Neural Networks Assessment of Beam-to-Column Joints

L. R. O. de Lima
P. C. G. da S. Vellasco
S. A. L. de Andrade
and J. G. S. da Silva
Universidade do Estado do Rio de Janeiro
Faculdade de Engenharia
Rua São Francisco Xavier, 524, sala 5016A
20550-900 Rio de Janeiro, RJ. Brazil
luciano@eng.uerj.br
vellasco@eng.uerj.br
andrade@civ.puc-rio.br
and jgss@eng.uerj.br

M. M. B. R. Vellasco
Pontifícia Universidade Católica do Rio de Janeiro
Departamento de Engenharia Elétrica
Rua Marquês de São Vicente, 225.
22453-900 Rio de Janeiro RJ. Brazil
marley@ele.puc.rio.br

This paper proposes the use of artificial neural networks to predict the flexural resistance and initial stiffness of beam-to-column steel joints using the back propagation supervised learning algorithm. Three types of steel beam-to-column joints were investigated: welded, endplate and bolted with top, seat and double web angles, respectively. The neural networks results proved to be consistent with experimental and design code reference values.

***Keywords**: structural engineering, semi-rigid joints, steel structures, neural networks, semi-rigid behaviour, flexural resistance and joint stiffness*

Introduction

Structural joints play a fundamental role in the steel structures global response. The real behaviour of a structural joint has been investigated through several experimental tests such as: Faella *et al.* (1999), Aggarwal (1994), Weynand and Sahl (1984), Zoetemeijer and Munter (1983), Simek and Wald (1991), Hummer and Tschemmernegg (), Cruz *et al.* (1998), Janss *et al.* (1987), Goverdan (1983), Nethercot *et al.* (1995), Bjorhovde *et al.* (1990), Chen *et al.* (1993), Kishi *et al.* (1987), Lima *et al.* (2002), Simões *et al.* (2001), Azizinamini *et al.* (1987), Azizinamini *et al.* (1989). The main objective of these tests was to determine the physical and geometric parameters that influence the joints structural behaviour.[1]

From these test data, the joints can be classified according to their bending moment and associated rotation capacity. Generally, the joints are classified as rigid or flexible. However, this hypothesis is not accurate, since most of the steel structural joints do not match any of these two extremes. Despite this fact, the traditional non-sway frame design usually adopts flexible joints. Unfortunately, when sway frame design is required, rigid stiffened joints have to be used. On the other hand, rigid joints have higher fabrication costs and give rise to a number of questions about their real structural behaviour. To overcome these difficulties, the semi-rigid joints fit as a natural solution, reducing the final cost and presenting a more realistic structural behaviour.

Few investigations using artificial neural networks to predict joints behaviour were found in literature. Abdalla and Stavroulakis (1994) and Stavroulakis and Abdalla (1995) have used neural networks to predict the global moment versus rotation curve of single web angle beam-to-column joints. Anderson *et al.* (1997) described the use of neural networks to predict a bilinear approximation of the moment versus rotation curves of minor axis beam-to-column endplate joints. The joints presented in this work were not previously used for predicting of the joints behaviour through neural networks.

This work proposes the use of artificial neural networks to predict the flexural resistance ($M_{j,Rd,ANN}$) and initial stiffness ($S_{j,ini,ANN}$) of semi-rigid beam-to-column joints. This structural engineering problem is characterized by the influence of several physical and geometric parameters and for the great difficulty to generate new data based on experimental tests. This was the main motivation for using artificial neural networks.

Nomenclature

b_{ep} = *endplate width*
b_{fb} = *beam flange width*
b_{fc} = *column flange width*
d_b = *bolt diameter*
d_h = *horizontal distance between bolts*
f_{ub} = *bolt ultimate stress*
f_{yb} = *beam yield stress*
f_{yc} = *column yield stress*
f_{yep} = *endplate yield stress*
h_1 = *first bolt row height*
h_2 = *second bolt row height*
h_3 = *third bolt row height*
h_b = *beam height*
h_c = *column height*
h_{ep} = *endplate height*
i = *number of epochs*
k = *ratio between total data and subset data*
l_{ep} = *distance from the beam top flange to the endplate free edge*
m = *number of available data*
s_i = *processing element input*
s_j = *processing element output*
t_{ep} = *endplate thickness*
t_{fb} = *beam flange thickness*
t_{fc} = *column flange thickness*
t_{wb} = *beam web thickness*
t_{wc} = *column web thickness*

Paper accepted June, 2005. Technical Editor: Atila P. Silva Freire.

$M_{j.Rd}$ = joint flexural resistance
$M_{j,Rd,ANN}$ = joint flexural resistance predicted by neural networks
$M_{j,Rd,exp}$ = experimental joint flexural resistance
$M_{j,Rd,EC3}$ = Eurocode 3 joint flexural resistance
$S_{i,ini}$ = joint initial stiffness
$S_{j,ini,ANN}$ = joint initial stiffness predicted by neural networks
$S_{j,in,\,exp}$ = experimental joint initial stiffness
$S_{j,ini,EC3}$ = Eurocode 3 joint initial stiffness

Greek Symbols

ϕ_{CD} = joint rotation capacity
α = momentum factor
η = learning rate

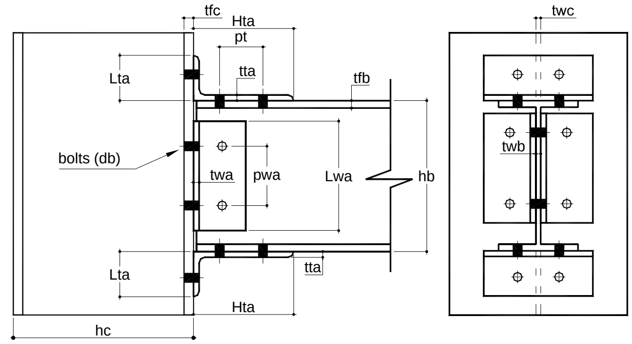

Figure 3. Bolted angle joint.

The Beam-to-Column Joint Model

In the present investigation three different types of joints were evaluated by the neural networks. From these studied joints it was possible to identify the bolted end-plate joints as one of the most adopted joints, see Fig. 1. They are widely used in constructional steel design because they can cover a wide range of structural solutions, from pinned to rigid joints, by performing minor geometrical modifications on the joint details.

In general, the required initial stiffness ($S_{j,ini}$) and the bending moment resistance ($M_{j,Rd}$) of the joint can be obtained using an appropriate configuration of the joint elements, such as number of bolts, endplate thickness and its geometrical configuration. A third variable, the joint rotation capacity (ϕ_{CD}), can also influence the global joint behaviour. Unfortunately, this variable was not easily found in the literature, making difficult its adoption on the artificial neural network prediction model.

The other joints investigated in this analysis were: welded joints and bolted joint with angles shown in Figs. 2 and 3, respectively.

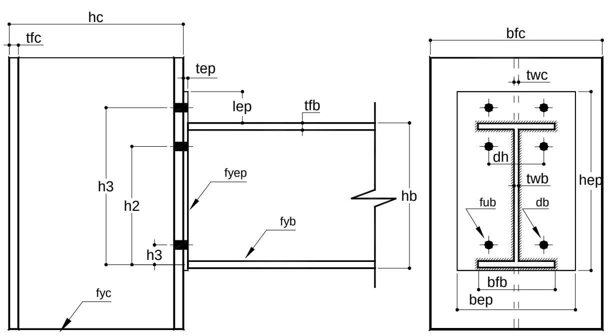

Figure 1. Extended endplate joint layout.

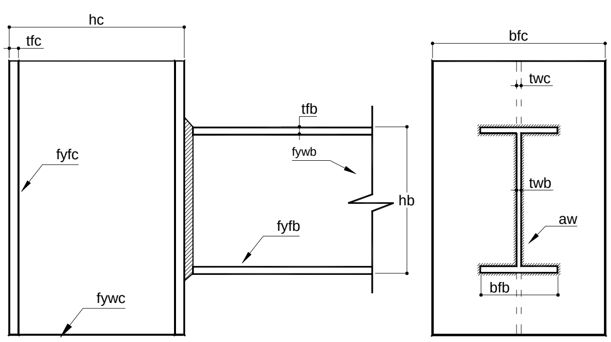

Figure 2. Welded joint layout.

There are several parameters related to the endplate beam-to-column joint design. The most significant variables are: column flange thickness (t_{fc}), column flange width (b_{fc}), column web thickness (t_{wc}), column height (h_c), column yield stress (f_{yc}), beam flange thickness (t_{fb}), beam flange width (b_{fb}), beam web thickness (t_{wb}), beam height (h_b), beam yield stress (f_{yb}), endplate width (b_{ep}), endplate height (h_{ep}), endplate thickness (t_{ep}), distance from the beam top flange to the endplate free edge (l_{ep}), endplate yield stress (f_{yep}), bolt diameter (d_b), bolt ultimate stress (f_{ub}), first bolt row height (h_1), second bolt row height (h_2), third bolt row height (h_3) and horizontal distance between bolts (d_h). All these variables are illustrated in Fig. 1. Additional variables utilized to characterize the other two investigated joints, Fig. 2 and 3, are: column flange yield stress (f_{yfc}), column web yield stress (f_{ywc}), beam flange yield stress (f_{yfb}), beam web yield stress (f_{ywb}), weld thickness (a_w), top and seat angle length (L_{ta}), top and seat angle height (H_{ta}), angle thickness (t_{ta}), horizontal distance between bolts (p_t), web angle thickness (t_{wa}), vertical distance between bolts (p_{wa}) and web angle length (L_{wa}).

The behaviour of beam-to-column joints can also be evaluated with the aid of the component method, largely adopted in research investigations and recently incorporated in European Committee for Standardization - Eurocode 3 (1997). Joint components have been introduced to a simple mechanical model to enable the prediction of beam-to-column moment versus rotation curves (Jaspart, 1997). Fig. 4 depicts an endplate beam-to-column joint together with its associate mechanical model. The mechanical model is composed of rigid links and springs, created to represent each relevant joint component. A comprehensive description of the joint components is presented by Silva and Coelho (2001).

The spring model presented in the Fig. 4 can be simplified by replacing each series of springs by an equivalent elasto-plastic spring, which retains all the relevant characteristics (Silva and Coelho, 2001). Using this procedure, a general non-linear equivalent model for the analysis of beam-to-column joints can also be obtained (Simões *et al.*, 2001). When the equivalent elastic model is defined, the design process continues with a post-buckling stability analysis using an energy-based formulation. Full details of the mathematical derivation can be found in Silva (Silva and Coelho, 2001). Since these procedures are still to be evaluated, the present work uses the bilinear approximation of the moment versus rotation curve related to the joint proposed in Eurocode 3, see Fig. 5.

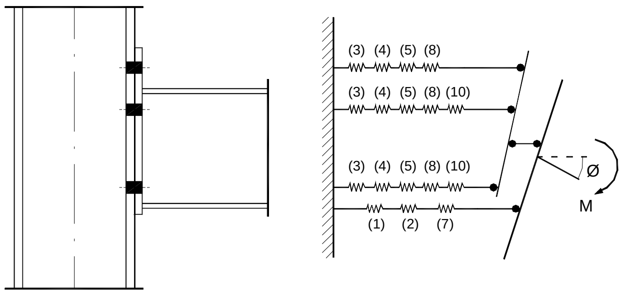

Figure 4. Characterization of the beam-to-column joints components.

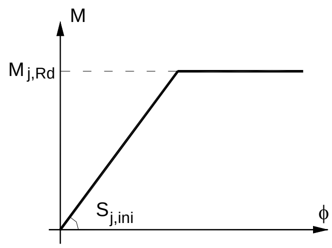

Figure 5. Bilinear approximation of the moment versus rotation curve.

The Proposed Neural Network System

Artificial neural networks (ANN) are computing systems that simulate the biological neural systems of the human brain (Bishop, 1994 and Haykin, 1999). They are massively parallel systems that rely on simple non-linear processing elements (PE) and dense arrangements of interconnections (Treleavan *et al.* 1989). These interconnection patterns can range from single-layer, feed-forward networks, like the early Perceptron model, to more complex topologies, formed by multilayers with backward propagation of errors, as in the back propagation model (Rumelhart and McClellan, 1986). These networks have demonstrated their ability to deliver simple and powerful solutions in areas that for many years have challenged conventional computing approaches.

An artificial neural network is represented by weighted interconnection between processing elements (PE). These weights are the parameters that actually define the non-linear function performed by the neural network. The process of determining such parameters is called training or learning and relies on the presentation of many training patterns.

The most widely used neural network learning algorithm is the Back Propagation. This is due to its relatively simplicity, together with its universal approximation capacity (Hornik *et al.*, 1989 and Cybenko, 1989). The Back Propagation algorithm defines a systematic way to update the synaptic weights of multi-layer feed-forward supervised networks composed of an input layer, that receives the input values, an output layer, which calculates the neural network output, and one or more intermediary layers, so called hidden layers. The back propagation supervised learning process is based on the gradient descent method that usually minimizes the sum of squared errors between the target value and the output of the neural network.

In this work, the back propagation (BP) learning algorithm has been used, where the network is presented with a set of input vectors and their respective desired output vectors. Two neural networks were used for each joint type, see Fig. 5. The first was used to predict the bending moment resistance while the second was utilized to forecast the joint initial stiffness. The input parameters, represented by the geometric and mechanical characteristics of all the experimental tests, are presented in Tabs. 1, 2 and 3, respectively.

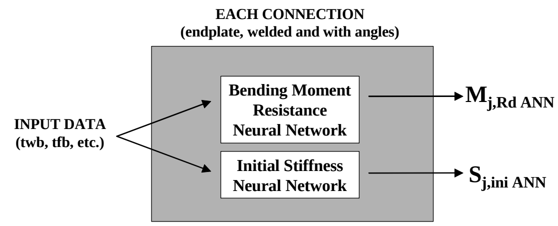

Figure 5. Neural network configurations.

The NeuralWorks Modelling Software (QNet for Windows, 2000) was used to train and test all neural networks. To avoid problems in the training process due to the reduced database, a methodology described by Mitchel (1997) was adopted. In this method, a k-fold cross-validation approach is used, where the m available examples are partitioned into k disjoint subsets, each of m/k size. The cross-validation procedure is performed k times, each time using one different subset as the validation set and the other k – 1 subsets as training set. On each experiment the above cross-validation approach is used to determine the number of iterations i (epochs) that yield the best performance on the validation set. The mean imean of these estimates for i is then calculated, and a final training of BP is performed with all m examples for imean iterations, with no validation set.

In this investigation, *m* was divided into *k* = 3 parts (I, II and III), enabling three different validations to be performed. In the first phase, groups I and II are used for training while the validation is made with group III. In the second stage, the training is made with groups I and III and validation is performed with group II. In the last stage, the training is accomplished with groups II and III and the validation is made with group I. Fig. 6 summarizes this procedure.

Several network configurations were tested varying the number of hidden processors (2, 3, 4, 5 and 6). The learning rate was considered adaptive, with an initial value equal to 0.2 while the momentum factor was changed between 0.4 and 0.8. The optimum Neural Network was obtained through a comparison of the generalization error obtained with the validation set.

The best network configuration for each joint type is presented in Tab. 4, where the number of input patterns, hidden processors, initial and final learning rates (η) and the momentum factor (α) are specified for each neural network.

Table 1. Geometrical characteristics (in mm) and mechanical properties (in MPa) for experiments with endplate joints.

ID	Test	b_{fc}	t_{fc}	h_c	f_{yc}	b_{fb}	t_{fb}	h_b	f_{yb}	t_{ep}	l_{ep}	f_{yep}	d_b	f_{ub}	h_1	h_2	d_h
1	T110001	300	13.5	296	475	220.0	15.5	543.0	300	25	105.0	416.0	24	1323	580.3	474.8	30
2	T110002	300	13.5	296	482	220.0	15.5	543.0	309	25	105.0	410.0	24	1323	580.3	474.8	30
3	T110005	300	12.5	296	532	220.0	15.5	547.0	290	25	105.0	404.0	24	1323	584.2	478.8	30
4	T109003	180	14.1	179	300	151.0	11.2	300.0	323	30	70.0	273.0	20	1000	334.4	244.4	46
5	T109004	180	14.0	180	306	192.0	14.0	454.0	285	41	84.0	323.0	24	1000	496.0	381.0	65
6	T109006	240	17.0	240	275	220.0	18.6	597.0	288	41	82.0	325.0	24	1000	634.7	514.7	62
7	T101007	163	12.6	160	280	99.7	8.4	198.8	351	15	60.0	315.5	16	1000	229.6	149.6	25
8	T101010	160	12.6	163	280	150.9	10.8	298.9	303	20	70.0	291.5	20	1000	333.5	243.5	30
9	T101013	120	9.7	241	310	99.7	8.4	198.8	351	18	60.0	330.5	16	1000	229.6	149.6	24
10	T101014	151	10.8	299	303	99.7	8.4	198.8	351	15	60.0	327.0	16	1000	229.6	149.6	25
11	T839	240	12.0	230	256	180.0	13.5	400.0	235	12	80.0	214.0	20	785	433.3	343.3	35
12	T8310	200	15.0	200	243	180.0	13.5	400.0	235	14	80.0	312.0	20	980	433.3	343.3	35
13	T8311	300	14.0	290	417	300.0	23.0	490.0	235	14	113.0	312.0	24	785	546.5	426.5	60
14	T911	301	14.4	302	317	181.0	14.6	401.0	323	30	90.0	266.0	24	980	443.7	338.7	61
15	T913	301	14.5	301	279	181.0	14.4	401.0	279	30	90.0	239.5	24	980	443.8	338.8	61
16	TC5	204	10.9	206	283	133.3	7.6	205.4	283	16	111.2	250.0	16	633	268.8	138.8	30
17	TC6	204	10.9	206	283	133.3	7.6	205.4	283	16	111.2	250.0	20	980	268.8	138.8	30
18	TC7	204	10.9	206	283	133.3	7.6	205.4	283	20	111.2	250.0	16	633	268.8	138.8	30
19	TC8	204	10.9	206	283	133.3	7.6	205.4	283	20	111.2	250.0	20	980	268.8	138.8	30
20	TC9	204	10.9	206	283	133.3	7.6	205.4	283	16	111.2	250.0	16	633	268.8	138.8	30
21	TC11	204	10.9	206	283	133.3	7.6	205.4	283	20	111.2	250.0	16	633	268.8	138.8	30
22	T109005	240	16.4	240	276	192.0	14.0	454.0	285	41	84.0	323.0	24	1000	496.0	381.0	65
23	T101004	160	12.6	163	280	99.7	8.4	198.8	351	15	60.0	315.5	16	1000	229.6	149.6	25
24	T912	301	14.3	302	317	181.0	14.4	401.0	317	30	90.0	261.0	24	980	443.8	338.8	61
25	TC10	204	10.9	206	283	133.3	7.6	205.4	283	16	111.2	250.0	20	980	268.8	138.8	30
26	TC12	204	10.9	206	283	133.3	7.6	205.4	283	20	111.2	250.0	20	980	268.8	138.8	30

Table 2. Geometrical characteristics (in mm) and mechanical properties (in MPa) for the experiments with welded joints.

ID	Test	b_{fc}	t_{fc}	t_{wc}	h_c	f_{yfc}	b_{fb}	t_{fb}	h_b	f_{yfb}	a_w
1	T107001	178	8.9	6.2	173	334.6	119	10.2	238	389.8	6.8
2	T107002	179	8.8	6.2	175	342.5	149	10.0	300	306.2	5.8
3	T107003	242	10.7	9.4	233	354.2	149	10.0	300	304.8	9.1
4	T105002	160	13.3	7.6	159	260.0	162	11.4	328	286.0	7.5
5	T105003	179	13.5	9.0	183	288.0	149	10.0	298	334.0	7.0
6	T105005	200	13.9	8.4	202	273.0	171	10.7	361	271.0	7.2
7	T105006	239	16.0	9.7	239	276.0	223	18.1	604	306.0	10.3
8	T105008	301	19.3	12.4	297	292.0	300	17.8	301	357.0	13.0
9	T105009	139	11.5	7.7	139	300.0	110	10.0	218	312.0	6.2
10	T105010	138	11.6	7.8	146	281.0	111	9.1	221	361.0	6.2
11	T105011	140	12.0	7.5	142	298.0	151	11.1	302	304.0	6.4
12	T105014	178	13.7	8.1	177	292.0	170	12.3	359	290.0	7.5
13	T105015	179	13.5	9.4	178	275.0	180	12.5	397	290.0	10.2
14	T105016	200	14.6	9.4	200	279.0	171	12.0	361	273.0	8.9
15	T105019	239	16.3	10.1	240	274.0	224	18.7	605	322.0	8.6
16	T105020	299	18.3	10.8	298	301.0	210	17.2	551	268.0	11.9
17	T105021	299	18.9	12.3	303	266.0	220	19.4	600	268.0	11.6
18	T105023	301	18.7	12.0	302	276.0	299	22.9	402	281.0	12.1
19	T105025	301	21.3	11.9	361	276.0	224	18.2	604	316.0	11.4
20	T106001	145	21.4	13.2	159	283.0	149	11.0	295	358.0	11.8
21	T106003	204	25.4	15.9	221	268.0	180	12.6	401	265.0	11.0
22	T106004	204	25.6	15.9	222	267.0	199	15.1	498	248.0	14.0
23	T106005	204	24.5	16.0	222	280.0	224	18.7	600	277.0	12.7
24	T106006	222	25.0	16.5	241	278.0	209	18.0	552	361.0	13.5
25	T106007	308	37.0	21.2	340	237.0	300	28.0	603	262.0	14.2
26	T108032	199	15.0	9.0	199	370.0	186	13.1	450	386.0	4.0
27	T108038	202	12.0	8.7	209	291.0	168	12.5	361	307.0	5.5
28	T107004	242	10.8	11.3	233	343.9	190	13.2	452	287.0	11.3
29	T105004	179	13.4	8.2	183	277.0	180	12.3	398	284.0	9.3
30	T105007	299	18.6	11.7	300	296.0	181	13.2	400	309.0	9.1
31	T105018	240	16.1	9.7	239	269.0	189	14.1	451	284.0	10.1
32	T105024	300	18.0	10.6	298	271.0	301	27.6	500	271.0	12.7
33	T106002	186	22.8	14.5	200	265.0	177	13.5	398	358.0	12.1
34	T108042	255	18.5	12.2	265	267.0	200	15.5	498	288.0	5.7

The NeuralWorks Modelling Software (QNet for Windows, 2000) was used to train and test all neural networks. To avoid problems in the training process due to the reduced database, a methodology described by Mitchel (1997) was adopted. In this method, a k-fold cross-validation approach is used, where the *m* available examples are partitioned into *k* disjoint subsets, each of *m/k* size. The cross-validation procedure is performed k times, each time using one different subset as the validation set and the other *k – 1* subsets as training set. On each experiment the above cross-validation approach is used to determine the number of iterations i (epochs) that yield the best performance on the validation set. The mean i_{mean} of these estimates for i is then calculated, and a final training of BP is performed with all m examples for i_{mean} iterations, with no validation set.

In this investigation, *m* was divided into *k* = 3 parts (I, II and III), enabling three different validations to be performed. In the first phase, groups I and II are used for training while the validation is made with group III. In the second stage, the training is made with groups I and III and validation is performed with group II. In the last stage, the training is accomplished with groups II and III and the validation is made with group I. Fig. 6 summarizes this procedure.

Several network configurations were tested varying the number of hidden processors (2, 3, 4, 5 and 6). The learning rate was considered adaptive, with an initial value equal to 0.2 while the momentum factor was changed between 0.4 and 0.8. The optimum Neural Network was obtained through a comparison of the generalization error obtained with the validation set.

The best network configuration for each joint type is presented in Tab. 4, where the number of input patterns, hidden processors, initial and final learning rates (η) and the momentum factor (α) are specified for each neural network.

Table 3. Geometrical characteristics (in mm) for the experiments with bolted joint with angles.

ID	Test	t_{fc}	h_b	t_{ta}	L_{ta}	L_{wa}	d_b
1	8S1	16.3	209.6	9.5	88.9	139.7	16.0
2	8S2	16.3	209.6	9.5	88.9	139.7	16.0
3	8S3	16.3	209.6	7.9	88.9	139.7	16.0
4	8S4	16.3	209.6	9.5	152.4	139.7	16.0
5	8S5	16.3	209.6	9.5	101.6	139.7	16.0
6	8S6	16.3	209.6	7.9	101.6	139.7	16.0
7	8S7	16.3	209.6	9.5	101.6	139.7	16.0
8	8S10	16.3	209.6	12.7	88.9	139.7	22.2
9	14S1	22.9	358.8	9.5	101.6	215.9	16.0
10	14S2	22.9	358.8	12.7	101.6	215.9	16.0
11	14S4	22.9	358.8	9.5	101.6	215.9	16.0
12	14S5	22.9	358.8	9.5	101.6	215.9	22.2
13	14S6	22.9	358.8	12.7	101.6	215.9	22.2
14	14S8	22.9	358.8	15.9	101.6	215.9	22.2
15	8S8	16.3	209.6	7.9	88.9	139.7	22.2
16	8S9	16.3	209.6	9.5	88.9	139.7	22.2
17	14S3	22.9	358.8	9.5	101.6	139.7	16.0
18	14S9	22.9	358.8	12.7	101.6	215.9	22.2

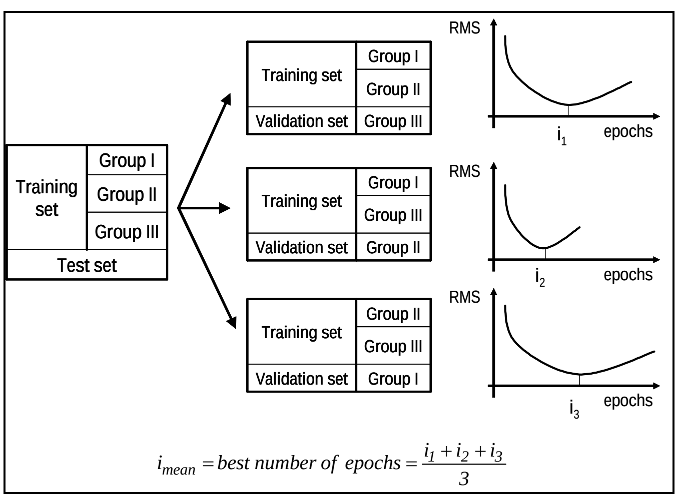

Figure 6. Cross-validation methodology used due to the reduced training database.

Table 4. Neural networks configurations.

Joint type	Endplate		Welded		Angles	
Number of patterns	26		33		18	
Training data	21		26		14	
Test data	5		7		4	
	$M_{j,Rd}$	$S_{j,inii}$	$M_{j,Rd}$	$S_{j,ini}$	$M_{j,Rd}$	$S_{j,ini}$
Hidden layers	1	1	1	1	1	1
Processors in each hidden layer	3	4	6	3	5	5
Initial learning rate (η)	0.3	0.3	0.3	0.3	0.3	0.3
Final learning rate (η)	0.28	0.25	0.27	0.28	0.28	0.28
Momentum (α)	0.6	0.6	0.6	0.6	0.6	0.6

Neural Network Results

Bolted Endplate Joints Results

For this type of joint, the results of 26 experimental tests (21 for training and 5 for testing) were used, producing satisfactory results for the prediction of the flexural resistance where the mean absolute percent error (MAPE) was 8.4%. The minimum and maximum percentile errors were –15.5% and 18%. For the prediction of the initial stiffness, the obtained values weren't so good. The mean error was 23.5% while –33.8% and 38.3% represent the minimum and maximum percentile errors.

Figure 7 illustrates a comparison of the ratio between the values predicted by the neural networks, the Eurocode 3 formulae, and the experimental values. In the sequence, a similar comparison for the joint initial stiffness is presented in the Figure 8.

It can be observed that the performance obtained in the prediction of flexural resistance was significantly better than the initial stiffness prediction. The initial stiffness prediction pointed out for the significant importance of obtaining new experimental data. Both results are summarized in Tabs. 5 and 6, respectively.

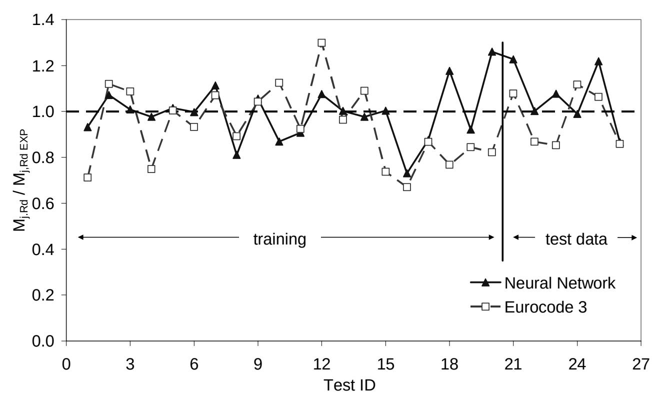

Figure 7. Flexural resistance relative comparison for endplate joints.

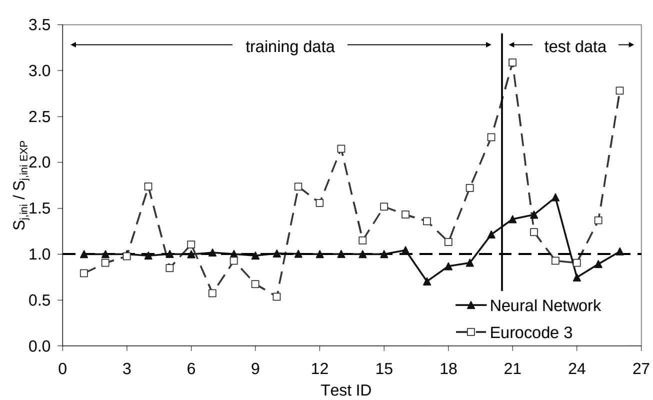

Figure 8. Initial stiffness relative comparison for endplate joints.

Welded Joints Results

Figure 9 depicts the comparison of the results obtained with NN and Eurocode 3 formulae for the welded joint flexural resistance. From this graph it is possible to conclude that the neural network results reached a good agreement with the joints experimental values, while the Eurocode 3 prediction values conducted to misleading results. The mean neural network error was 8.9% with –5.4% and 12.4% of minimum and maximum percentile error values, respectively.

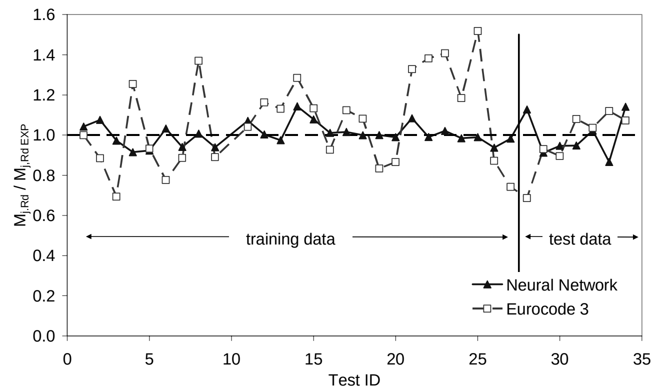

Figure 9. Flexural resistance relative comparison for welded joints.

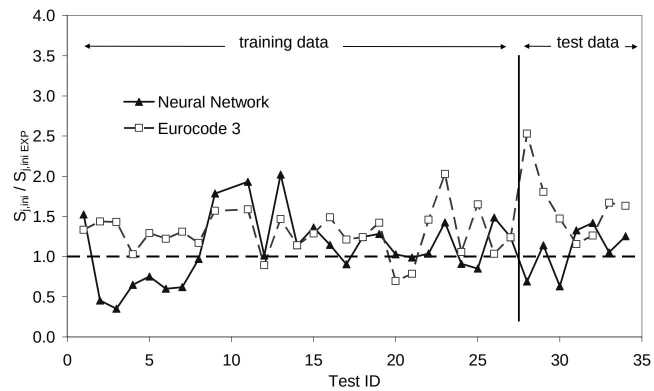

Figure 10. Initial stiffness relative comparison for welded joints.

Figure 10 depicts the welded joint initial stiffness results. The mean error was 28% with -58.4% and 30% of minimum and maximum percentile error values respectively. Again, the obtained initial stiffness results were not as good as the moment prediction values but it is fair to mention that the values from Eurocode 3 formulae also did not present a good agreement with the experimental data. The summary of the obtained results is presented in Tabs. 7 and 8.

Bolted Joints with Angles Results

Figure 11 presents the results obtained for bolted joints with angles. For flexural resistance results, the mean error was 11.6% with –18.3% and 4.7% of minimum and maximum percentile error values, respectively. The results for the initial stiffness prediction presented in Figure 12 led to the conclusion that neural network results were more accurate than the values obtained from the theoretical analysis evaluated by Kishi & Chen formulation, [12] and [13].

The potential of the neural networks to predict the joints ultimate moment and initial stiffness was confirmed by these graphs. Although some of the neural network initial stiffness values differ up to 59% from the experiments, this can be explained by the difficulties in the laboratory measuring devices and associated experimental errors, which can produce misleading values for the experimental test results. The summary of the obtained results is presented in Tabs. 9 and 10.

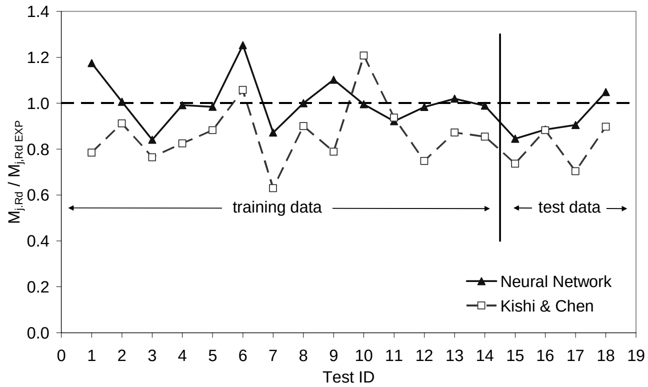

Figure 11. Flexural resistance relative comparison for bolted joints with angles.

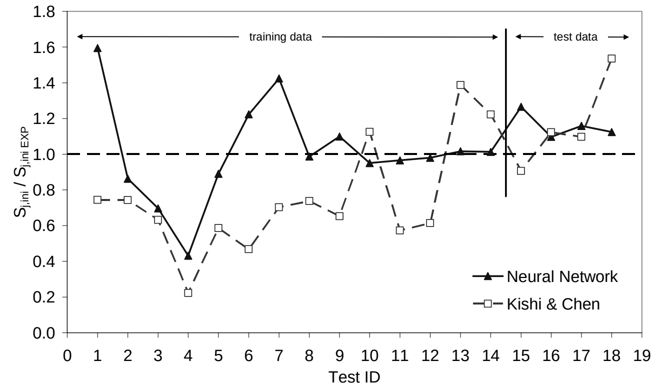

Figure 12. Initial stiffness relative comparison for bolted joints with angles.

Table 5. Flexural resistance comparison for endplate joints.

Test		Author	$M_{j,Rd\ EXP}$ (kN.m)	$M_{j,Rd\ ANN}$ (kN.m)	$M_{j,Rd\ ANN}$ / $M_{j,Rd\ EXP}$	$M_{jRd\ EC3}$ (kN.m)	$M_{jRd\ EC3}$ / $M_{j,Rd\ EXP}$
T110001	Training data	Faella *et al.* (1999)	785.0	731.4	0.93	558.84	0.71
T110002		Faella *et al.* (1999)	488.7	523.8	1.07	547.27	1.12
T110005		Faella *et al.* (1999)	535.0	539.5	1.01	581.20	1.09
T109003		Hummer and Tschemmernegg	155.1	151.4	0.98	116.12	0.75
T109004		Hummer and Tschemmernegg	188.1	190.9	1.01	188.90	1.00
T109006		Hummer and Tschemmernegg	354.7	353.6	1.00	330.62	0.93
T101007		Janss *et al.* (1987)	52.6	58.5	1.11	56.25	1.07
T101010		Janss *et al.* (1987)	96.4	78.2	0.81	85.95	0.89
T101013		Janss *et al.* (1987)	51.0	53.9	1.06	53.19	1.04
T101014		Janss *et al.* (1987)	50.6	44.0	0.87	56.86	1.12
T839		Zoetemeijer and Hunter (1983)	99.2	90.1	0.91	91.71	0.92
T8310		Zoetemeijer and Hunter (1983)	127.8	137.5	1.08	166.01	1.30
T8311		Zoetemeijer and Hunter (1983)	231.3	231.8	1.00	222.70	0.96
T911		Simek and Wald (1991)	196.9	192.3	0.98	214.57	1.09
T913		Simek and Wald (1991)	392.0	393.3	1.00	288.72	0.74
TC5		Aggarwal (1994)	70.5	51.5	0.73	47.21	0.67
TC6		Aggarwal (1994)	63.1	55.2	0.88	54.68	0.87
TC7		Aggarwal (1994)	61.5	72.4	1.18	47.21	0.77
TC9		Aggarwal (1994)	55.9	51.5	0.92	47.21	0.84
TC11		Aggarwal (1994)	57.5	72.4	1.26	47.21	0.82
TC12		Aggarwal (1994)	62.8	77.0	1.23	67.68	1.08
T109005	Test data	Hummer and Tschemmernegg	311.7	312.2	1.00	270.60	0.87
T101004		Janss *et al.* (1987)	54.1	58.2	1.08	46.07	0.85
T912		Simek and Wald (1991)	200.0	197.8	0.99	223.46	1.12
TC8		Aggarwal (1994)	63.2	77.0	1.22	67.22	1.06
TC10		Aggarwal (1994)	63.8	55.2	0.87	54.68	0.86

Table 6. Initial stiffness comparison for endplate joints.

Test		Author	$S_{j,ini\ EXP}$ (kN.m)	$S_{j,ini\ ANN}$ (kN.m/rad)	$S_{j,ini\ ANN}$ / $S_{j,ini\ EXP}$	$S_{j,ini\ EC3}$ (kN.m/rad)	$S_{j,ini\ EC3}$ / $S_{j,ini\ EXP}$
T110001	Training data	Faella *et al.* (1999)	490385	490355	1.00	388345	0.79
T110002		Faella *et al.* (1999)	137937	137933	1.00	124638	0.90
T110005		Faella *et al.* (1999)	135149	135166	1.00	131893	0.98
T109003		Hummer and Tschemmernegg	18746	18450	0.98	32573	1.74
T109004		Hummer and Tschemmernegg	74135	74279	1.00	62759	0.85
T109006		Hummer and Tschemmernegg	115704	115461	1.00	127783	1.10
T101007		Janss *et al.* (1987)	21276	21668	1.02	12198	0.57
T101010		Janss *et al.* (1987)	25316	25371	1.00	23471	0.93
T101013		Janss *et al.* (1987)	12739	12533	0.98	8569	0.67
T101014		Janss *et al.* (1987)	16161	16284	1.01	8627	0.53
T839		Zoetemeijer and Hunter (1983)	33098	33249	1.00	57428	1.74
T8310		Zoetemeijer and Hunter (1983)	52222	52240	1.00	81296	1.56
T8311		Zoetemeijer and Hunter (1983)	29375	29461	1.00	63079	2.15
T911		Simek and Wald (1991)	55294	55293	1.00	63578	1.15
T913		Simek and Wald (1991)	85454	85555	1.00	129702	1.52
TC5		Aggarwal (1994)	6183	6455	1.04	8848	1.43
TC6		Aggarwal (1994)	6680	4704	0.70	9069	1.36
TC7		Aggarwal (1994)	8600	7470	0.87	9729	1.13
TC9		Aggarwal (1994)	7125	6455	0.91	12264	1.72
TC11		Aggarwal (1994)	6150	7470	1.21	13983	2.27
TC12		Aggarwal (1994)	4730	6533	1.38	14607	3.09
T109005	Test data	Hummer and Tschemmernegg	67915	97192	1.43	84194	1.24
T101004		Janss *et al.* (1987)	13289	21528	1.62	12321	0.93
T912		Simek and Wald (1991)	72308	54025	0.75	65353	0.90
TC8		Aggarwal (1994)	7330	6533	0.89	10026	1.37
TC10		Aggarwal (1994)	4565	4704	1.03	12694	2.78

Table 7. Flexural resistance comparison for welded joints.

Test		Author	$M_{j,Rd\ EXP}$ (kN.m)	$M_{j,Rd\ ANN}$ (kN.m)	$M_{j,Rd\ ANN}$ / $M_{j,Rd\ EXP}$	$M_{jRd\ EC3}$ (kN.m)	$M_{jRd\ EC3}$ / $M_{j,Rd\ EXP}$
T107001	Training data	Not available	71.2	74.3	1.04	71.2	1.00
T107002			97.3	104.6	1.08	86.0	0.88
T107003			161.2	156.7	0.97	111.6	0.69
T105003			102.4	93.7	0.92	128.4	1.25
T105004			190.8	176.0	0.92	177.9	0.93
T105005			185.6	191.6	1.03	143.9	0.78
T105006			445.4	419.3	0.94	394.6	0.89
T105008			244.8	246.5	1.01	335.1	1.37
T105009			60.6	56.9	0.94	53.9	0.89
T105011			82.4	88.2	1.07	85.7	1.04
T105014			119.8	120.2	1.00	139.3	1.16
T105015			153.0	149.0	0.97	173.0	1.13
T105016			131.4	150.3	1.14	168.8	1.28
T105019			323.6	349.0	1.08	366.7	1.13
T105020			512.4	518.0	1.01	474.7	0.93
T105021			488.4	496.1	1.02	548.7	1.12
T105023			355.3	355.2	1.00	384.3	1.08
T105025			741.4	741.3	1.00	617.8	0.83
T106001			186.1	184.2	0.99	161.1	0.87
T106002			187.4	203.1	1.08	248.9	1.33
T106004			302.5	299.6	0.99	417.9	1.38
T106005			427.5	436.4	1.02	601.7	1.41
T106006			515.5	507.4	0.98	610.6	1.18
T106007			604.1	597.6	0.99	916.6	1.52
T108038			136.1	127.5	0.94	118.6	0.87
T108042			377.4	370.5	0.98	279.8	0.74
T107004	Test data	Not available	309.0	348.4	1.13	211.8	0.69
T105002			119.9	109.3	0.91	111.4	0.93
T105007			345.3	326.9	0.95	309.1	0.90
T105018			255.7	242.4	0.95	276.0	1.08
T105024			362.9	371.1	1.02	376.2	1.04
T106003			266.1	230.6	0.87	297.9	1.12
T108032			218.5	249.3	1.14	234.3	1.07

Table 8. Initial stiffness comparison for welded joints.

Test		Author	$S_{j,ini\ EXP}$ (kN.m)	$S_{j,ini\ ANN}$ (kN.m/rad)	$S_{j,ini\ ANN}$ / $S_{j,ini\ EXP}$	$S_{j,ini\ EC3}$ (kN.m/rad)	$S_{j,ini\ EC3}$ / $S_{j,ini\ EXP}$
T107001	Training data	Not available	20123	30649	1.52	26844	1.33
T107002			29090	13197	0.45	41773	1.44
T107003			44366	15503	0.35	63405	1.43
T105003			69707	45252	0.65	71618	1.03
T105004			94903	71426	0.75	122489	1.29
T105005			81278	48644	0.60	99294	1.22
T105006			250565	155032	0.62	327779	1.31
T105008			83115	80520	0.97	97168	1.17
T105009			9555	17052	1.78	14985	1.57
T105011			16331	31522	1.93	25924	1.59
T105014			46663	47279	1.01	41686	0.89
T105015			38442	77620	2.02	56351	1.47
T105016			46415	53074	1.14	52876	1.14
T105019			113997	155418	1.36	146575	1.29
T105020			95555	109471	1.15	142192	1.49
T105021			165577	149758	0.90	200717	1.21
T105023			73928	91871	1.24	91818	1.24
T105025			125306	160598	1.28	178057	1.42
T106001			70526	72473	1.03	49086	0.70
T106002			120454	119081	0.99	94700	0.79
T106004			103710	107656	1.04	151362	1.46
T106005			97945	139544	1.42	198496	2.03
T106006			182755	166204	0.91	192871	1.06
T106007			207268	176463	0.85	341795	1.65
T108038			30591	45472	1.49	31632	1.03
T108042			72616	90133	1.24	90032	1.24
T107004	Test data	Not available	72594	49965	0.69	183629	2.53
T105002			49837	56773	1.14	89934	1.80
T105007			106281	67078	0.63	156396	1.47
T105018			73919	98026	1.33	85526	1.16
T105024			93851	133223	1.42	118421	1.26
T106003			64634	67974	1.05	107983	1.67
T108032			34948	43781	1.25	57033	1.63

Table 9. Flexural resistance comparison for bolted joints with angles.

Test	Author	$M_{j,Rd\ EXP}$ (kN.m)	$M_{j,Rd\ ANN}$ (kN.m)	$M_{j,Rd\ ANN}$ / $M_{j,Rd\ EXP}$	$M_{jRd\ EC3}$ (kN.m)	$M_{jRd\ EC3}$ / $M_{j,Rd\ EXP}$
8S1	Azizinamini *et al.* (1987) and Azizinamini *et al.* (1989) (Training data)	37.2	43.7	1.17	29.2	0.78
8S2		43.4	43.7	1.01	39.6	0.91
8S3		47.7	40.1	0.84	36.4	0.76
8S4		18.6	18.4	0.99	15.3	0.83
8S5		38.1	37.5	0.98	33.6	0.88
8S6		27.6	34.6	1.25	29.2	1.06
8S7		43.0	37.5	0.87	27.1	0.63
8S10		71.6	71.6	1.00	64.5	0.90
14S1		77.7	85.6	1.10	61.3	0.79
14S2		107.0	106.5	1.00	129.2	1.21
14S4		92.9	85.6	0.92	87.1	0.94
14S5		86.2	84.8	0.98	64.5	0.75
14S6		119.0	121.4	1.02	103.8	0.87
14S8		176.4	174.5	0.99	150.6	0.85
8S8	Azizinamini *et al.* (1987) and Azizinamini *et al.* (1989) (Test data)	42.9	36.3	0.85	31.6	0.74
8S9		47.8	42.3	0.89	42.2	0.88
14S3		73.9	66.9	0.90	52.0	0.70
14S9		115.7	121.4	1.05	103.8	0.90

Table 10. Initial stiffness comparison for bolted joints with angles.

Test	Author	$S_{j,ini\ EXP}$ (kN.m)	$S_{j,ini\ ANN}$ (kN.m)	$S_{j,ini\ ANN}$/ $S_{j,ini\ EXP}$	$S_{j,ini\ CHEN}$ (kN.m)	$S_{j,ini\ CHEN}$/ $S_{j,ini\ EXP}$
8S1	Azizinamini *et al.* (1987) and Azizinamini *et al.* (1989) (Training data)	7540	12026.16	1.59	5611	0.74
8S2		13940	12026.16	0.86	10368	0.74
8S3		11830	8245.749	0.70	7481	0.63
8S4		1730	746.042	0.43	385	0.22
8S5		8670	7717.94	0.89	5082	0.59
8S6		4460	5455.3	1.22	2084	0.47
8S7		5420	7717.94	1.42	3812	0.70
8S10		48200	47576.94	0.99	35564	0.74
14S1		22030	24203.53	1.10	14365	0.65
14S2		33330	31692.2	0.95	37491	1.12
14S4		25070	24203.53	0.97	14365	0.57
14S5		27900	27337.21	0.98	17128	0.61
14S6		32300	32826.89	1.02	44826	1.39
14S8		65400	66235.6	1.01	79953	1.22
8S8	Azizinamini *et al.* (1987) and Azizinamini *et al.* (1989) (Test data)	7900	9995.946	1.27	7154	0.91
8S9		11800	12944.25	1.10	13250	1.12
14S3		13090	15159.87	1.16	14365	1.10
14S9		29200	32826.81	1.12	44826	1.54

Conclusions

This paper proposes the use of artificial neural networks to predict the flexural resistance and initial stiffness of beam-to-column joints. The neural network results for the prediction of the flexural resistance for all joints types conducted to satisfactory results. However, the results obtained for the initial stiffness showed the necessity to incorporate new experimental data. These results are summarized in Tab. 11.

The authors would like to emphasize that the initial stiffness experimental values are strongly influenced by the measurement system. Recent investigations (Neves *et al.*, 2003), pointed out to the use of the elastic unload stiffness value instead of the initial stiffness values found in the first loading stages. The main reason for that procedure is related to the various accommodation displacements/slip found in these joints in early loading phases. The elastic stiffness found in the unloading phase does not present these accommodations, which provides a better representation of the joint initial stiffness. Since all the joints data do not use the above mentioned procedure, scattered results can be expected in the experimental initial stiffness joint values.

The mean errors obtained in this investigation were 8.4%, 8.9% and 11.6% for the prediction of the flexural resistance, demonstrating a reasonable agreement between the neural networks and the experimental test values. These errors are acceptable when compared to the level of safety factors used in structural engineering and the intrinsic errors associated with the used experimental data.

Table 11. Error summary.

Joint Type		MAPE $_{training}$ (%)	MAPE $_{test}$ (%)	Minimum percentile training error (%)	Maximum percentile training error (%)
Endplate	$M_{j,Rd\ ANN}$	9.8	8.4	-15.5	18.0
	$S_{j,ini\ ANN}$	5.9	23.5	-33.8	38.3
Welded	$M_{j,Rd\ ANN}$	4.0	8.9	-15.4	12.4
	$S_{j,ini\ ANN}$	35.6	28.0	-58.4	30.0
Bolted with angles	$M_{j,Rd\ ANN}$	6.8	11.6	-18.3	4.7
	$S_{j,ini\ ANN}$	22.3	13.6	-131.9	37.3

It is also fair to mention that the small number of experimental data can be one of the factors associated to the relative large Neural Networks errors. The incorporation of new data, acquired in laboratory tests, will surely improve the quality of the Neural Networks predictions.

The present investigation confirmed the possibility of using this technique to generate trustworthy data. The use of artificial neural networks coupled with experimental data will enable the execution of a parametric analyses. These numerical analyses will surely help the calibration of the design code formulations like the Eurocode 3.

Acknowledgements

Financial support from “CAPES – Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brazil” and “CNPq – Conselho Nacional de Desenvolvimento Científico e Tecnológico” are gratefully acknowledged.

References

Abdala, K. M. and Stavroulakis, G. E., A., 1995, “Backpropagation Neural Network Model for Semi-Rigid Joints”, Microcomputers in Engineering, vol. 10, pp. 77-87.

Aggarwal, A. K., 1994, “Comparative Tests on end Plate Beam-to-Column Joints”, Journal of Constructional Steel Research, Vol. 30, pp. 151-175.

Anderson, D. et al., 1997, “Application of Artificial Neural Networks to the Prediction of Minor Axis Joints”, Computers & Structures, Vol. 63, pp. 685-692.

Azizinamini, A., Bradburn, J. H. and Radziminski, J., 1987, “Initial Stiffness of Semi-Rigid Steel Beam-to-Column Joints”, Journal of Constructional Steel Research, Vol. 8, pp. 71-90.

Azizinamini, A. and Radziminski, J., 1989, “Static and Cyclic Performance of Semi-Rigid Steel Beam-to-Column Joints”, Journal of Structural Engineering, ASCE, Vol. 115, Nº 12.

Bjorhovde, R., Colson, A. and Brozzetti. J., 1990, “Classification System for Beam-To-Column Joints”. Journal of Structural Division, ASCE, Vol. 116, ST11, pp. 3059-3076.

Chen, W. F., Lorens, R.F. and Kato, B., 1993, “Semi-Rigid Joints in Steel Frames”. McGraw-Hill, Inc.

Cruz, P. J. S., Silva, L. A. P. S. da, Rodrigues, D. S. and Simões, R. A. D., 1998, “Database for the Semi-Rigid Behaviour of Beam-to-column Joints in Seismic Regions”, Journal of Constructional Steel Research, Vol. 46, pp. 1-12.

Cybenko. 1989, “Approximation by Superpositions of a Sigmoidal Function”, Mathematics of Control, Signals and Systems”, Vol. 2, pp. 303-314.

CEN, Eurocode 3, EN1993-1-8: Design of Joints, May 2003, CEN, European Committee for Standardization, Brussels, p. 124.

Faella, C., Piluso, V. and Rizzano. G., 1999, “Structural Steel Semi-Rigid Joints - Theory, Design and Software”, CRC Press, p. 505.

Goverdan, A. V., A, 1993, “Collection of Experimental moment-Rotation Curves and Evaluation of Prediction Equations for Semi-Rigid Joints”, Vanderbilt University, Nashville, Tennessee.

Haykin, S., 1999, “Neural Networks - A Comprehensive Foundation”, Macmillan College Publishing Company, Inc.

Hornik, K., Stinchcombe, M. and White, H., 1989, “Multilayer Feedforward Networks are Universal Approximators”. Neural Networks, Vol. 2, pp. 359-366.

Hummer, C. and Tschemmernegg, T., “A Non-Linear Joint Model for the Design of Structural Steel Frames”. Costruzioni Metalliche, No. 1.

Bishop, C. M., 1994, “Neural Networks and Their Applications”. Review Scientific Instruments, American Institute of Physics, Vol. 65, Issue 6, pp. 1803-1832.

Janss, J., Jaspart, J. P. and Maquoi. R., 1997, “Experimental Study of Non-linear Behaviour of Beam-to-column Bolted Joints”, Joints in Steel Structures: Behaviour, Strength and Design – Proceedings of the 1st International Workshop on Joints, France.

Jaspart, J. P., 1997, “Recent Advances in the Field of Steel Joints - Column Bases and Further Configurations for Beam-to-Column Joints and Beam Splices”, Chercheur qualifié du F.N.R.S., Universite de Liege, Faculte des Sciences Appliques.

Kishi, N., Chen, W. F. and Matsuoka, K. G., 1987, “Moment-Rotation Relation of Top-and-Seat Angle with Double Web-Angle Joints”, Joints in Steel Structures, Bjorhovde, Brazzeti and Colson Editors, Elsevier, pp. 121-134.

Lima, L. R. O. de, Vellasco, P. C. G. da S., and Andrade. S. A. L. de, Silva, L. A. P. S. da, 2002, “Experimental and Mechanical Model for Predicting the Behaviour of Minor Axis Beam-to-Column Semi-Rigid Joints”, International Journal of Mechanical Sciences, Australia, Vol. 44, Nº. 6, pp. 1047-1065.

Mitchel, T. M.,1997, “Machine Learning”, McGraw-Hill.

Nethercot, D. A., Li, T. Q. and Choo, B. S., 1995, “Determination of Rotation Capacity Requirements for Steel and Composite Beams”, Journal of Constructional Steel. Research, Vol. 32, pp. 303-332.

Neves, L. F. da C., Silva, L. A. P. S. da and Vellasco, P. G. C. da S., 2003, “Experimental Behaviour of End Plate I-beam to Concrete-filled Rectangular Hollow Section Column Joints Under Cyclic Loading”, Proceedings of the Fourth International Conference on Behaviour of Steel Structures in Seismic Areas, Naples, Italy, pp. 277-283.

“Qnet for Windows – Neural Network Modelling”, 2000, V2K build 721. User Manual, Vesta Services, Inc., Copyright ©

Rumelhart, D. E. and McClelland, J. L., 1986, “Parallel Distributed Processing: Explorations in the Microstructure of Cognition”, MIT Press, Cambridge.

Silva, L. S. da and Coelho, A. M. G., A., 2001, “Ductility Model for Steel Joints”, Journal of Constructional Steel Research, Vol. 57, pp. 45-70.

Simek and Wald, F., 1991, “Test Results on Endplate Beam-to-Column Joints”. CTU, G-1121 Report. Prague.

Simões, R. Simões da Silva, L. and Cruz, P., 2001, “Behaviour of End-Plate Beam-to-Column Composite Joints Under Cyclic Loading”, International Journal of Steel and Composite Structures, Vol. 1, Nº 3, pp. 355-376.

Stavroulakis, G. E. and Abdala, K. M., 1994, “A systematic Neural Network Classificator in Mechanics”, Application in Semi-Rigid Steel Joints, International Journal of Engineering Analysis and Design, Vol. 1 pp. 279-292.

Treleaven P., Pacheco, M. A. C. and Vellasco, M. M. B. R., 1989, “VLSI Architectures for Neural Networks”, IEEE Micro Vol. 9, Nº 6, pp. 8-27.

Weynand, K. and Sahl. R., 1984, “The Structure for Databases of Test Results of Semi-Rigid Joints”, COST-C1 Second State of the Art Workshop, Prague, pp. 405–418.

Zoetemeijer, P. and Munter. H., 1983, “Extended Endplate with Disappointing Rotation Capacity: Test Results and Analysis”, Report 6-75-20 KV-4, University of Technology, Delft.