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A neural network model with finite element method for steel beams design

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Abstract. This work aims to create an artificial neural network model to assist steel beam design either beam profile and its connection with the column. The input data for the model are the beam length and the applied distributed load. The output data are the beam profile, the connection angle profile, and the number and diameter of connection bolts. We selected for training 10 W-type profiles, 3 angle-type profiles, and 2 bolt diameters. The data for training the neural network has been acquired from the design results according to the Brazilian standard NBR-8800:2008 criteria. The bending moment and shear forces have been calculated from beam internal stresses. The internal stress diagrams have been obtained from the finite element method (FEM) results. The beam analysis with the FEM has been carried out with a flat shell quadrilateral element (plane stress plus Kirchhoff-Love plate effects) for profiles and a three-dimensional frame element for bolts. All nodes at the hole edge and the bolt element in the same plane are coupled. The modeled neural network has been evaluated with its confusion matrix and its accuracy in indicating configurations that attend the design criteria. The results show a good prediction performance and errors obtained are acceptable when compared to the level of safety factors of structural engineering.

Keywords: Steel design, Finite Element Method, Artificial Neural Network

1 Introduction

The use of neural networks for the design and connections in steel structures has been a subject of several authors. To predict the flexural resistance and initial stiffness of beam-to-column steel joints Lima et al. [1] proposed the use of artificial neural networks (ANN) using the back propagation supervised learning algorithm. Lima et al. [1] believe that the errors obtained are acceptable when compared to the level of safety factors of structural engineering and the ANN results proved to be consistent with experimental and design code reference values, however, the results obtained need to incorporate new experimental data. To provide an estimator for the mechanical behavior of steel structure connection elements Abdalla and Stavroulakis [2] proposed a supervised learning backpropagation ANN. One of the Abdalla and Stavroulakis [2] conclusions is an appropriate data set should be used for training the network that includes all possible combinations of design variables that arise in practice and the choice of the ANN configuration depends on the case and that the values must be chosen after numerical experiments and can be adjusted iteratively during the training phase. According to Harshada [3] the ANN can predict solutions that are close to exact solutions with acceptable margins which are close to optimal design solutions provided by training data if the data reflects that optimal solutions.

The objective of this work has been to create a model of artificial neural networks to assist in the design of the beam profile and its connection with the column. The input parameters are the beam length L and the applied distributed load q. The output parameters are the beam's W profile, the angle profile, the diameter, and the number of bolts.

2 Methodology

The first step in the modeling of artificial neural networks that aim to assist steel beams connected to columns through web bolted double angle connections design was to select the W-section profiles, the angle-type profiles, and the bolt diameters that will be used for training neural networks. For this, we selected civil construction profiles from a manufacturer catalog. We selected 10 W-type profiles (table 1) with ASTM A36 or ASTM A325, 3 angle

Table 1. Dimensions of the W sections and values for the profile input for the neural network that predicts the connection.

Short name	Section (mm x kg/m)	d (mm)	b_f (mm)	t_w (mm)	t_f (mm)	Input value
A	W 150 x 13.0	148	100	4.3	4.9	0.000
B	W 150 x 18.0	153	102	5.8	7.1	0.111
C	W 150 x 22.5	152	152	5.8	6.6	0.222
D	W 150 x 24.0	160	102	6.6	10.3	0.333
E	W 200 x 15.0	200	100	4.3	5.2	0.444
F	W 200 x 35.9	201	165	6.2	10.2	0.556
G	W 200 x 86.0	222	209	13.0	20.6	0.667
H	W 200 x 100.0	229	210	14.5	23.7	0.778
I	W 250 x 25.3	257	102	6.1	8.4	0.889
J	W 250 x 28.4	260	102	6.4	10.0	1.000

profiles (a: L 45 x 3 x 2,12, b: L 45 x 4 x 2,77 and c: c L 45 x 5 x 3,38) and 2 bolt diameters (12.7 mm (1/2"), 15.88 mm (5/8")). We choose the angle profiles and the bolt diameters for the connections to attend the minimum spacing recommended by the ABNT [4] standard. We tested beams connected through the web bolted double angle connections in the web or the flange of column profile. We assembled connections with 2 or 3 ASTM A325 bolts per angle leg.

We analyzed different combinations of W profiles and web bolted double angle connections using the element method to obtain the beam bending moment and shear forces diagrams. Then, we used these diagrams to design checks according to the ABNT [4] standard. Later, we applied the design results as parameters for neural network training.

2.1 Mechanical Modelling

We evaluated each of the beams with their connection using the finite element method and, for this, we employed two types of elements. We adopted for the W profile and the angle mesh the four nodes' flat shell element. This element has the plane stress and plate effects according to Kirchhoff-Love Jawad [5] theory and has 2 degrees of freedom referring to the plane stress effects and 3 degrees of freedom referring to the plate ones.

For the bolts modeling of the bolts, we used the spatial frame element with two nodes and a constant section. Each element node has 6 degrees of freedom, being 3 displacements and 3 rotations Azevedo [6]. We implemented the finite element method used in the work in Python. The figure 1a presents a beam mesh connected to the column flange and the figure 1b presents one connected to the column web.

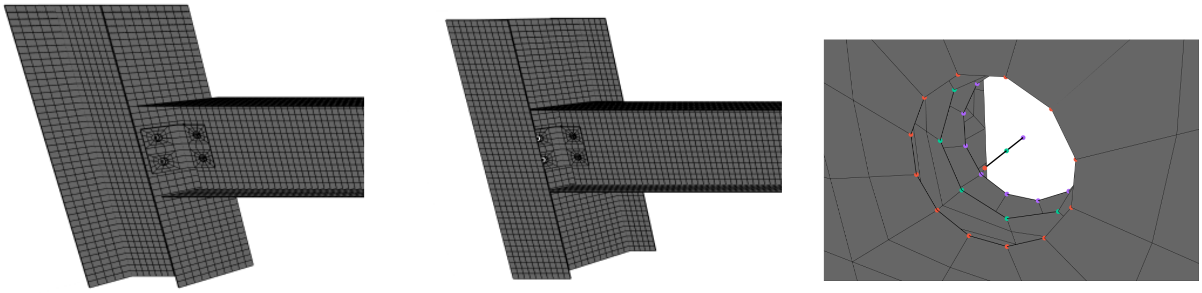
We considered that the nodes at the hole edge have the same displacements in all degrees of freedom of the corresponding node in the frame element (except the torsional one) representing the bolt. The contact is illustrated in the figure 1c.

In this work, materials are considered linear elastic, the relation displacements-deformation is considered only the first order, and loads with a limited intensity are applied to guarantee that there are small displacements and rotations in the cross-section, thus guaranteeing the validity of the Euler-Bernoulli beam theory. We used the stress results obtained in the finite element mesh elements to obtain the bending moment and shear forces in predetermined sections along the beam according to equations 1 and 2, respectively.

$$M_y = \int_A z\sigma_x dA \tag{1}$$

$$Q_z = \int_A \tau_{xz} dA \tag{2}$$

We calculated the design values of shear and bending moment diagrams to check the profiles. To obtain the design values, we considered that the beam has a buckling length equal to its length L, is not laterally restrained,



(c) Contact detail.

(a) Beam connected to the flange of the column.

(b) Beam connected to the web of the column.

Figure 1. Finite element mesh details.

and does not have web stiffeners. At the end of the beam check, we calculated beam utilization factor f_{beam} as:

$$f_{beam} = \max\left(\frac{V_{Sd}}{V_{Rd}}, \frac{M_{Sd}}{M_{Rd}}\right) \tag{3}$$

To verify the connection, we calculated the values of the traction forces applied to the bolt $F_{t,Sd}$, the shearing force applied to the bolt $F_{v,Sd}$, the contact force due to the pressure of bolt contact with the edge of the hole $F_{c,Sd}$, and the shear collapse force $F_{r,Sd}$. Then, we calculated according to the ABNT [4] standards, the design values of the traction forces in the bolt $F_{t,Sd}$, the shear force in the bolt $F_{v,Rd}$, the contact force of the bolt with the edge of the hole $F_{c,Rd}$, and the force resistant to collapse by tearing $F_{r,Rd}$. In addition, we verified the angle profile using the Von Mises maximum stress criterion $\sigma_{vonmisses}$ on the profile steel ultimate strength f_u. At the end of the check, we calculated the utilization factor of the $f_{connection}$ connection as:

$$f_{connection} = \max\left(\frac{F_{t,Sd}}{F_{t,Rd}}, \frac{F_{v,Sd}}{F_{v,Rd}}, \frac{F_{c,Sd}}{V_{c,Rd}}, \frac{F_{r,Sd}}{F_{r,Rd}}, \frac{\sigma_{vonmisses}}{f_u}\right) \tag{4}$$

2.2 Neural network modelling

We defined two models of neural networks, one for the beam profile and the other for the connection elements. The first model of neural networks has as input parameters the beam span L and the linear load q distributed on the beam. The output parameters are the classification of whether or not a given W profile verifies the design criteria. Its architecture is multi-layered, with fully connected layers. For the inner layers, we used the activation function ReLU because the gradient of a ReLu is either zero or a constant, so it is possible to outcome the vanishing exploding gradient issue. ReLU activation functions have been shown to train better in practice than sigmoid activation functions Patterson and Gibson [7]. In the output layer, we used the sigmoid activation function as it assumes values between 0 and 1.

The input values are the normalized values of the length L and the distributed load q. Each value y_i of the output vector is calculated as:

$$f_{m,i} = \begin{cases} 1 & f_{beam,i} \geq 1 \\ \dfrac{m_{max} - m_i}{m_{max} - m_{min}} & f_{beam} < 1 \end{cases} \tag{5}$$

$$y_i = \tanh(f_{beam,i} f_{m,i}) \tag{6}$$

being $f_{m,i}$ the mass factor for the profile i, m_i is the profile mass value, m_{min} is the profile masses smallest value, m_{max} is the profile masses highest value, $f_{beam,i}$ is the profile utilization factor value and y_i is the profile expected neural network output value i.

We used the $\tanh$ function for normalization because its value for $x = 0$ is equal to zero and has an upper limit equal to 1, being a good representation for the utilization factors values that are higher values than zero, begin that there is a greater interest in the values of x in the range between 0 and 1.

In the same way as the first network, the second neural network has as parameters the length L, the linear distributed load q and also includes the beam profile as an input parameter. This network has the same architecture and activation functions as the first one. The output layer classifies a given angle configuration, diameter, and the number of bolts that verify the design criteria. The number of units of the output layer has the same number of connection element configurations grouped by angle, diameter, and number of bolts used for training.

We adopted the input values according to the table 1. Each y_i value of the output vector is calculated as:

$$f_{m,i} = \begin{cases} 1 & f_{connection,i} \geq 1 \\ \dfrac{m_{max} - m_i}{m_{max} - m_{min}} & f_{connection} < 1 \end{cases} \tag{7}$$

$$y_i = \tanh(f_{connection,i} f_{m,i}) \tag{8}$$

being $f_{m,i}$ the configuration mass factor$i$, m_i is the angles mass value, m_{min} is the angles masses smallest value, m_{max} is the angles masses highest value, $f_{connection,i}$ is the connection utilization factor and y_i is the expected neural network output value for the i configuration. A profile verifies the design criteria when the output value is less than or equal to 0.8, as this is the normalized value when the utilization factor is equal to 1. We used the Adam algorithm as an optimizer for training both neural networks because it is computationally efficient Kingma and Ba [8].

3 Results

We tested the neural network models using a test set of beams and their connections. We choose the spans and loads for testing randomly within the range of values used for training. For each beam and its test connection, we calculated the utilization factors according to the design criteria, following the same steps used for the training data. With these results and the results obtained by the neural network, we created the confusion matrix. A case is positive when the configuration verifies the design criteria and negative when it does not verifies the design criteria. Thus a case is true positive when the configuration verifies the design criteria and the neural network has indicated that the configuration indeed verifies the criteria. The 2 table shows the number of hidden layers, the number of epochs used for training, the values of the confusion matrix, and the accuracy of the four neural network models used.

Table 2. Architecture, confusion matrix and accuracy for each neural network.

Type	Connected to	Size of hidden layers	Epochs	TP	TN	FP	FN	Accuracy (%)
Profile	web	32,64,64,32	20	19646	655	38	253	98.6
Profile	flange	32,64,64,32	20	19757	524	169	142	98.5
Connection	web	64,128,128,64	20	198	14496	5403	495	71.4
Connection	flange	64,128,128,64	20	198	14498	5401	495	71.4

We chose a case to show the application of the neural network models developed previously. The case is a set of beams representing the beams of a 9.3 m by 5.2 m floor, split into 5.7 m and 3.6 m within the major length.

Beams at floor major length are connected to column flanges. In this example, there are beams connected both in the web and in the column profile flange. We presented in the table 3 for each beam, the length values, applied distributed load values, and which elements of the column profile are connected.

We show the neural network output values for each of the W profiles of each beam in the 3a graph. We present the neural network output values for each of the connections of each of the beams in the graphs 3b, 3c and 3d, 3e and 3f. The normalized value 0.8 represents the limit to be considered for a given profile or connection to verify the design criteria.

Considering the output results of the neural network, for the profile of beams V1 and V3, it chose section W 250x25.3, for beams V2, V4, and V5, section W150x13.0, for beam V6, section W150x24.0, and beam V7 the section W150x22.5. For beams V1, V3 and V6, it chose the connection with the 45x5x3.38 angle profile with two 12.7mm bolts. For beams V2, V4, and V5, angle profile 45x3x2.12 with 2 bolts of 12.7mm. And finally, for the V7 beam, the angle 45x3x2.12 with 3 bolts of 12.7mm. We present in the figure 2 the beams profiles and connections three-dimensional drawing that it chose.

Table 3. Beams of the case.

Beam	Length (m)	Load (kN/m)	Connected to	Beam	Length (m)	Load (kN/m)	Connected to
V1	5.70	21.8	Flange	V5	5.20	8.4	Web
V2	3.60	14.6	Flange	V6	5.20	24.8	Web
V3	5.70	21.8	Flange	V7	5.20	20.2	Web
V4	3.60	14.6	Flange				

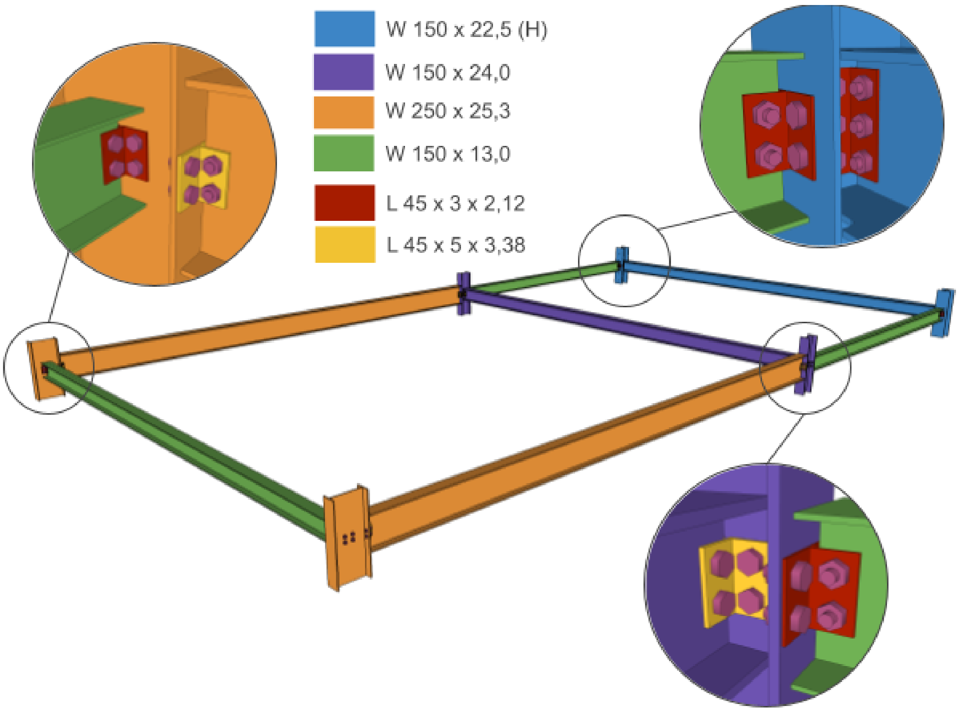


Figure 2. Three-dimensional drawing of the beams of the case with the profiles and connections predicted by the neural networks

4 Discussion

In this work, we used only the shear and bending diagrams. We not considered the normal forces because its values are less than 1 kN.

The neural networks trained in this work can be used during the design to find out if a beam profile and its connection verifies the design criteria or not. We achieved better results from the neural network for the beam profile when compared to the neural network results of the connection elements. For a more practical application of these neural network models, it is necessary to investigate and improve the results of the neural network that defines the elements of the link. Also, both networks need a training set with more profiles and thus make the use more widespread.

We do not trained the neural networks considering the influence of other connected beams on the column profiles. Depending on the stiffness of the connection and the column, other connected beams may influence the results, so it is important to consider that we have approximated results.

Another limitation of the work is the reduced set of profiles, beam lengths and applied load values, with beam lengths being limited to the range of 3 to 6 m and the values of distributed loads being limited to the range of 5 to 25 kN/cm.

In addition, another limitation of the neural networks trained at this work is the indication of predetermined profiles. An alternative approach would be not to indicate a profile, but to make the neural networks more generic,

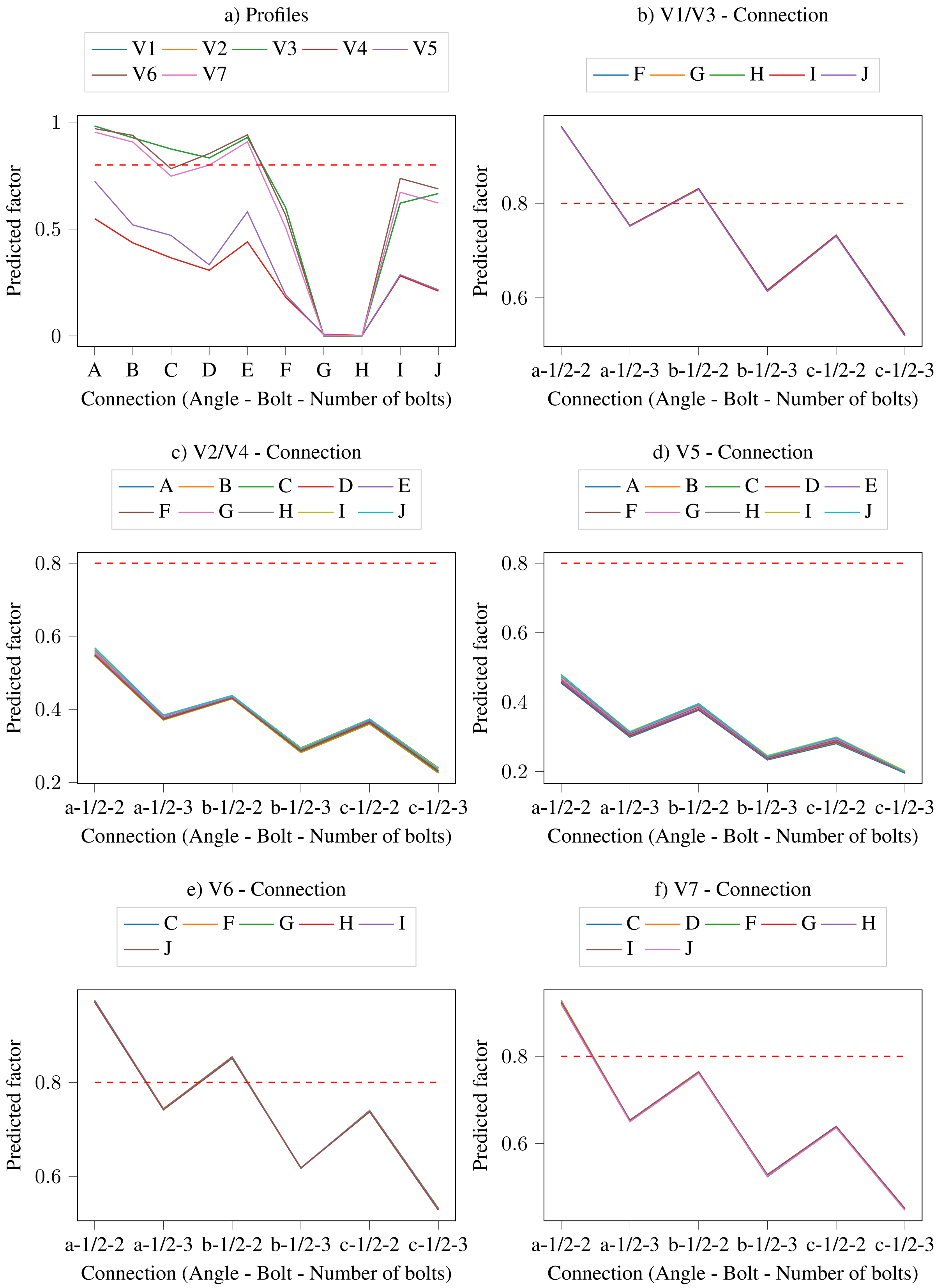


Figure 3. Predicted values for beam profiles in the case

for example, indicating the necessary dimensions for the profiles to then define the profiles. The results of neural networks are also limited to the design criteria of ABNT [4] standard and to the ultimate limit state.

In general, the use of neural networks can facilitate and make the design of the beam in steel structures easier, but more studies are needed before their use in projects.

5 Conclusions

Even with the limitations already described above, it can be said that we achieved the objective of developing a tool to aid in the design of beams of steel structures with a W-section connected to columns of the same type through double-angle bolted connections.

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References

[1] L. Lima, P. Vellasco, S. Andrade, da J. G. S. Silva, and M. Vellasco. Neural networks assessment of beam-to-column joints. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, 2005.

[2] K. Abdalla and G. Stavroulakis. A backpropagation neural network model for semi-rigid steel connections. *Computer-Aided Civil and Infrastructure Engineering*, , n. 10, pp. 77 – 87, 2008.

[3] M. Harshada and K. Satish. Use of artificial neural network for initial design of steel structures. *IOP Conference Series: Materials Science and Engineering*, 2019.

[4] ABNT. Abnt nbr 8800: 2008: Projeto de estruturas de aço e de estruturas mistas de aço e concreto de edifícios, 2008.

[5] M. H. Jawad. *Design of Plate and Shell Structures*. ASME Press, 2004.

[6] A. F. M. Azevedo. *Método dos elementos finitos*. Faculdade de Engenharia da Universidade do Porto, 2003.

[7] J. Patterson and A. Gibson. *Deep Learning: A practioner's approach*. O'Reilly, 2017.

[8] D. P. Kingma and J. L. Ba. Adam: A method for stochastic optimization, 2014.