FAILURE LOAD PREDICTION OF CASTELLATED BEAMS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This paper explores the use of artificial neural networks in predicting the failure load of castellated beams. 47 experimental data collected from the literature cover the simply supported beams with various modes of failure, under the action of either central single load, uniformly distributed load or two-point loads acting symmetrically with respect to the center line of the span. The data are arranged in a format such that 8 input parameters cover the geometrical and loading properties of castellated beams and the corresponding output is the ultimate failure load.

A back-propagation artificial neural network is developed using Neuro-shell predictor software, and used to predict the ultimate load capacity of castellated beams. The main benefit in using neural network approach is that the network is built directly from the experimental or theoretical data using the self-organizing capabilities of the neural network. Results are compared with available methods in the literature such the Blodgett's Method and the BS Code. It is found that the average ratio of actual to predicted failure loads of castellated was 0.99 for neural network, 2.2 for Blodgett's Method, and 1.33 for BS Code. It is clear that neural network provides an efficient alternative method in predicting the failure load of castellated beams.

Keywords: castellated beam, failure load, neural network, back-propagation, BS code

1. INTRODUCTION

Castellation is the process of cutting the web of a rolled section in a zigzag pattern. One of the halves is then turned for end and welded to the other; this increases the depth (h) of the original beam by the depth of the cut (d), Ref. [1]. The shape of the castellated beam is shown in Figure 1. This shape fits the dictionary definition of castellated as "castle-like" or battlemented.

Historical Development
Castellated beams appear to have been first used in 1910, Ref. [2]. Known initially as the

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"Boyd beam", these products were first marketed in the United Kingdom in the early 1940s. Boyd's patent specification discussed various geometries of castellation, and his beam type was later adopted as the standard castellated beam geometry in the United Kingdom.
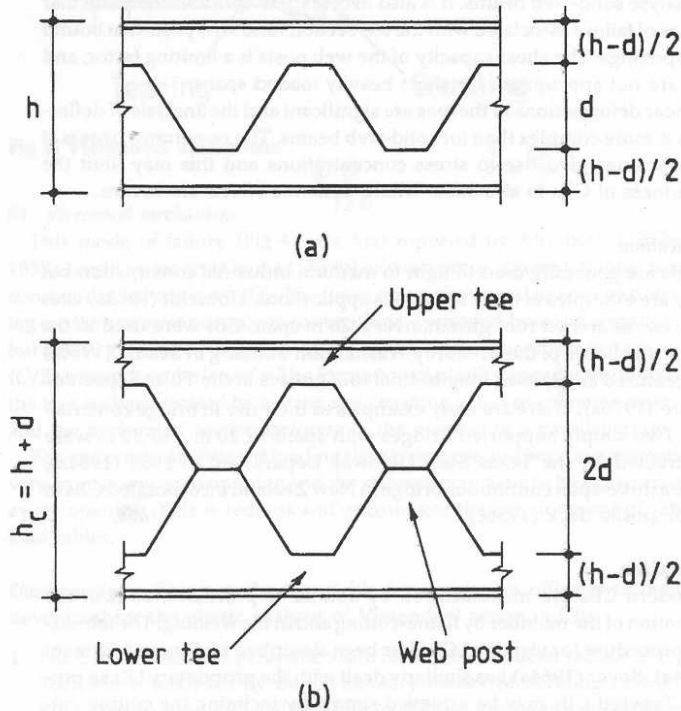
Figure 1. Castellation process

The Litzka castellation process was developed by Litzka Stahlbau of Bavaria [1,3,4]. They also produced a variation on the standard castellated beams, where the depth of section was increased by the provision of increment plates. The end product is characterized by octagonal rather than hexagonal openings and is known as the Litzka beam or the extended castellated beam.

Advantages of Castellated Beams

The principal advantage of castellation is the increase in vertical bending stiffness; castellated beams have proved to be efficient for moderately loaded longer spans where the design is controlled by moment capacity or deflection. Castellated beams, because of their high strength-to-weight ratios and their lower maintenance and painting costs, can sometimes advantageously replace built-up girders. Numerous examples may be seen of the application of castellated beams as either secondary or main units in light to medium constructions for medium to long spans.

They are used in multi-storey buildings, commercial and industrial buildings warehouses,

and portal frames. Incidental benefits are their attractive appearance and the possible utilization of the web openings as passages for services. The latter leads to useful savings in the overall heights of multi-storey structures.

Disadvantages of Castellated Beams
Due to the presence of the holes in the web, the structural behavior of castellated beams will be different from that of the plain webbed beams. Because of different possible modes of failure or even new modes also, they are highly indeterminate structures, which are not susceptible to simple methods of analysis. The shear capacity of the web posts is a limiting factor, and castellated beams are not appropriate for short heavily loaded spans. Shear deformations in the tees are significant and the analysis of deflections is more complex than for solid-web beams.   The re-entrant corners at the openings give rise to stress concentrations and limit the usefulness of castellated beams in situations where dynamic effects are severe.

2. ANALYSIS AND DESIGN OF CASTELLATED BEAMS

The geometry of a castellated beam is dictated by three parameters such as the cutting angle ϕ, the expansion ratio α, the welded length c as shown in Figure 2.
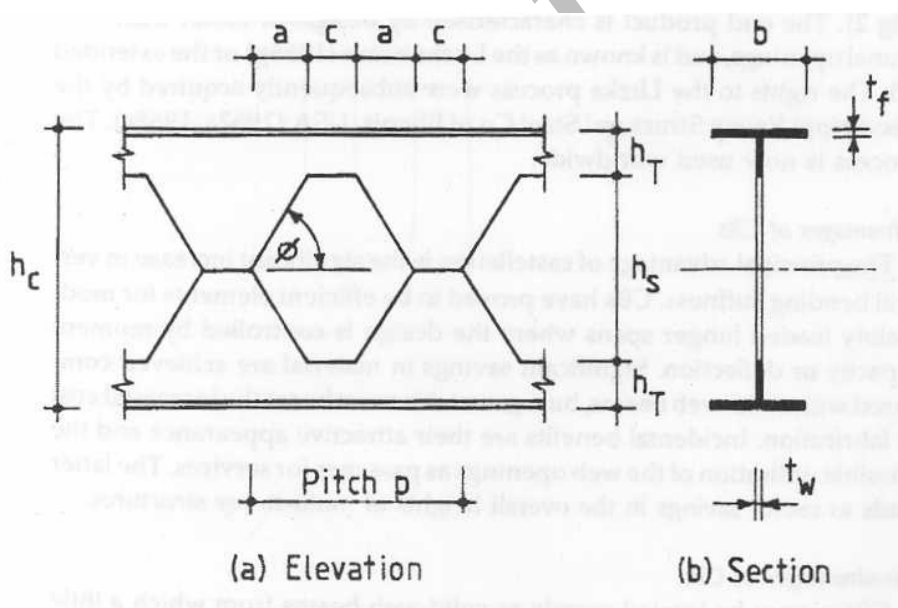

Figure 2. Castellated beam

Cutting angle ϕ
The cutting angle influences the number of castellation N per unit length of the beam. N is small when the angle is flat and large when it is steep. Tests have shown that while an

increase in N has little effect on the elastic stiffness of a castellated beam, it considerably enhances the ductility and rotation capacity, current practice shows that the adoption of the 60° angle is an effective industry standard [1].

Expansion ratio α
The expansion ratio is a measure of the increased depth achieved by castellation. In theory the original beam depth could almost double, but the overall depth of the tees is a limiting factor. If tees are very shallow, they will fail by Vierendeel bending over the span 'c'.

In practice the depth of cut 'd' is half the serial depth h_s of the section. Thus

$$h_T = \frac{h_s}{4} , \ h_C = \frac{h_s}{2} + h \ , \ \ \alpha = \frac{h_C}{h} \ \approx \ 1.5 \tag{1}$$

For 60° cutting angle it becomes

$$\alpha = \frac{0.5 \ h_S}{\sqrt{3}} \ = \ 0.289 \ h_S \tag{2}$$

Welding length c
If the welded length is too short, then web weld will fail in horizontal shear, and too long welded lengths gives long tees which may fail in Vierendeel bending, so reasonable balance between these two failure modes is $c = h_s/4$ [5].

In spite of the extensive literature on castellated beams [1-8] there is little in the way of firm design recommendations in codes of practice, and steel handbook usually lists the section properties. Load tables have been published based on elastic analysis, but are valid only for simple spans and uniform systems of loading. Thus castellated beams of major structures are sometimes subject to proof loading before delivering. Their experimental behavior has demonstrated the need to treat them as structures, in which the strengths of the component tees and web posts must be carefully assessed.

Failure modes
Seven potential failure modes are associated with castellated beams and are of two different categories:

1. Formation of a flexure mechanism.
2. Lateral–torsional buckling of the entire beam.
3. Formation of Vierendeel mechanism.
4. Rupture of the welded joint in a web post.
5. Shear bucking of a web post.
6. Compression buckling of a web post.
7. Compression buckling of a tee.

Modes 1and 2 are similar to the corresponding modes for solid-web beams and may be

analyzed in almost identical fashion. Modes 3 to 7 are peculiar to castellated beams, in that they are associated with the tees and web posts that bound the openings. Although there is an obvious relationship between mode 4 and the shear failure of a solid web and between mode 6 and the buckling of such a web, it has generally been necessary to develop new analytical techniques for 3 to7. The detailed explanations of these failure modes are given in [8-13].

Prediction of Failure Loads
Number of methods exist in literature for the prediction of the failure loads of castellated beams, the most accurate among these, which are selected and used in this study for the aim of comparing results from the neural network are outlined in the following.

Blodgett's Approach
It was found that the failure load predicted by using a column in compression approach adopting Blogett's force distribution model and an effective length factor K=0.5 provided good agreement with the experimental results [4]. The proposed formula is

$$P_u = 2F_c S t_w \tag{3}$$

Where P_u is the ultimate capacity of beams, F_c is the maximum permissible compressive stress, S is the length of the web weld joint, t_w is the thickness of web. This approach treats the web post as a column having a width equal to the narrowest width of the webs, a length equal to the clear height of the castellation and a thickness equal to the web thickness.

On the basis of the similarity in proportions between sections of the standard British module a simplified version of this approach using an average compressive strength of about 160 MPa has been suggested by Okubo and Nethercot [11], leading to

$$P_u = 160 \times 10^{-3} S t_w \tag{4}$$

For the most extreme geometries this can overestimate the strength by up to 14% or be conservative by up to 25%.

British Standards
The recommended formula in the code is given in BS 449, Clause 28a, which is for 45° dispersion angle is

$$P_u = FS F_C t_w B \tag{5}$$

Where, P_u is the ultimate failure load, FS is the factor of safety taken as 1.7, F_c is the maximum permissible compressive stress, t_w is the thickness of the web, and B is the effective width of web in bearing. It was reported by Okubo and Nethercot [11] that test/code ratios were conservative with a mean test /code ratio of 1.327.

The application of BS 449 to castellated beams requires a consideration of width to

thickness ratios so that the section can be correctly classified for local buckling. The rules specifically apply only to sections castellated to the profile normally adopted in the U.K, although many of the rules may well apply to other types of sections they have not been fully proved to the code writers, this is especially true with unrestrained beams [5].

3. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network is a system that mimics the human brain and therefore a great deal of the terminology is borrowed from neuroscience. The most basic element of the human brain is a specific type of cell, which provides us with the abilities to remember, think and apply previous experience to our every action. These cells are known as neurons as shown in Figure 3, each of these neurons can connect with up to 200,000 other neurons. The power of brain comes from the numbers of these basic components and the multiple connections between them [15-22].
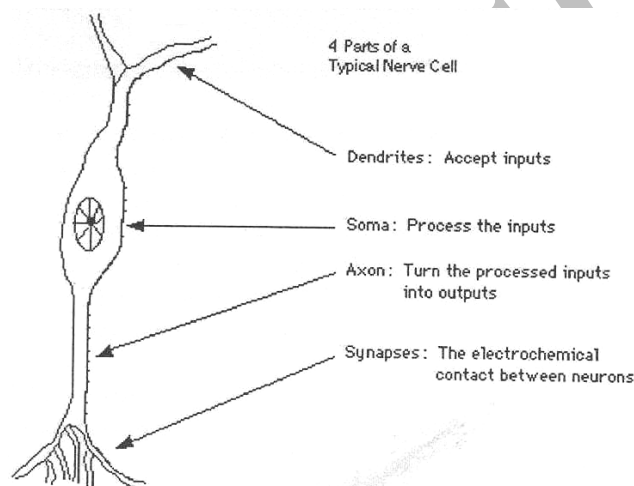

Figure 3. A biological neuron and its components

All natural neurons have four basic components, which are dendrites, soma, axon, and synapses. Basically a biological neuron receives inputs from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then output the final result [17-19]. Artificial Neural Network attempts to simulate the multiple layers of simple processing elements called neurons. Each neuron is linked to certain of its neighbors with varying coefficients of connectivity that represent the strengths of these connections. Learning is accomplished by adjusting these strengths to cause overall network to output appropriate results.

A trained network presents some distinct advantages over the numerical computing. It provides a rapid mapping of a given input into the desired output quantities. The other important advantage of neural networks is either correct or nearly correct responses to the

incomplete tasks, their extraction of information from noisy or poor data and their production of generalized results.

This makes neural networks a very powerful tool to solve many civil engineering problems, particularly in the problems which data maybe complex or in insufficient amount.
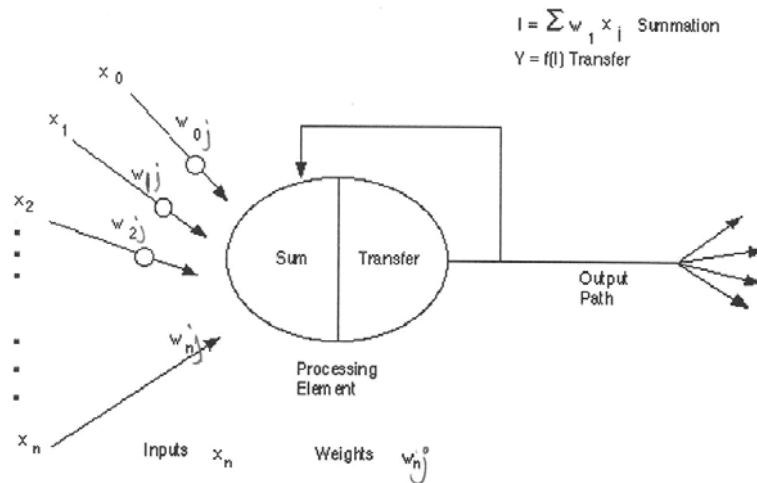

$$I = \sum w_1 x_i \quad \text{Summation}$$
$$Y = f(I) \quad \text{Transfer}$$

Figure 4. A processing unit

There are several important neural network models such as Hopfield net, Hamming net, Single-layer preceptor and Multi-layer network [20]. The most important and powerful nets are multi-layer networks that have been developed from single layer networks; most multi-layer networks have a learning algorithm called back propagation. This method involves sending the input forward through the network and then comparing the output with the required training pattern output, if differences exist, a set of changes are applied to the weighted factors in a back propagation manner.

The processing units in back propagation neural networks always consist of a least three layers; an input layer, a hidden layer, and an output layer, as illustrated in Figure 5.
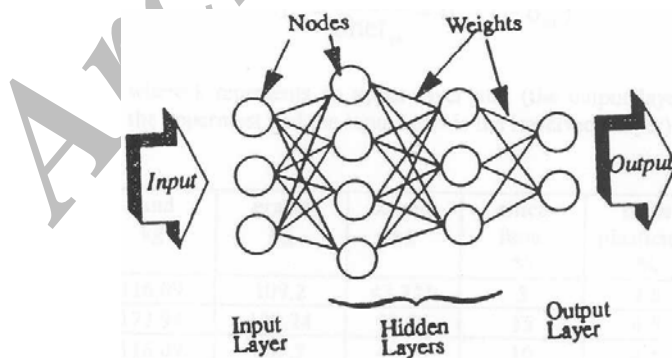

Figure 5. Topology of back propagation network with hidden layers

For some applications more than one hidden layer is used. The presence of these hidden layers allow the network to present and compute more complicated associations between patterns. The number of neurons in the input layer is equal to the number of inputs and each of these neurons receives one of the inputs. The output of the neurons in the output layer is the output of the network, and too few neurons in hidden layer will not allow the network to produce accurate maps from the input to the desired output, while too many neurons will result difficulties in dealing with new types of input patterns.

In a back propagation network, no interconnections between neurons in the same layer are permitted. The back propagation network uses supervised learning so the input and output patterns must be both known.

In feed forward phase, the input layer neurons pass the input pattern values onto the hidden layer. Each of the hidden layer neurons computes a weighted sum of its input, and passes the sum through its activation function and presents the activation value to the output layer. Following the computation of a weighted sum of each neuron in the output layer, the sum is passed through its activation function, resulting in one of the output values for the network. Finally the training process is successfully completed when the iterative process has converged.

Basics of Neural Computing

The processing element receives a set of inputs $x_i = 1, 2, 3, \ldots n$. These inputs are similar to electro-chemical signals received by a neuron in a biological model, then these input signals are multiplied by the connection weight w_{ij}, and the effective input to the element is the weighted sum of the inputs:

$$z = \sum_{i=1}^{n} w_{ij} x_i.$$ (6)

In order to obtain an output signal, the weighted sum of inputs are processes by an activation function $F(z)$. Various forms of activation functions have been proposed. The ones most commonly used are a simple linear function, a threshold function, and a sigmoid function. The sigmoid function given by the expression:

$$F(z) = \frac{1}{1 + e^{-(Z+T)}},$$ (7)

where Z is the weighted input and T is a bias parameter. The advantage of this function is its ability to handle both large and small input signals.

The output obtained from the activation function may be treated as an input to other neurons in the network. The determination of the proper weighted coefficients and bias parameter are embodied in the network learning process which is an error minimization problem, the output obtained from the network is compared to the actual output, and the error E is computed as follows:

$$E_i = (T_i - Y_i) \tag{8}$$

Where T_i is target output of neuron i, Y_i is actual output of neuron i. After obtaining the error E_i, the error signal is multiplied by the derivative of the activation function for the neuron in question to obtain the delta signal, which is employed to compute the changes for all the weight values according to equation (12).

$$\delta_{i,k} = \frac{\partial Y_{i,k}}{\partial z} E_i \tag{9}$$

Where, the subscripts i and k denote the ith neuron in the output layer k. Note that the derivative of the output Y_i of the sigmoid function is obtained as follows:

$$\frac{\partial Y_i}{\partial z} = Y_i(1 - Y_i) \tag{10}$$

The strength of connections between all neurons in the preceding hidden layer to the ith neuron in the output layer are adjusted by an amount $\Delta w_{pi,k}$ as follows:

$$\Delta w_{pi,k} = \eta \delta_{i,k} Y_{pj} \tag{12}$$

Where, Y_{pj} denotes the output of neuron p in the hidden layer j immediately before the output layer, $\Delta w_{pi,k}$ is the change in value of the weight between neuron p in the hidden layer to neuron i in the output layer k, and η denotes a learning rate coefficient (typically selected between 0.01 and 0.9).

Rumelhart and McClelland [20] presented a modification to the approach by including a "momentum" term as follows:

$$\Delta w_{pi,k}^{t+1} = \eta \delta_{i,k} Y_{p,j} + \alpha \Delta w_{pi,k}^{t} \tag{13}$$

Where, superscript t denotes the cycle of weight modification. The inclusion of the α term, which seeks to incorporate a memory in the learning process, increases the stability of the scheme, and helps to a degree in preventing convergence to a local optimum.

This basic approach described above is applicable in the modification of weights in other hidden layers with some changes. The output of hidden layers cannot be compared to a known output to obtain an error term. Hence the procedure used is as follows: The δ_s and w_s are used to generate the δ_s for the hidden layer immediately preceding the output layer as follows:

$$\delta_{p,j} = Y'_{p,j} \left(\sum \delta_{i,k} \ w_{pi,k} \right) \tag{14}$$

Where, $\delta_{p,j}$ is the δ corresponding to the pth neuron in the hidden layer, and $Y'_{p,j}$ is the derivative of the activation function of this neuron. Once the δs corresponding to this hidden layer are obtained, the weight connections of the next hidden layer are modified. This process is repeated for all input training patterns until the desired level of error is attained.

In general, designing a neural network consists of:
- Arranging neurons in various layers.
- Deciding the type of connections among neurons for different layers.
- Deciding the way a neuron receives input and produces output.
- Determining the strength of connection with the network.

4. EXPERIMENTAL DATA

The experimental data collected from literature include 47 castellated beam results, which are taken from the tests carried out by Okubo and Nethercot [11], Aglan and Redwood [2], Van Ostrom and Sherbourne [12], Hosain and Speirs [10], Redwood and Demirjian [9], Maalek and Buredin [14] and Sherbourne and Van Ostrom [6]. All beams tested are of standard British castellated beams with various modes of failure, under the action of, either central single load, uniformly distributed load or two-point loads acting symmetrically with respect to the center line of the span. All specimens were simply supported, laterally braced at load points and at reaction points. The basic parameters that control the failure load based on previous research works are:

- Minimum web yield stress (F_{yw})
- Span of the castellated beam (L)
- Overall depth (h_c)
- Minimum width of the web post $S = 0.25 \, D_s$
- Web thickness (t_w)
- Flange thickness (t_f)
- Width of flange (B)
- Loading condition

The data were grouped into two subsets, a training set of 40 data, and a testing set of 7 data. Each set of experimental data was in a different format. After a study of the tables and diagrams given in the above references, the data are rearranged in a way that the basic parameters that control the ultimate failure load of castellated beams are listed as inputs and the corresponding ultimate failure load as an output value.

Table 1. Experimental data for failure load of castellated beams

Specimen No.	Loading Condition	F_{yw} (Mpa)	h_c (mm)	B (mm)	t_w (mm)	t_f (mm)	S (mm)	L (m)	P_{exp} (KN)
1	3	230	280	100	10.8	5.7	40	3.33	194.1
2	2	352.9	380.5	66.9	3.56	4.59	66.55	1.22	92.7
3	1	352.9	380.5	66.9	3.56	4.59	66.55	1.22	100.9
4	1	352.9	380.5	66.9	3.56	4.59	66.55	1.83	94.8
5	1	352.9	380.5	66.9	3.56	4.59	66.55	2.44	84.4
6	2	355	693.7	153.5	11.7	11.7	114.3	2.5	1300
7	1	290	524.3	124.4	7.02	10.73	176	1.35	280
8	1	290	524.3	124.6	7.04	10.7	179	2.6	275
9	1	294.7	524.8	124.4	7.03	10.79	180	2.6	280
10	1	294.7	524.1	124.3	7.07	10.73	177	1.35	240
11	1	295.5	526.1	124.7	7.08	10.77	176	1.35	260
12	1	295.5	526.7	124.7	7.08	10.68	176	2	232
13	1	293.2	606.2	145.6	7.31	11.4	200	1.5	280
14	1	277	605.5	145.4	7.3	11.34	203	1.6	288
15	1	277	605.5	143.3	7.27	11.25	199	1.5	253
16	1	293.2	603.6	143.7	7.28	11.27	196	1	226
17	1	290.8	451.4	123.9	7.51	10.7	150	1.15	275
18	1	297.3	450.3	123.4	7.54	10.68	150	1.15	279
19	1	290.3	451.8	123.4	7.55	10.72	150	2.14	285
20	1	290.8	451.6	124.1	7.62	10.66	146	2	280
21	1	304	459.6	103	7.15	10.7	157	2.3	273
22	1	304	460.4	103.1	7.21	10.73	143	1.1	267
23	3	292.8	381	101.6	5.84	6.83	127	1.8	186
24	3	292.8	381	101.6	5.84	6.83	101.6	2.4	89
25	1	438	381	101.6	5.84	6.83	165.1	3.5	277.2

Specimen No.	Loading Condition	F_{yw} (Mpa)	h_c (mm)	B (mm)	t_w (mm)	t_f (mm)	S (mm)	L (m)	P_{exp} (KN)
26	3	335	381	101.6	5.84	6.83	165.1	1.75	310.3
27	3	335	381	101.6	5.84	6.83	165.1	1.6	358.6
28	1	335	381	101.6	5.84	6.83	127	1.6	290
29	1	335	381	101.6	5.84	6.83	127	2.4	303.4
30	1	320	381	101.6	5.84	6.83	44.45	3	265.5
31	1	320	381	101.6	5.84	6.83	34.93	3	269
32	1	395	381	101.6	5.84	6.83	28.58	3	352
33	3	335	381	101.6	5.84	6.83	101.6	1.37	300
34	3	335	381	101.6	5.84	6.83	89	1.3	295
35	1	335	229	76.2	5.84	9.58	38.1	1.32	117.6
36	3	335	229	76.2	5.84	9.58	38.1	1.32	137.2
37	3	320	229	76.2	5.84	9.58	38.1	1.32	147
38	3	320	229	76.2	5.84	9.58	38.1	1.15	196
39	1	335	500	150	7.1	10.7	100	5.8	73.5
40	1	335	440	150	7.1	10.7	70	5.8	145
41	1	320	380	150	7.1	10.7	40	5.8	176.5
42	3	292.8	381	101.6	5.84	6.83	88.9	2.5	89
43	3	292.8	266.7	101.6	6.35	9.83	44.5	1.5	113.7
44	2	292.8	381	114.3	7.62	12.83	63.5	1.6	299
45	3	292.8	381	127	9.14	14.02	63.5	1.8	249.1
46	3	292.8	381	203.2	10.16	19.89	63.5	1.3	310.5
47	3	292.8	342.9	117.8	10.16	20.96	57.15	1.3	279.6

Table 1 shows the experimental data for failure load of castellated beams. The first 8 columns represent the loading condition, the minimum web yield strength, the overall depth, flange width, web thickness, flange thickness, minimum width of the web post, and finally the span. The last column is the output, which is the failure load of the castellated beams.

Network Data Preparation

Preprocessing the data by scaling was carried out to improve the training of the neural network to avoid the slow rate of learning near the end points specifically of the output range due to the property of the sigmoid function, which is asymptotic to values 0 and 1. The input and output data were scaled between the interval 0.1 and 0.9. The linear scaling equation: $y = \left(\dfrac{0.8}{\Delta}\right)x_{min} + \left(\dfrac{0.9 - 0.8\,x_{max}}{\Delta}\right)$ was used in this study for a variable limited to minimum (x_{min}) and maximum (x_{max}) and $\Delta = x_{max} - x_{min}$.

Each specimen was classified according to the loading location, number 1 was given to specimens which were loaded by single central loading, number 2 for specimens which were loaded by two-point loads acting symmetrically with respect to the center line of the span, and finally number 3 for uniformly distributed loads. This classification was added to the inputs after scaling.

4. NEURO SHELL PREDICTOR AND DESIGN OF THE NEURAL NETWORK

The software used is The Neuro Shell ® predictor, which is designed to simplify the creation of a neural network application to solve forecasting and pattern recognition problems. To train the neural network using the experimental data, a three layer neural network was developed using the back propagation-learning algorithm. This training is done to adjust the weights connecting the input layer neurons, hidden layer neurons, and output layer neurons so that a set of inputs produces the desired outputs. Several trials were conducted to select the simplest, most accurate network configuration. The number of input neurons were fixed but hidden neurons number changed from one trial to another and the performance of the different configurations were compared with respect to the net performance, average error and net performance on testing set. After artificial neural simulations with varying number of hidden nodes, a neural network was selected based on comparison of the average error obtained. The results show three trials with different level of learning, average error and net performance.

Neural Training Strategy Statistics

• **Best network performances:** The value for network performance ranges from 0 to 1. The closer the value is to 1, the better the net is able to make predictions. The net is not able to make good predictions if the value is near 0.

• **Number of hidden neurons trained:** Training the net involves adding hidden neurons until the net is able to make good predictions.

• **Optimal number of hidden neurons:** This is the number of hidden neurons that best solves the prediction problem.

Net Performance on Testing Set

The Neuro Shell® predictor shows a graph that indicates the learning progress by hidden

Neurons. This graph shows the progress of the network training performance against an increasing number of hidden neurons as they are added to the network. This gives a statistical measure of the goodness of fit between the actual and predicted outputs. This measure, called R-squared (the coefficient of multiple determination) on the graph is performed each time a hidden neuron is added, as learning gets better and better the graph shows higher and higher values.

4.3 Artificial Neural Network Designed by Neuro Shell Predictor
The neural network developed by Neuro Shell® predictor which is used in predicting the failure load of castellated beams is shown in Figure 6.
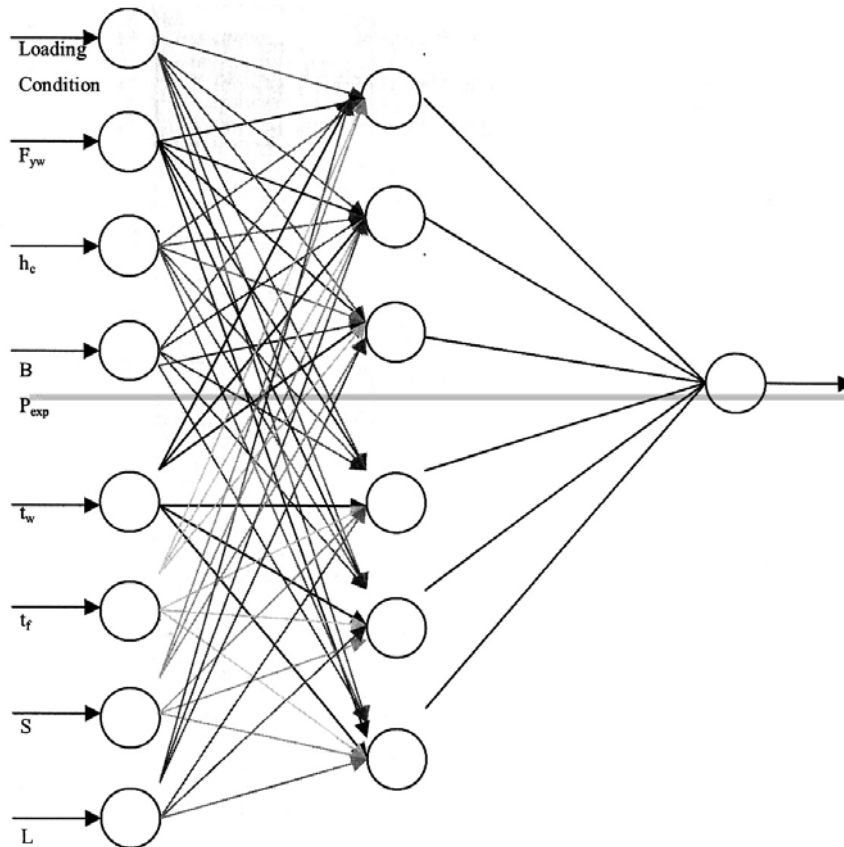
Figure 6. The best neural network model

For obtaining the best experimental data arrangement nine trials were tried by swapping the rows shown in Table 1 once at a time and run the Neuro Shell® predictor software each time a swap was made. The best arrangement, however, is the one that gives the highest network performance of the tested data and the least average error. Arrangement and rows swapping is necessary because network performance is a function of how the rows are arranged. The performance of the best model is presented through Figures 7 to 9.
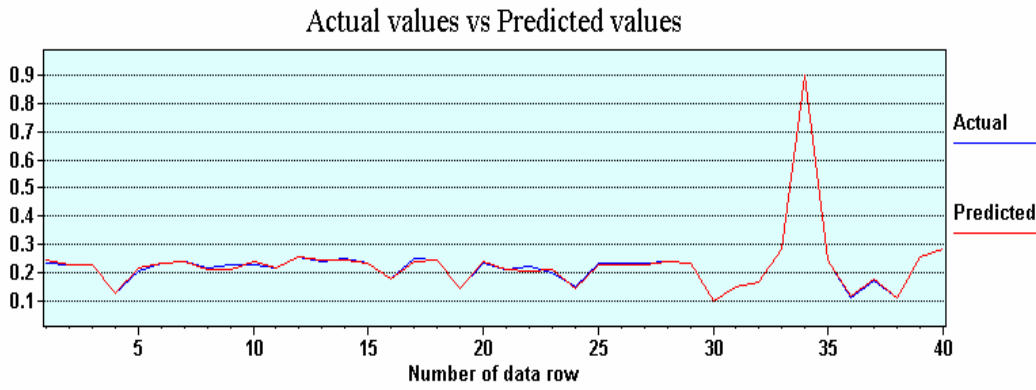
Figure 7. Actual scaled values of failure loads against the predicted ones
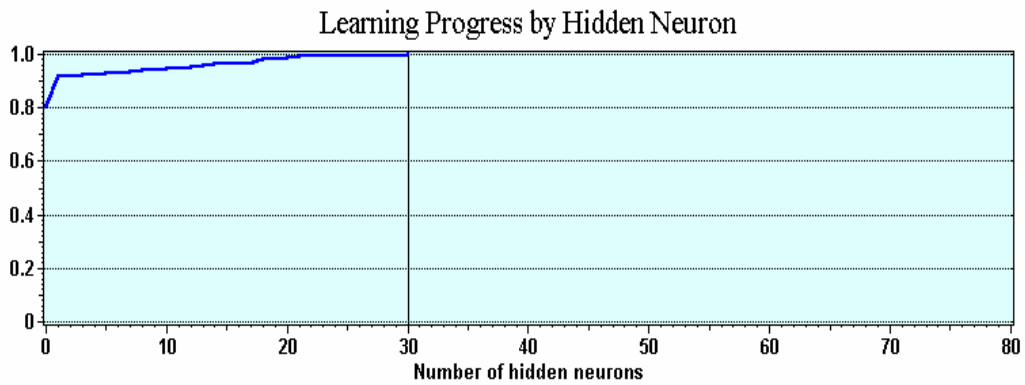

Figure 8. Progress of the network training performance with the number of hidden neurons
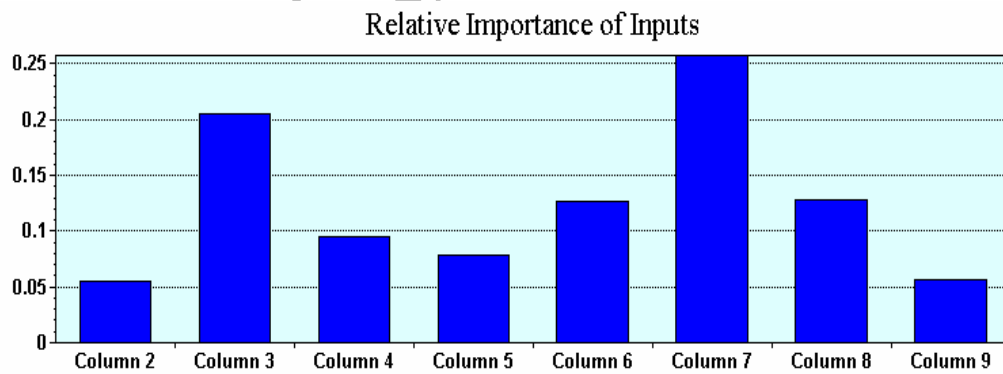

Figure 9. The significance of each input in predicting the output values of the best model

As shown in Figure 6 the best performed artificial neural network model has 8 input

nodes, 30 hidden neurons, and one output node representing the failure load. The best network performance obtained is 0.9976. Actual values vs. predicted ones is shown in Figure 7, they are very close in all trained data rows, which is an indication of how good the training is. The neural network had the best performance using 30 hidden neurons, which is the optimum number of neurons. As shown in Figure 8 the learning progress of hidden neurons reached the maximum value of 1 at 21 hidden neurons.

Figure 9 shows the relative importance of each input parameter. It is noticed that the importance of inputs is distributed such that each input contributes significantly in the prediction of the output, which agrees with the design methods of castellated beams.

5. ANALYSIS OF RESULTS

There are number of design approaches that can be used in predicting the failure load of castellated beams such as Blodgett's approach, BS code approach, Roberts and Markovic approach, elastic analysis for plate elements approach, in elastic analysis for plate elements approach and Rotherdam tests [3-6]. Among these approaches Blodgett's and BS code were selected to perform a comparative study. Other methods are not selected due to the fact that either they require additional information that was not available in the experimental data or they are very sensitive to patch length or they were very conservative.

The results obtained from the Blodgett's approach, the BS code and the Neural Network developed by using the Neuro Shell predictor are shown in Figures 10, 11 and 12. It is clear from the results that both the BS code and Blodgett's approach are quite conservative in predicting the actual failure load. The average ratio of actual failure load to predicted failure load of all specimens is 1.33 in the British Standards Code method, 2.2 in Blodgett's approach and 0.99 in the Neural Network.
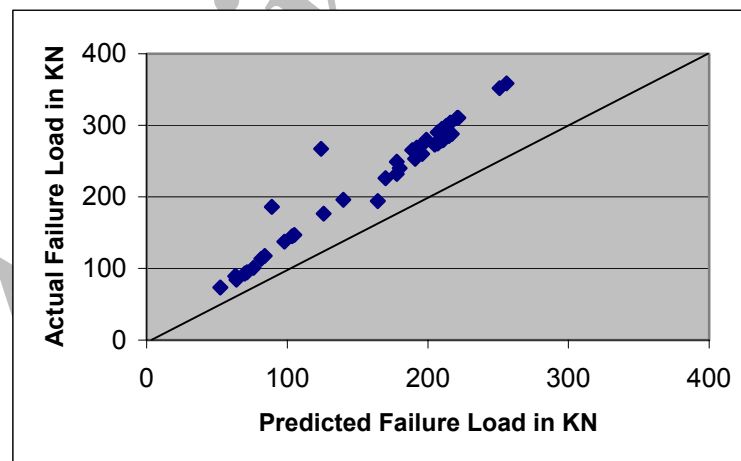

Figure 10. Comparison of ultimate failure loads of castellated beams obtained by BS Code method
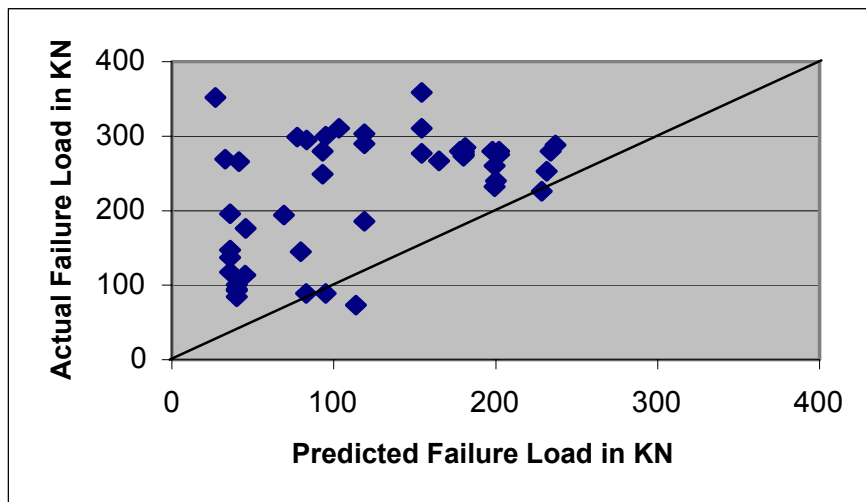
Figure 11. Comparison of ultimate failure loads of castellated beams obtained by Blodgett's approach
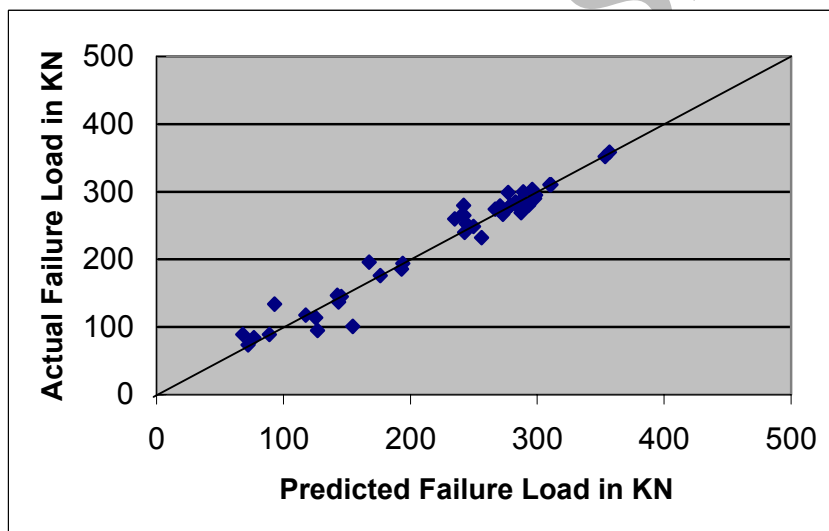

Figure 12. Comparison of ultimate failure loads of castellated beams obtained by neural network

The neural network developed is used together with Blodgett's method and BS code method to obtain the failure loads of seven castellated beams reserved for testing that are not employed in training. The results obtained are given in Table 2. The average ratio of actual failure load to predicted failure load in this set of data is 1.35 for the BS code, 1.8 for Blodgett's approach and 0.99 for the Neural Network. These values clearly show that the Neural Network performs much better than the methods selected in this study.

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Table 2. Performance of Selected Methods for Predicting Ultimate Failure
Load of 7 castellated Beams

	Actual Failure Load/Predicted Failure Load		
Specimen number	**BS method**	**Blodgestt's Approach**	**Neural Network**
45	1.40	1.5	1.10
46	1.40	0.93	1.27
47	1.39	2.2	0.90
1	1.33	2.0	0.65
2	1.33	2.3	0.75
3	1.32	2.1	1.10
4	1.30	1.5	1.15
Average	1.35	1.8	0.99

6. CONCLUSIONS

It has been shown that artificial neural networks can effectively be used to predict the failure loads of castellated beams. It has also been shown that the network designed predicted the outputs with acceptable accuracy, covering the range from shallow to larger depth of castellated beams. It should be noted that once the network was trained, the time required to output results for a given set of inputs was instantaneous. This indicates the potential of neural networks for solving time-consuming problems. Furthermore, artificial neural networks directly use the experimental results in training, there is no need to make any assumptions on material parameters particularly in problems that have more than one existing calculation method, or the one based on only empirical approximations.

For selecting the best configuration of the networks, there are no special guidelines, and trial and error approach should be employed that takes into consideration the best network performance, average error and the best network performance for the testing data. Among the number of configurations tried it is found that a network with a network performance of 0.9976 and an average error of 0.018 is the best.

In the comparative study it is found that the failure load values obtained from the artificial neural network are much more accurate than those determined from British Standards Code or the Blodgett's approach. Although the average value of the ratio of actual failure load to the predicted failure load was 1.33 in the BS code 2.2 in the Blodgett's

approach it was only 0.99 in the Neural Network. These average ratios change to 1.35, 1.81 and 0.989 respectively, when the methods are employed for seven castellated beams that are not used in training the network. These results clearly demonstrate the accuracy and efficiency of the trained neural network in predicting the failure load of castellated beams over the other two methods.

Artificial neural networks give better results if the number of the training data is large. However, collecting this data for castellated beams is difficult because little experimental study exists in the literature. Therefore, the present artificial neural networks model can further be improved using more experimental dataset.

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