Application of Artificial Neural Networks for Web-Post Shear Resistance of Cellular Steel Beams

Vireen Limbachiya [1], Rabee Shamass [2]

[1,2] Senior Lecturer in Civil Engineering, London South Bank University, School of Built Environment and Architecture, London, UK

Abstract

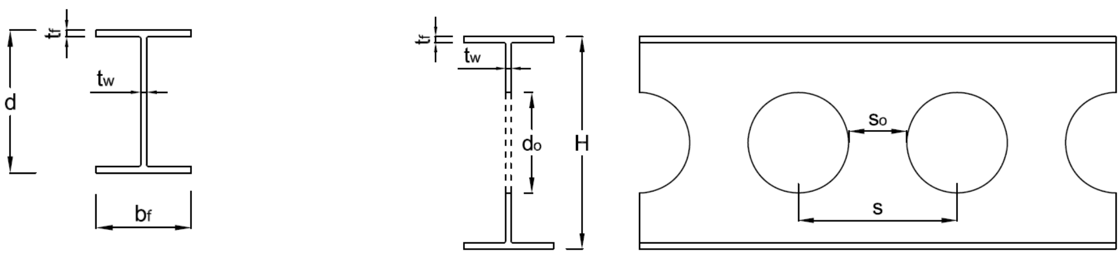
The aim of this paper is to predict web-post buckling shear strength of cellular beams made from normal strength steel using the Artificial Neural Networks (ANN). 304 developed finite-element numerical models were used to train, validate and test 16 different ANN models. To verify the accuracy of the ANN model, the ANN predictions were compared with experimental and analytical results. Results show that ANN models that used geometric parameters as an ANN input were able to predict web-post buckling strength to a higher level of accuracy in comparison to models using only geometric ratios as an ANN input. An ANN-based formula with 4 neurons was proposed in this study. In comparison to existing design guidance, it is shown that an ANN model trained with the Levenberg-Marquardt backpropagation algorithm is capable of predicting the web-post shear resistance to a higher level of accuracy. The formula developed can be easily implemented in Excel or in user graphical interface. It can be a potential tool for structural engineers who aim to accurately estimate the web-post buckling of cellular steel beams without the use of costly resources associated with FE analysis.

1. Introduction

Cellular beams are widely used to achieve long spans that allow for fewer columns and footings in the structure, resulting in shorter construction times and cheap infrastructure costs [1, 2]. They have been used for different structures that would benefit from open spaces such as roofing with long spans, renovation, and strengthening and modernising historical buildings while preserving their aesthetic design. Selecting cellular beams can reduce floor zone depths as the services can be integrated with the floor beams which lower the building height and cost.

Cellular beams can span much further than the regular I- beam sections since they have higher depth-to-weight ratio, section modulus, and moment of inertia. They are usually manufactured by cutting along the web of hot-rolled I-beam section in a certain pattern and re-welding the upper and lower tees to form a cellular beam. Cellular beams will be named all perforated beams with circular web opening.

Figure 1 shows parent I-beam and cellular beam sections. In this figure, H is the total height of the cellular section; t_f and t_w are the flange and web thicknesses; b_f is the flange width; d is the height of the parent section; d_o is the opening diameter; s and s_o are the centre-to-centre spacing and edge-to-edge spacing of adjacent openings, respectively.



(a) (b)

Figure 1: (a) Parent I-beam section; (b) Cellular beam geometry

The structural behaviour and type of failure of cellular beams are different from regular I-beam sections. The failure modes of cellular beams observed experimentally are: global bending failure (BF), Vierendeel bending failure (BF), lateral torsional buckling (LTB), web-post rupture of weld joints, and web-post buckling (WPB), or lateral torsional buckling of web-post due to high in-plane horizontal shear stress in the web-post. WPB consists of lateral displacements of the web-post in double curvature accompanied by twisting deformations [3], as can be observed in the Figure 2.

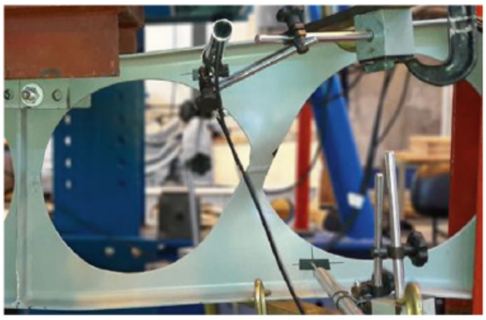


Figure 2. Web-post buckling mode of failure [4]

Many experimental tests have been conducted on cellular beams to investigate their structural behaviour and failure modes [4-7]. It was observed from these experiments that the dominated failure mode of cellular beams is the web-post buckling, particularly for thin/narrow web-post cellular beams.

There are different approaches to predict the shear resistance of the web-post of cellular beams. The design method by SCI publication 100 [8] was an early semi-empirical design method for the WPB which proposed a relationship between maximum allowable web- post moment and the web-post geometries. Grilio et al [4] proposed resistance curves to determine the shear resistance in cellular beams for the web-post buckling. Lawson et al [9] suggested another design approach to obtain the shear resistance of web-post based on the design of strut analogy acting diagonally in the web-post. This method was adopted by SCI publication 355 [10] for WPB of cellular beams with large opening. More recently, Shamass and Guarracino [11] proposed a new design model obtained from a simplified mechanical approach for WPB which is based on the elementary model of an ideal inclined compressed strut. This model can adjust the width, inclination and boundary conditions of the compressed ideal strut to the geometry of the cellular beam and is applicable for normal and high strength steel.

However, plastic buckling of structures remains a rather complicated problem depending on a number of factors, as recently shown by investigations of one of the present authors [12-15] and for such a reason the recourse to artificial intelligence methods, such as neural networks and fuzzy logic (FL) may turn beneficial to these kinds of problems.

In fact, over the years, the application of modelling methods based on neural networks and fuzzy logic (FL) have been implemented to solve various engineering problems. Artificial Neural Networks (ANN) solve complex problems with the help of interconnected computer elements and consist of 3 layers (input, hidden and output). The inputs in this case are the geometric variables within a cellular steel section shown in Figure 1. The hidden layer consists of neurons which recognises patterns and computes values from the input which in turn predicts the response variable. Fuzzy control theory needs only to set a simple controlling method based on engineering experience. Therefore, it is particularly useful in complicated structural control system [16]. When comparing the two forms of modelling, both provided great levels of accuracy, however, it has been concluded that ANN provides better statistical results in comparison to FL [16-17].

ANN has been used to predict various forms of structural behaviour in steel elements such as I-beams [18], composite columns [19], frames [20], welded flange plate steel connections [21] and unstiffened steel plates [22], with some studies focusing on cellular and castellated steel beam [23-29]. It was reported that ANN showed more accurate ultimate moment capacities of castellated steel beams under lateral-distortional buckling (LTB) than those predicted by current design rules such as EC3 and AISC, the later provided unsafe and unconservative predictions [23]. In another study it was concluded that ANN-based formula model trained on 140 castellated beams modelled using finite-element (FE) and Levenberg-Marquardt algorithm provided accurate web-post buckling strength of castellated beams [29]. Sharifi et al. [26] used 96 data-based verified simulation to train ANN that predicted the strength capacity of cellular beams under LTB. They reported that ANN gave reliable estimations of the LTB strength capacity of steel cellular beams. Sharifi et al [25] trained an ANN network with a database of 99 cellular steel beams which were loaded under two concentrated loads and failed in LTB mode. The study compared 9 training algorithms in MATLAB and found that the Levenberg-Marquardt algorithm provided the most accurate predictions when reviewing the mean-squared error of the predicted results from the considered training algorithms. Abambres et al [27] proposed ANN-based formula to predict elastic buckling load of cellular beams subjected to distributed load. It was concluded that the ANN-based formula yielded accurate predictions. Overall, studies showed that ANN is able to provide fast results with the high level of accuracy when compared to experimental and numerical results.

In this context, it can be noted that there is currently no research that aims at predicting the web-post buckling of cellular beams using ANN. Therefore, the scope of this paper is to predict the vertical shear strength of cellular beams made from normal strength steel S355 using ANN and to propose an ANN-based formula to accurately compute the web-post buckling strength, in terms of independent geometrical parameters. The study makes use of the FE model developed by Shamass and Guarracino [11] to generate the data that is successively employed to train the ANN. The output of the ANN is then compared to experimental data and current analytical analysis, with satisfactory results.

2. Development and validation of the numerical models

Full beam models are generally used for numerical validation and to investigate the structural behaviour of cellular elements. The single web-post models are widely used in the literature to investigate numerically the effect of geometric properties of the cellular beams on the shear resistance of the web-post [4, 5, 7]. In this study, both the full beam and the single web-post models are developed and validated.

Shamass and Guarracino [11] previously developed finite-element (FE) model using ABAQUS software for simply supported cellular beams subjected to a point load. The same FE model is used in this study since it has proven capable of providing a good prediction of the behaviour of steel cellular beams in terms of vertical shear resistance, load-displacement response and WPB failure. The steel cellular beams test results conducted by Grilo et al. [4] and Tsavdaridis and D'Mello [5] were used for the validation of the both full beam and the single web-post numerical models since all the cellular beams in these tests failed by pure WPB. The material was modelled using a multi-linear stress-strain relationship, including strain hardening. The cellular beam section and stiffeners were modelled using a general-purpose three-dimensional reduced integration shell element named S4R in ABAQUS. Simply supported boundary conditions were used in the beams and loading was applied on the top flange of the beams under displacement control. A linear buckling analysis was first performed, followed by a nonlinear analysis using the Newton-Raphson solution method. Geometric imperfections were considered in the numerical model.

The single web-post model used in this study shares the same numerical considerations of the full beam model with respect to the type of element, material properties and initial imperfection. The boundary conditions and the load application of the web-post model are described in Grilo et al. [4] and shown in Figure 3.

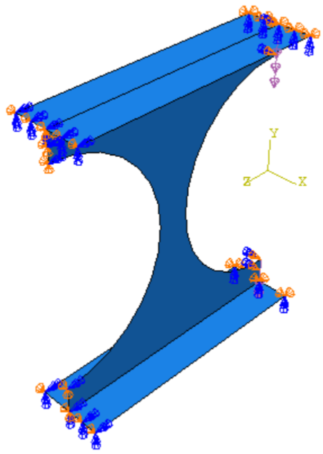


Figure 3: Single web-post model

Table 1 shows comparisons between the buckling shear loads observed experimentally (V_{Test}) by Grilo et al. [4] and Tsavdaridis and D'Mello [5] with those obtained numerically (V_{FE}) for both the full beam and single web-post models. It can be observed that the buckling shear loads from the single web-post model tend to be more conservative in comparison to those from the full beam model. Grilo et al. [4] conducted numerical models for full beam, single web-post and long beam models and found that long beam models predicted shear buckling results close to those predicted by the single web-post models, since the long beam models were less sensitive to border effects. Therefore, the single web-post models were not influenced by the border effect. In summary, the validation of the single web-post model confirms that the model can reasonably be utilised for further parametric study to predict buckling shear load of WPB with minimum computational effort.

Table 1: Comparison between experimental and numerical vertical shear buckling load

Specimen	Bucking shear strength (V) (kN)			Percentage difference (%)	
	Test (V_{Test})	Numerical model (V_{FE})			
		Full beam	Single web-post	Full beam/test	Single web-post/test
A1	38	40.0	37.1	5.26	-2.3
A2	61.9	59.2	58.2	-4.34	-6.0
A3	70.7	65.6	65.2	-7.21	-7.8
A5	99.1	98.4	71.9	-0.75	-27.4
A6	102.2	102.5	96.7	0.26	-5.4
B1	54	54.9	53.1	1.57	-1.6
B2	79	75.6	78.9	-4.32	-0.2
B5	138.5	134.5	110.0	-2.91	-20.6
B6	150	148.6	137.7	-0.93	-8.2
C1	144.35	147.7	147.7	2.35	2.3
C2	127.5	120.0	101.4	-5.88	-20.5

3. Parametric study

In this section, the single web-post model described in the Section 2 is used to predict the shear buckling loads. The numerical shear buckling loads will then be used to train the artificial neural network models.

The steel grade is S355 with, elastic modulus E, yield stress f_y, ultimate stress f_u , strain at the onset of hardening ε_{st} and ultimate strain ε_u equal to 210 Gpa, 355 Mpa, 510 Mpa, 2.5% and 18 %, respectively. The imperfection size is taken as H/500 [7].

The parameters characterising the web-post geometries resulting from the cutting process of the rolled I-beam are [8]:

$$e = \frac{d_o}{2} - \sqrt{\left(\frac{d_o}{2}\right)^2 - \left(\frac{s - d_o}{2}\right)^2} \quad (1)$$

$$H = d + \frac{d_o}{2} - e \quad (2)$$

$$s_o = s - d_o \quad (3)$$

In this study rolled sections presented in the Table 2 are used as the parent I-beam sections with slenderness ratios d/t_w range from 34.56 to 62.19. The opening ratio d_o/d is taken equal to 0.8, 0.9, 1, 1.1, and 1.2 and the spacing ratio s/d_o is taken equal to 1.1, 1.2, 1.3, 1.4, and 1.5.

Table 2: Parent I-beam sections used in this study

Section UB	152×89×16	203×102×25	245×102×28	254×146×37	305×102×28
d/t_w	33.91	35.65	41.33	40.63	51.45
Section UB	305×127×48	356×171×45	406×140×39	406×178×60	457×191×67
d/t_w	34.56	50.2	62.19	51.44	53.34
Section UB	457×191×74	457×152×82	533×165×85	610×178×100	
d/t_w	50.78	46.47	51.93	53.75	

4. Artificial neural network

4.1 Neural Network Architecture

The network architecture used in this paper is a Multi-Layer Perceptron Network (MLPN). The neural network toolbox with MATLAB [30] solves an input-output fitting problem with a two-layer feedforward neural network. Two-layer feed-forward network can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons are provided to its hidden layer. It has been shown that the number of neurons within the hidden layer have an impact on the accuracy of the output. Figure 4 illustrates an example of 4 neurons ANN structure consisting of 4 input parameters and 1 output parameter. Each input parameter layer links with every neuron in the hidden layer and subsequently the neurons in the hidden layer links with the output layer. Each link is assigned with a synaptic weight (real number) which is dependent on the analysis of the training and validation data sets. $Bias_k$ and $Bias_s$ in Figure 4 are constant values that are added at the hidden layer and output, respectively.

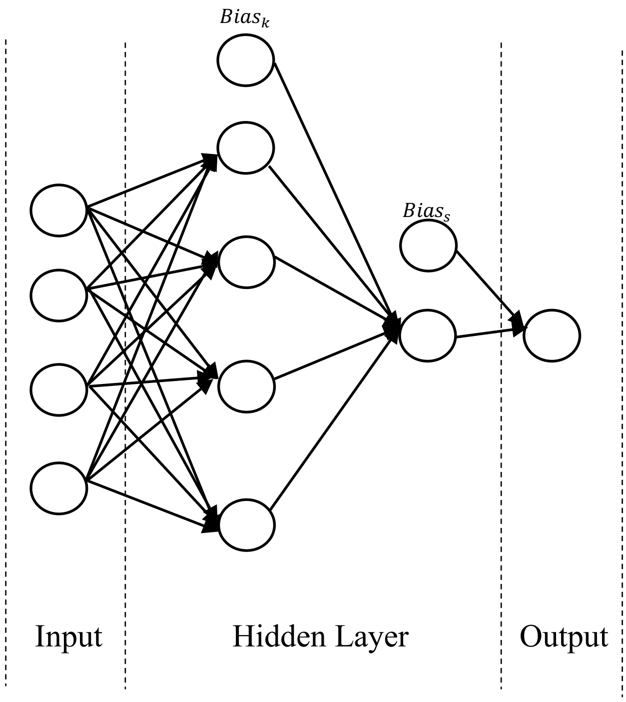


Figure 4: ANN Model with 4 neurons in the hidden layer

4.2 Input and Output Normalisation

The progress of training can be reduced if training data defines a region that is relatively narrow in some dimensions and elongated in others [27]. Therefore, normalisation for variables across all data patterns should be implemented to improve the training process. In order to normalize the input and output parameters, Equation 4 was applied to all input and target parameters.

$$\mathrm{Y} = \frac{(\mathrm{Y_{max}} - \mathrm{Y_{min}})(\mathrm{X} - \mathrm{X_{min}})}{(\mathrm{X_{max}} - \mathrm{X_{min}}) + \mathrm{Y_{min}}} \tag{4}$$

Where Y_{min} is the minimum value for each row of Y (default is –1), Y_{max} is the maximum value for each row of Y (default is +1), X_{max} is the maximum value of the input/target output parameter, X_{min} is the minimum value of the input/target output parameter, X is the actual value and Y is the normalised value

4.3 Learning Algorithm

The synaptic weight and bias are network unknown parameters that are identified through the learning. The ANN learning consists of training, validation and testing. The data points are randomly grouped into training set, validation set and testing set, with 15%,15% and 70% of the data being assigned respectively. While the training set is used to compute the gradient and update the weights and biases, a process of cross validation takes place using the validation data set so the generalization performance of the network can be verified. When the optimum network parameters are defined, the test set will be used to assess the module accuracy. The Levenberg-Marquardt back propagation training algorithm is adopted in this study due to the high level of accuracy noted in previous studies [23-27] and it is suitable for training small- and medium-sized problems. Golafshani et al. [31] stated that the back-propagation algorithm involves two phases. The first one is the forward phase where the activations are propagated from the input to the output layer. The second one is the backward phase where the error between the observed actual value and the desired nominal value in the output layer is propagated backwards in order to modify the weights and bias values.

4.4 Setting up Artificial Neural Network

In total, 304 input and output parameters were obtained from the numerical FE models to produce the ANN. Equation 4 was applied to all input and output parameters and Table 3 provides the values required in order to normalise and de-normalise the inputs and outputs.

Table 3: Parameters used to normalise input and target values

Input/Target Parameter	**Y_{max}**	**Y_{min}**	**X_{min}**	**X_{max}**
H	1	-1	205.19	970.01
d_o	1	-1	121.92	728.88
s	1	-1	146.30	947.54
t_w	1	-1	4.5	11.3
d	1	-1	152.4	607.4
d_o/t_w	1	-1	19.06	505.89
H/d_o	1	-1	27.09	74.63
s/d_o	1	-1	1.27	1.75
d/d_o	1	-1	1.10	1.50
V	1	-1	19.06	505.89

Table 4 provides the details of the 16 models that were developed and analysed in this study. For each of the input parameters reviewed, ANN models with 4, 6, 8 and 10 neurons in the hidden layer were created and analysed.

Table 4: Parameters of 16 ANN models produced

Model	**Input parameters**	**Number of neurons in hidden layer**				**Output parameter**
1	H, d_o, t_w, s, d	4	6	8	10	V
2	H, d_o, t_w, s	4	6	8	10	V
3	d_o/t_w, H/d_o, s/d_o	4	6	8	10	V
4	d_o/t_w, H/d_o, s/d_o, d/d_o	4	6	8	10	V

Equations 5 and 6 show the calculations which includes the transfer function that is required in order to determine the normalised output value based on the inputs provided [32].

$$O_s = Bias_s + \sum_{k=1}^{r} w_{k,l}^{ho} \cdot \frac{2}{(1 + e^{(-2H_k)}) - 1} \tag{5}$$

$$H_k = \mathrm{Bias}_k + \sum_{j=1}^{q} w_{j,k}^{ih} . I_j \tag{6}$$

Where, O_s represents the normalised output value, q is the number of input parameters; r is the number of hidden neurons; s is the number of output parameters; Bias_s and Bias_k are the biases of s^{th} output neuron and k^{th} hidden neuron (H_k), respectively; $w_{j,k}^{ih}$ is the weights of the connection between I_j and H_k; $w_{k,l}^{ho}$ are the weights of the connection between H_k and O_l.

4.5 Assessing Accuracy of Neural Network Output

To assess the accuracy of the output the regression (R^2), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were calculated using Equations 7, 8 and 9 respectively.

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N}(O_i - t_i)^2}{\sum_{i=1}^{N}(O_i)^2}\right) \tag{7}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(O_i - t_i)^2}{N}} \tag{8}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|O_i - t_i| \tag{9}$$

Where t_i and O_i are the actual and predicted shear resistance of the web-post of cellular beam, and N is the total number of data points in each set of data.

4.6 Impact of Individual Input

The weight from the input node to the hidden layer plays a crucial role in understanding the importance of the input parameters. An input value with a high positive weight will indicate that the input parameter has a significant impact on increasing the value of the output. If the weight of an input result is close to zero then this has minimal effect on the output. Similarly, an input value with negative weight will indicate that increasing this value will decrease the output value. In order to calculate the importance of each weight the Connection Weight Approach was adopted. There are many approaches that can be used, and it was concluded that the Connection Weight Approach provides the best method for accurately quantifying variable importance [33]. It is important to note that this approach does not assess the accuracy of the ANN model created using MATLAB, as it simply quantifies the contributions of the predictor variables in the network. It provides a form of validation to the model, as it can be used to compare with what would be expected to occur if there was to be variation in a given input parameter. The Connection Weight Approach uses raw connection weights, which accounts for the direction of the input–hidden–output relationship and results in the correct identification of variable contribution [33]. Equation 10 shows the calculation required to determine the impact of each input parameter based on the Connection Weight Approach [33]. In this equation, the Input_x represents the importance, XY represents the input-hidden connection weights and Hidden represents the hidden-output connection weights.

$$\mathrm{Input_x} = \sum_{\mathrm{Y=A}}^{\mathrm{E}} \mathrm{Hidden_{XY}} \tag{10}$$

5. Results and discussion

5.1 ANN predictions

Table 5 provides the regression values for the training, validation and testing data sets. Table 6 provides the overall statistics for the 16 ANN models when applying Levenberg-Marquardt backpropagation algorithm. Figures 5 and 6 are examples of the actual against predicted V for models 1 and 2 with 4 neurons, respectively. Results from the Table 6 clearly show that the ANN models consisting of individual geometric input parameters provides more accurate predictions than the ANN models using geometric ratios only. The highest accuracy with geometric ratios is found for model 4 with 10 neurons for which the corresponding regression value is 0.7355. Although a regression value of 0.7355 shows some form of accuracy, the MAE and RMSE values mean that it is unsuitable to predict the shear resistance with high degree of accuracy. When reviewing models 1 and 2 which only take into consideration the input geometric parameters of the cellular beam (without geometric ratios), model 1 and model 2 with 8 and 10 neurons, respectively, provide the highest accuracy among the other ANN models. In conclusion, the ANN model 1 and model 2 predict the shear resistance of the web-post of cellular beam with high level of accuracy.

Table 5: Regression values for training, validation and testing data sets

MODEL	**INPUT PARAMETERS**	**NO. OF NEURONS**	**R^2**		
			Training	Validation	Testing
1	H, d_o, t_w, s, d	4	0.9945	0.9964	0.9950
		6	0.9989	0.9984	0.9990
		8	0.9997	0.9996	0.9995
		10	0.9996	0.9993	0.9991
2	H, d_o, t_w, s	4	0.9981	0.9977	0.9972
		6	0.9985	0.9979	0.9978
		8	0.9985	0.9987	0.9991
		10	0.9998	0.9995	0.9992
3	d_o /t_w, H/d_o, s/d_o	4	0.7671	0.8109	0.7711
		6	0.8493	0.8666	0.7759
		8	0.8541	0.8482	0.7712
		10	0.7037	0.7696	0.7068
4	d_o/t_w, H/d_o, s/d_o, d/d_o	4	0.7109	0.7014	0.7015
		6	0.8376	0.8279	0.8269
		8	0.8351	0.8365	0.7879
		10	0.8741	0.8233	0.8173

Table 6: Output of ANN models

MODEL	INPUT PARAMETERS	NO. OF NEURONS	R^2	MAE	RMSE
1	H, d_o, t_w, s, d	4	0.9953	5.49	7.08
		6	0.9977	3.32	5.00
		8	0.9992	2.09	2.86
		10	0.9989	2.24	3.36
2	H, d_o, t_w, s	4	0.9959	5.03	6.67
		6	0.9967	4.5	5.94
		8	0.9973	4.01	5.49
		10	0.9993	1.81	2.76
3	d_o/t_w, H/d_o, s/d_o	4	0.6015	52.27	65.16
		6	0.7064	44.00	55.9
		8	0.7012	45.72	56.66
		10	0.5088	55.97	72.5
4	d_o/t_w, H/d_o, s/d_o, d/d_o	4	0.502	57.30	73.47
		6	0.6942	45.10	57.21
		8	0.6805	46.72	58.41
		10	0.7355	43.01	53.07

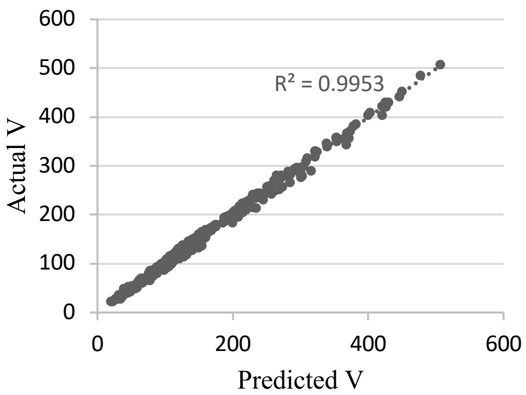


Figure 5: Actual vs Predicted shear buckling Model 1 with 4 Neurons

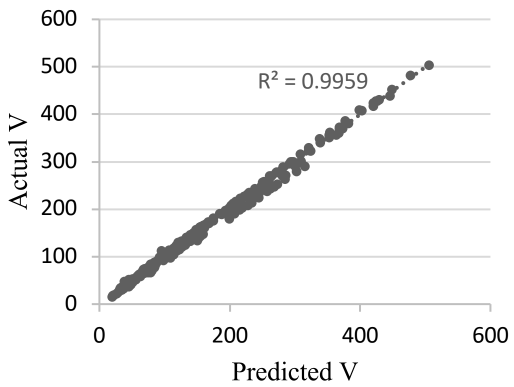


Figure 6: Actual vs Predicted shear buckling Model 2 with 4 Neurons

In order to further validate the obtained results, the impact of inputs was assessed using the connection weight approach explained in Section 4.3. Figure 7 provides the impact that each input parameter within the ANN model has on the shear resistance outputs for the different neural network setups. When reviewing model 1 and 2, it can be seen that there is a consistency in the impact of each geometric input parameter for all neural networks analysed. The results further validate the ANN model as it shows that the input parameters that have positive impact on strength are s, H and t_w. This agrees with what would have been expected, as increasing these parameters leads to an increase in shear strength. The input parameters that have a negative impact on strength is d_o. This once again agrees with what is expectable, as increasing this parameter results in a decrease in strength. Although model 3 shows some form of consistency in the impact of inputs, model 4 showed no level of consistency. Based on the results obtained it can be concluded that geometric ratios as inputs, used for models 3 and 4 are not effective parameters to predict the shear resistance of web-post using the ANN. The low statistical accuracy that can be noted in Table 6 is reflected in the irregular consistency that can be noted in Figure 7 c) and d). As noted previously, these results do not correlate to the accuracy of the ANN model therefore the potential of an ill function. The results simply provide another form of validation for the Models 1 and 2, in which the input parameters are impacting the output variable as would be expected. In conclusion, since Models 1 and 2 provide predictions with high level of accuracy and the impact of the inputs on the shear strength is as theoretically expected, they are used in the following sections.

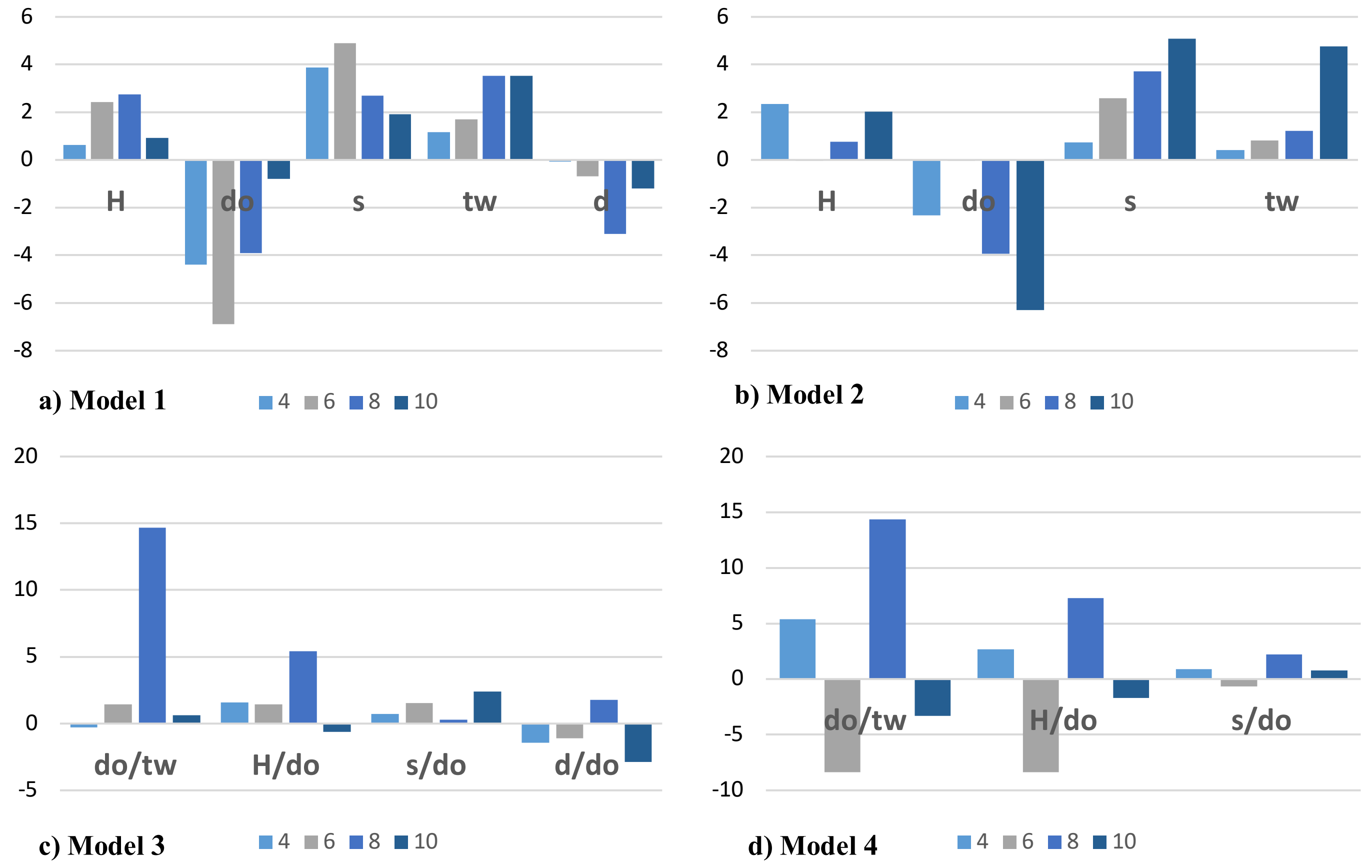


Figure 7: Impact of input parameter on WPB shear resistance

5.2 Comparison to existing analytical models

Table 7 illustrates statistics comparison between the shear resistance of the web-post results predicted by FE models with those predicted by design guidance for cellular beams given in SCI P355 [10] and more recent analytical model proposed by Shamass and Guarracino [11]. The FE results are also compared with those predicted by ANN Model 1 and Model 2 with 4 and 10 neurons. It is worth mentioning that in the analytical model proposed by Shamass and Guarracino [11], the boundary condition coefficient was assumed to be no less than 0.3 and the width of the ideal strut was taken no more than $0.5s_o$.

From the Table 7, it can be noted that the ANN Model 1 with 4 and 10 neurons and Model 2 with 4 and 10 neurons overestimate the shear buckling results by up to 23.9% ,11.1%, 18.5%

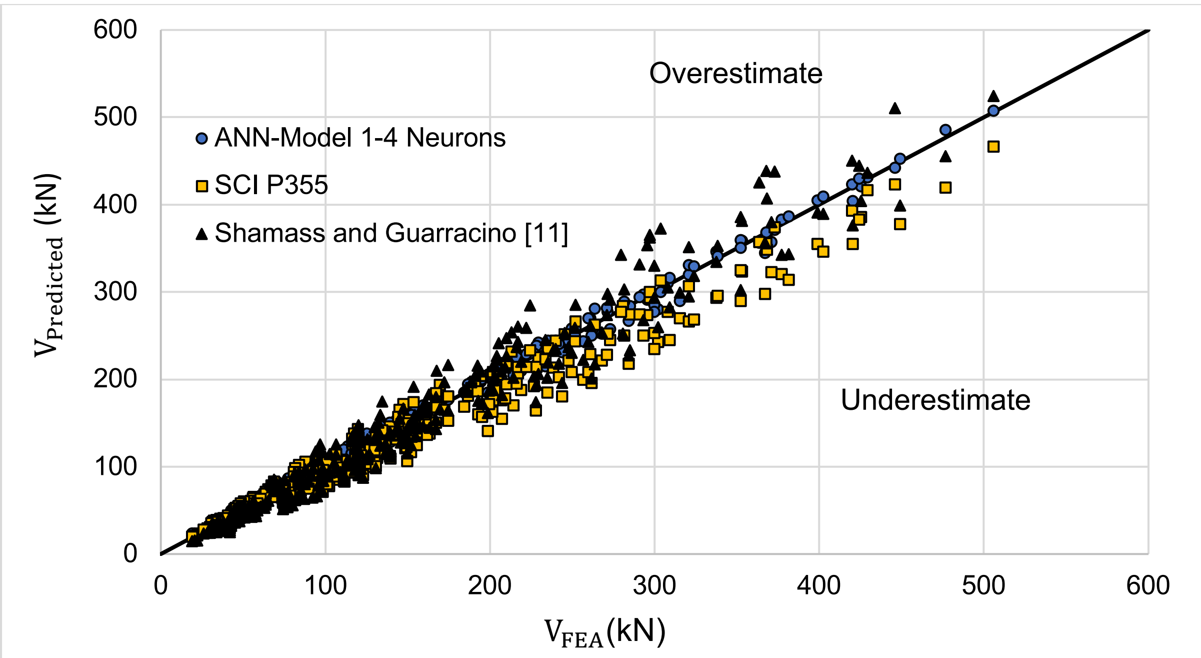
and 8.7%, respectively, while the design guidance SCI P355 [10] and Shamass and Guarracino [11] analytical model overestimates the shear buckling by up to 21.4% and 29%, respectively. For other cellular beams, the ANN Model 1 with 4 and 10 neurons and Model 2 with 4 and 10 neurons underestimate the shear buckling results by up to 14.8% ,11.9%, 19.5% and 13%, respectively, while the design guidance SCI P355 [10] and Shamass and Guarracino [11] analytical model underestimates the shear buckling by up to 30.4% and 40%, respectively. This is not surprising, given that the intrinsic regression provided by ANN, which naturally smooths the deviations which can be shown, on the contrary, by the other models.

It can be pointed out that the RMSE values for the shear resistance predicted by the ANN models range between 2.76 and 7.07 while it is 23.76 and 22.23 for the shear resistance predicted by the design guidance SCI P355 [10] and Shamass and Guarracino [11] analytical model, respectively. Thus, the RMSE values for the predicted shear resistance by ANN are much lower than those for the predicted shear resistance by the design guidance [10] and the analytical model [11]. It should be mentioned that Shamass and Guarracino [11] compared their analytical model and SCI P355 [10] predictions with the finite-element predictions for normal and high strength steel. The finite-element element predictions were obtained from the full beam models. Based on their results, the RMSE for the shear strength results predicted by their analytical model and the design guide SCI P355 [10] were 18.5 and 29.3, respectively, for normal strength steel. It was evident that their formulation provided shear buckling results that were in much more agreement with FE results than those predicted by SCI P355 [10].

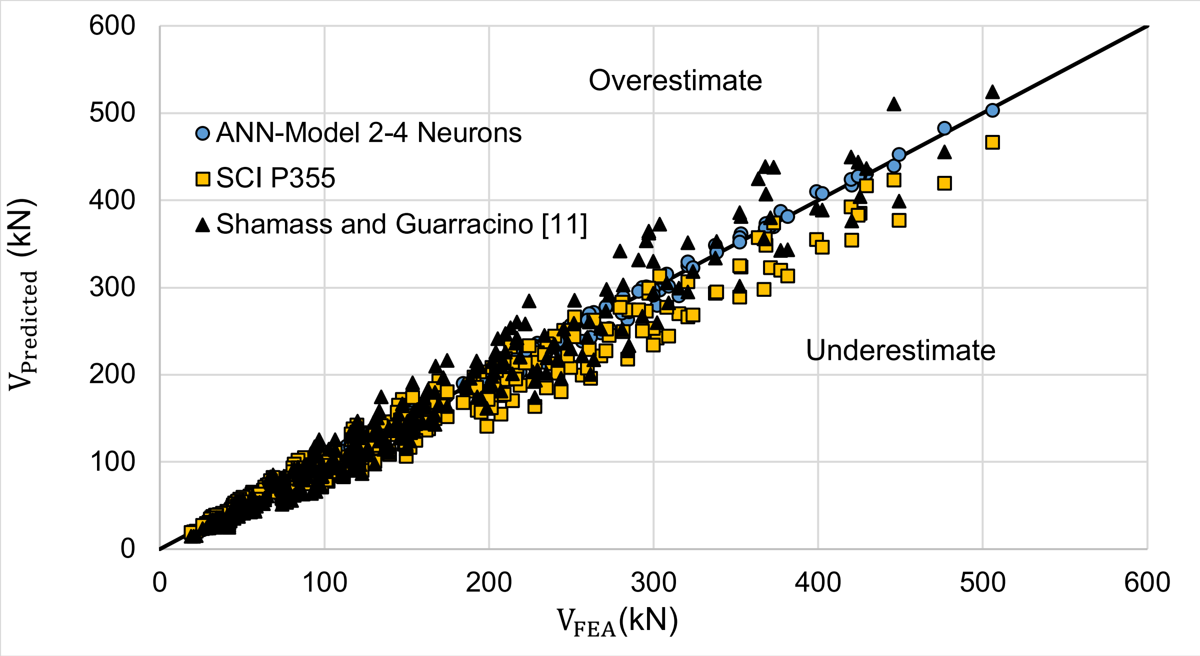
Based on the regression values R^2, it can be observed that ANN models provide the most accurate predictions. Figures 8(a) and 8(b) show a graphical representation of ANN Model 1 and 2 with 4 neurons, the design guidance [10] and the analytical model [11] predictions together with the FE predictions. Overall, the ANN model tends to provide the most accurate shear resistance predictions while the analytical models tend to underestimate the predicted web-post shear resistance of cellular beams.

Table 7: comparison between FEA shear buckling results with analytical and ANN predictions

	Model 1- 4 neurons	Model 1- 10 neurons	Model 2- 4 neurons	Model 2- 10 neurons	SCI P300 [10]	Shamass and Guarracino [11]
Maximum percentage difference (%)	23.9	11.0	18.5	8.7	21.4	29
Minimum percentage difference (%)	-14.8	-11.9	-19.5	-13.0	-30.4	-40
R^2	0.995	0.999	0.996	0.999	0.981	0.986
RMSE	7.07	3.36	6.67	2.76	23.76	22.23



(a)



(b)

Figure 8: Comparison of the predicted shear strength with the FE shear strength

4.2 Comparison with experimental results

Equation 5 shows that as the number of hidden neurons increases, more terms are expected to determine the normalised output value of the shear strength. It can be seen from the Table 7 that ANN Model 1 with 4 neurons provides accurate shear strength predictions and the ANN-based formula to predict normalised shear resistance $(V)_n$ is shown in the Equation 11. In order for engineers to use this equation, the cellular beams geometric parameters H, d_o, s and t_w would have to fall within the X_{min} and X_{max} range stated in Table 3. These parameters will then need to be normalised using Equation 4 and used in Equation 12. Hence, $(H)_n$, $(d_o)_n$, $(s)_n$, and $(t_w)_n$ are the normalised values of the height, opening diameter, opening spacing and web thickness, respectively. Thereafter, in order to determine the shear strength of the web-post (V) from normalised values of the shear strength ($(V)_n$), Equation 4 will need to be used. Table 8 illustrates comparison between web-post shear resistances observed experimentally by Grilo et al. [4] and Tsavdaridis and D'Mello [5] with those predicted by ANN-based formula, design guidance SCI P355 [10] and finite element (FE) results. It can be seen that ANN provides good web-post shear resistance predictions with RMSE of 19.7 and MAE of 16.5. ANN-based formula generally provides conservative predictions in comparison with the test results. The reason is due to the fact that the FE web-post shear resistance results used to train and validate the ANN models are obtained for mild steel with yield stress of 355 Mpa while the actual values yield stress of the experimentally tested cellular beams range from 375.5 Mpa to 449 Mpa. If we assume that there is a linear relationship between shear strength of web-post of cellular beams and the yield stress of normal strength steel, the ANN predictions can be multiplied by the factor of $355/f_{y(tested)}$. The updated shear strength results predicted using ANN-based formula are shown in the Table 8 and it can be seen that further improvement of the results is obtained.

It can be pointed out that the RMSE and MAE values for the shear resistance predicted by the ANN-based formula are lower than those obtained for the shear resistance predicted by the design guidance SCI P355 [10]. Based on the regression values R^2, it can be observed that ANN-based formula predicts results more in-line with test results than those obtained by SCI P355 design guidance. Figures 9 shows a graphical representation of ANN-based formula, SCI P355 and FE shear strength predictions together with the experimental predictions. It can be noted that the ANN predictions are in-line with FE predictions.

$$(V)_n = -0.1 - 0.23\frac{2}{(1+e^{(-2H_1)})-1} + 1.22\frac{2}{(1+e^{(-2H_2)})-1} + 3.69\frac{2}{(1+e^{(-2H_3)})-1} - 1.53\frac{2}{(1+e^{(-2H_4)})-1} \qquad (11)$$

Where:

$$\begin{aligned} H_1 &= 1.89 + 1.92(H)_n - 1.86(d_o)_n + 2.6(s)_n - 0.9(t_w)_n \\ H_2 &= 0.91 + 0.6(H)_n - 1.55(d_o)_n + 2.32(s)_n - 0.93(t_w)_n \\ H_3 &= -0.77 - 0.21(H)_n - 0.55(d_o)_n + 0.36(s)_n + 0.55(t_w)_n \\ H_4 &= -1.64 - 1.86(H)_n - 0.75(d_o)_n + 1.84(s)_n + 0.42(t_w)_n \end{aligned} \qquad (12)$$

Table 8: Comparison with experimental results

Spec.		Percentage difference (%)			
	V_{test} (kN)	V_{ANN}	$(355/f_{y(tested)})V_{ANN}$	SCI P355	FE
A1	38	-31.4	-13.3	-43.2	-2.3
A2	61.9	-11.8	3.4	-35.1	-6.0
A3	70.7	-13.5	-3.3	-36.0	-7.8
A5	99.1	-26.8	-14.2	-36.8	-27.4
A6	102.2	-13.3	-3.0	-26.6	-5.4
B1	54	-22.8	-13.5	-28.6	-1.6
B2	79	-10.4	-7.8	-31.1	-0.2
B5	138.5	-27.2	-18.4	-25.6	-20.6
B6	150	-17.0	-6.9	-16.9	-8.2
C1	144.4	-0.4	5.3	0.5	2.3
C2	127.5	-22.3	-17.8	-15.7	-20.5
R^2		0.949	0.983	0.911	0.974
RMSE		19.7	12.3	24.5	15.0
MAE		16.5	9.7	22.6	10.4

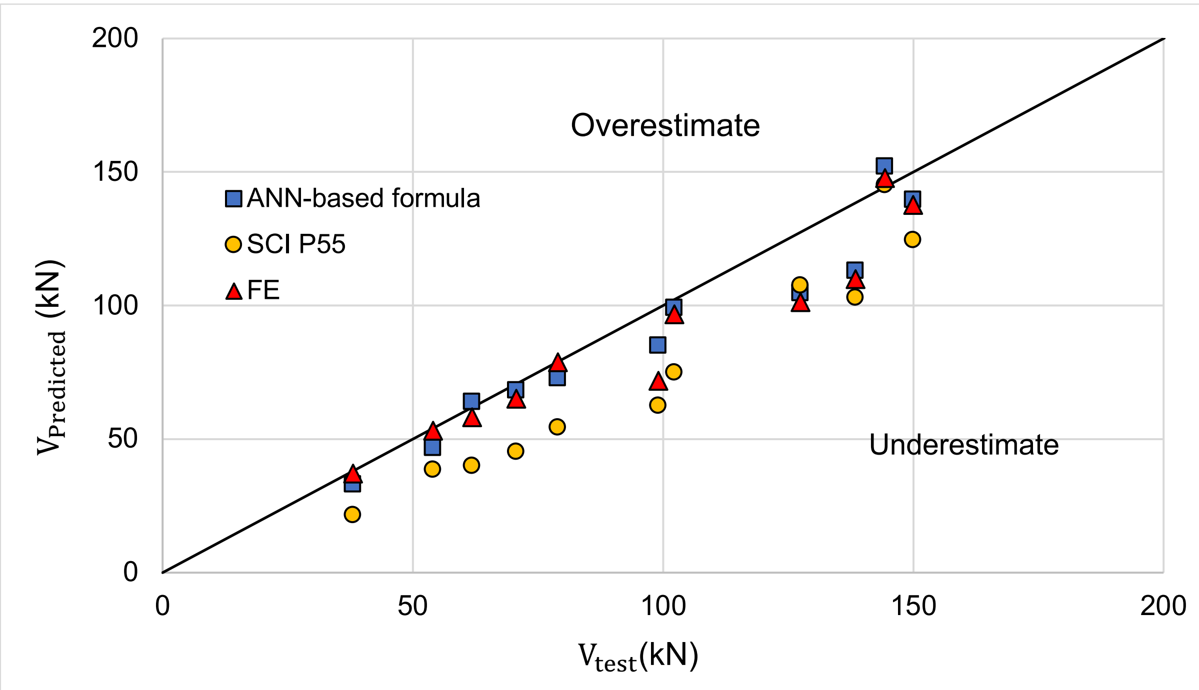


Figure 9: Comparison of the predicted shear strength with the experimental shear strength

6. Concluding Remarks

The aim of this study is to predict the vertical shear strength of cellular beams made from normal strength steel S355 using ANN and to propose an ANN-based formula to accurately compute the web-post buckling strength of cellular beams, as a function of independent geometrical parameters. Based on analysis and results obtained, it can be concluded that:

- Out of the 4 different ANN models produced, the models relying on the input of geometric parameters provided a much greater level of accuracy than models based on geometric ratios only. Results showed that the most accurate results were obtained for ANN model 2 which consisted of H, d_o, t_w, s as the input parameters.
- The general trend for each model was that as the number of neurons increased in the hidden layer, the level of accuracy increased, too.
- When reviewing the impact of inputs in each of the models, the ANN models based on geometric parameters were further validated as the impact correlates with what is expected to occur.
- ANN model 1 and 2 had a lower RMSE, lower MAE and higher regression for the predicted web-post shear resistance when compared to the design guidance SCI P355 [10] and the analytical model [11], leading to higher level of accuracy
- When compared to experimental data, ANN-based formula provided good predictions of the web-post shear buckling with regression value of 0.949. A greater level of accuracy can be obtained between experimental and ANN predictions if the actual yield stress of the cellular beam is taken into consideration. Additionally, the ANN-based formula provides results that are more in-line with test results that those predicted by SCI P355 design guidance.
- On account of the high accuracy shown by the ANN-based formula, it can constitute a potential tool for structural engineers who aim to accurately estimate the web-post

buckling of cellular steel beams without the use of costly resources associated with FE analysis. This formula can be easily implemented in Excel or in user graphical interface.

Acknowledgment

The authors would like to acknowledge the Centre for Civil and Building Services Engineering at London South Bank University for the encouragement and providing technical supports for this research. Furthermore, they would also like to acknowledge the assistance of our postgraduate student Elida Ceka for her assistance in the parametric study of the FE analysis.

References

[1] Mesquita, L.M.R., Gonçalves, J., Gonçalves, G., Piloto, P.A.G. and Kada, A. (2015). Intumescente fire protection of cellular beams. In *X Congresso de Construção Metálica e Mista* (pp. 623-630). CMM-Associação Portuguesa de Construção Metálica e Mista.

[2] Fares, S. S., Coulson, J. & Dinehart, D. W. (2016). Castellated and Cellular, Beam Design. *American Institute Of Steel Construction - Steel Guide.*

[3] Aglan, A.A. and Redwood, R.G., (1974). WEB BUCKLING IN CASTELLATED BEAMS. *Proceedings of the Institution of Civil Engineers*, *57*(2), pp.307-320.

[4] Grilo, L.F.; Fakury, R.H. and de Souza Veríssimo, G. (2018). Design procedure for the web-post buckling of steel cellular beams. *Journal of Constructional Steel Research*, 148, pp.525-541.

[5] Tsavdaridis, K.D. and D'Mello, C. (2011). Web buckling study of the behaviour and strength of perforated steel beams with different novel web opening shapes. *Journal of Constructional Steel Research*, 67(10), pp.1605-1620.

[6] Erdal, F. and Saka, M.P. (2013). Ultimate load carrying capacity of optimally designed steel cellular beams. *Journal of constructional steel research*, 80, 355-368.

[7] Panedpojaman, P.; Thepchatri, T. and Limkatanyu, S. (2014). *Novel design equations for shear strength of local web-post buckling in cellular beams*. Thin-walled structures, 76, pp.92-104.

[8] Ward, J. (1990). Design of Composite and Non-Composite Cellular Beams, 100, The Steel Construction Institute, SCI Publication.

[9] Lawson, R.M., Lim, J., Hicks, S.J. and Simms, W.I. (2006). *Design of composite asymmetric cellular beams and beams with large web openings*. Journal of Constructional Steel Research, 62(6), pp.614-629.

[10] Lawson, R.M. and Hicks, S.J. (2011). Design of composite beams with large web openings–SCI-P-355. *The Steel Construction Institute: Ascot*.

[11] Shamass, R. and Guarracino, F. (2020). Numerical and analytical analyses of high-strength steel cellular beams: A discerning approach. *Journal of Constructional Steel Research*, 166, p.105911.

[12] Shamass, R. Alfano, G. and Guarracino, F. (2014). A numerical investigation into the plastic buckling paradox for circular cylindrical shells under axial compression. *Engineering Structures*, 75, pp.429-447.

[13] Shamass, R. Alfano, G. and Guarracino, F. (2015). An analytical insight into the buckling paradox for circular cylindrical shells under axial and lateral loading. *Mathematical Problems in Engineering*, Article number 514267, doi: 10.1155/2015/514267, pp. 1-11.

[14] Shamass, R. Alfano, G. and Guarracino, F. (2015). An investigation into the plastic buckling paradox for circular cylindrical shells under non-proportional loading. *Thin-Walled Structures*, 95, , pp. 347-362.

[15] Shamass, R. Alfano, G. and Guarracino, F. (2017). On Elastoplastic Buckling Analysis of Cylinders Under Nonproportional Loading by Differential Quadrature Method. *Int J of Structural Stability and Dynamics*, 17 (7), Article number 1750072.

[16] Ozcan, F., Atis, C., 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*, 40 (9), pp.856-863.

[17] Golafshani, E.M., Rahai, A., Sebt, M.H. and Akbarpour, H. (2012). Prediction of bond strength of spliced steel bars in concrete using artificial neural network and fuzzy logic. *Construction and Building Materials,* 36, pp.411-418.

[18] Kamane, S.K., Patil, N.K. and Patagundi, B.R. (2020). Use of artificial neural networks to Predict the Bending Behaviour of Steel I Beam Externally attached with FRP Sheets. *Materials Today: Proceedings*, (in press)

[19] Tran,V., Thai, D. and Nguyen, D. (2020). Practical artificial neural network tool for predicting the axial compression capacity of circular concrete-filled steel tube columns with ultra-high-strength concrete. *Thin-Walled Structures*, 151, 106720.

[20] Hedayat, A.A., Afzadi, E.A., Kalantaripour, H., Morshedi, E. and Iranpour,A. (2019). A new predictive model for the minimum strength requirement of steel moment frames using artificial neural network. *Soil dynamics and Earthquake Engineering,* 116, pp.69-81.

[21] Hedayat, A., Jazebu, E., AsadAbadi, S. and Iranpour, A. (2018). Flexural Strength Prediction of Welded Flange Plate Connections Based on Slenderness Ratios of Beam Elements Using ANN. *Advances in Civil Engineering*, 2018, 8059190.

[22] Pu, Y. and Mesbahi, E. (2006). Application of artificial neural networks to evaluation of ultimate strength of steel panels. *Engineering Structures,* 28 (8), pp.1190-1196.

[23] Hosseinpour, M., Sharifi, Y. and Sharifi, H. (2020). Neural network application for distortional buckling capacity assessment of castellated steel beams. *Structures*, 27, pp.1174-1183.

[24] Tohidi, S. and Sharifi, Y. (2014) Inelastic lateral-torsional buckling capacity of corroded web opening steel beams using artificial neural networks. *The IES Journal Part A: Civil & Structural Engineering*, 8, pp. 24-40.

[25] Sharifi, Y., Moghbeli, A., Hosseinpour, M. and Sharifi, H. (2019). Study of neural network models for the ultimate capacities of cellular steel beams. *Iranian Journal and Science and Technology*, *Transactions of Civil Engineering,* 44, pp.579-589.

[26] Sharifi, Y., Moghbeli, A., Hosseinpour, M. and Sharifi, H. (2019). Neural networks for lateral torsional buckling strength assessment of cellular steam I-beams. *Advances in Structural Engineering*, 22(3), 136943321983617

[27] Abambres, M., Rajana, K., Tsavdaridis, K.M. and Ribeiro, T.P. (2018). Neural network-based formula for the buckling load prediction of I-section cellular steel beams. *Computers,* 8(1), pp.1-26.

[28] Nguyen, Q.H., Ly, H., Le, T. and Nguyen, T. (2020). Parametric Investigation of Particle Swarm Optimization to Improve the Performance of the Adaptive Neuro-Fuzzy Inference System in Determining the Buckling Capacity of Circular Opening Steel Beams. *Materials,*13(10), 2210.

[29] Gholizaadeh, S., Pirmoz, A. and Attarnejab, R. (2011). Assessment of load carrying capacity of castellated steel beams by neural networks, *Journal of Construction Steel Research*, 67 (5), pp.770-779.

[30] MATLAB and Statistics Toolbox Release 2019a, The MathWorks, Inc., Natick, Massachusetts, United States.

[31] Golafshani, E. M., Rahai, A., Sebt, M. H. and Akbarpour, H. (2012) Prediction of bond strength of spliced steel bars in concrete using artificial neural network and fuzzy logic, *Construction and Building Materials*, 36 , p. 411-418.

[32] Gupta, T., Patel, K. A., Siddique, S., Sharma, R. K. and Chaudhary, S. (2019) Prediction of mechanical properties of rubberised concrete exposed to elevated temperature using ANN, *Measurement*, 147 , p. 106870.

[33] Olden, J. D., Joy, M. K. and Death, R. G. (2004) An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data, *Ecological Modelling*, 178 (3), pp. 389-397.