots and holes have been exactly reproduced. The element type SOLID45 was also carefully applied for the load plates modelling. The eight-node solid three-dimensional element with three degrees of freedom per node is frequently used for linear and nonlinear analysis in the same way. On a central node of the outer face of both load plates, the displacements are properly appointed, i.e. the line defined by these two nodes is the load line. All node displacements of the bottom plate have been set up to zero, and the transversal displacements of the node at the top plate has also been set up to zero. The axial displacement of the load line is gradually increased step by step until the stub can be no longer in force. The displacement controlled method has been used to simulate the experimental process of ultimate load on the top end of the stub column. The displacement is added in continuous increments until it obviously begins to decrease or remains unchanged for an extraordinary lapse of displacement. At that moment, the maximum load in the stub can be considered the failure force, i.e. so-called ultimate load. As an example, the result is demonstrated for FEM simulation of M90 column compression in Fig. 7.

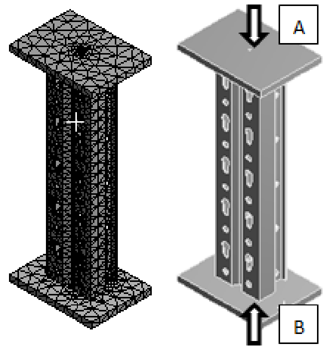

Fig. 6 Mesh, constraint and load setting of simulation model

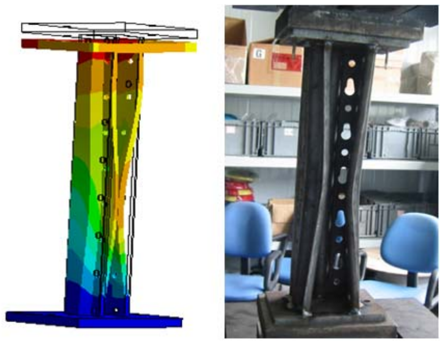

Fig. 7 The comparison between FEM simulation and physical test (M90 column)

TABLE I
RELATIONAL MAPPING BETWEEN INPUT AND OUTPUT PARAMETERS

Column type	Input index									Output index
	Web Width (mm)	Thickness (mm)	Flange Width (mm)	Opening Size (mm)	Sample Length (mm)	Ratio of hole area (%)	Number of bends	Number of right angles	Number of reinforcement	Ultimate load (N)
M60	60	1.8	55	34	350	14.951	8	4	0	80309.17
M75	75	1.8	58	45	400	12.190	12	4	1	122051.82
M90A	90	2	65	50	400	11.287	12	4	1	137228.18
M100B	100	2.5	90	52	400	10.667	20	4	3	205633.26
M120A	120	3	95	76	500	8.889	12	4	1	269336.45

TABLE II
COMPARISON AMONG THE MEASURED VALUES, PREDICTED VALUES AND FINITE ELEMENT NUMERICAL VALUES

Column type	Measure (N)	Predict (N)	Absolute error (%)	FEM (N)	Absolute error (%)
M45-1.5	48385.6	48429.2	0.09	49856.3	3.04
M60-2	107142.8	104077.6	2.86	116348.7	8.59
M75-1.8	120057	115392.3	3.89	130147.5	8.41
M90A-2	136364.2	140316.6	2.90	144199.2	5.73
M100B-2	159740	162860.8	1.95	167594.5	4.92
M120A-3	268689.3	271741.8	1.14	283439.5	5.49
M120B-3.5	413894	417135.6	0.78	449071.2	8.50
			…		
Mean absolute error (%)			1.85		6.05
Correlation coefficient. R			0.99		0.97
Cases with over 5% error			2		13

V. RESULT AND DISCUSSION

Within the total of 90 data sets from stub columns tests, the first 70 data sets are used for network training, and the others are set aside to evaluate the trained network's performance (prediction). Network training is terminated based on the accepted prediction accuracy of these models such as for the corresponding deviation not more than 5% between the expected values and the real values. After the completion of model development or training, the other 20 datasets are input to the intelligent model to verify the accuracy of model generalization. The results are shown in Table II, where "Measure", "Predict", and "FEM" refer to the measured values, the predicted values and finite element numerical values, respectively. Statistical parameters such as the correlation coefficient R between the expected and real value, and mean absolute error % are used to judge the predictive power of the ANN models. It is evident that the accuracy of the predictive models is relatively high in all (R>95%), while ANN model in the mean absolute error and the ratio of the cases with more than 5% error is lower than FEM model. So, the ANN models can be more suitable to assist the security estimation during the steel member design.

VI. Conclusion

Due to computational accuracy and complexity, the analytical expressions for the ultimate load of thin-walled steel perforated sections are not used for steel member design so far. In this paper, the load predictions from the neural network were compared with those obtained from the FEM model. It was found that the prediction performance based on ANN technique was apparently much better than those obtained from the FEM models. Of course, the advantages of FEM lie in that thin-walled section buckling and their mechanization is comparatively clear. We only demonstrate that, trained with the datasets from engineering experiment, the ANN model is able to predict the design load of different columns through continually self-learning, which can help the engineer to make the better design decision. Although the results of our work seem to be very preliminary, it has been observed that the ANN model for the solving the hard problem of complex perforated members design is promising. With advancement of advanced big data and cloud computing techniques, much of the engineer's subject intuition in constructional steel industry will finally be replaced by more smart and friendly expert systems in the future.

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Zhi-jun Lu is an associate professor from the Donghua University, Shanghai, P.R.China. He received the Ph.D degree and master degree in mechanical engineering from the same university, in 2007 and 1993, respectively. His research interests are focus on computational intelligence, complex system modeling, and thin-walled steel.