Steel and Composite Structures, *Vol. 17, No. 3 (2014) 215-236*
DOI: http://dx.doi.org/10.12989/scs.2014.17.3.215

Prediction of the flexural overstrength factor for steel beams using artificial neural network

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(*Received October 10, 2013, Revised February 06, 2014, Accepted July 11, 2014*)

Abstract. The flexural behaviour of steel beams significantly affects the structural performance of the steel frame structures. In particular, the flexural overstrength (namely the ratio between the maximum bending moment and the plastic bending strength) that steel beams may experience is the key parameter affecting the seismic design of non-dissipative members in moment resisting frames. The aim of this study is to present a new formulation of flexural overstrength factor for steel beams by means of artificial neural network (NN). To achieve this purpose, a total of 141 experimental data samples from available literature have been collected in order to cover different cross-sectional typologies, namely I-H sections, rectangular and square hollow sections (RHS-SHS). Thus, two different data sets for I-H and RHS-SHS steel beams were formed. Nine critical prediction parameters were selected for the former while eight parameters were considered for the latter. These input variables used for the development of the prediction models are representative of the geometric properties of the sections, the mechanical properties of the material and the shear length of the steel beams. The prediction performance of the proposed NN model was also compared with the results obtained using an existing formulation derived from the gene expression modeling. The analysis of the results indicated that the proposed formulation provided a more reliable and accurate prediction capability of beam overstrength.

Keywords: experimental database; flexural overstrength; modeling; neural networks; steel beams

1. Introduction

The flexural behaviour of beams significantly influences the nonlinear performance of steel structures. In particular, for seismic design of moment resisting frames (MRFs) and dual braced frames (namely systems having MRFs and concentric or eccentric bracing frames acting in parallel) steel beams are conceived as dissipative elements and should provide adequate local ductility to guarantee the formation of a global dissipative mechanism. This implies that steel beams should be

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http://www.techno-press.org/?journal=scs&subpage=8 ISSN: 1229-9367 (Print), 1598-6233 (Online)

able to develop plastic hinges rotating until the collapse mechanism is completely developed, without dropping their moment capacity, thus assuring the required redistribution of bending moments. The plastic deformation of ductile beams is characterized by an amount of strain hardening, which is responsible for the development of bending moments larger than the plastic bending strength. Therefore, according to hierarchy criteria the quantification of the maximum bending moment experienced by the beams is fundamental to design non-dissipative elements (namely connections and columns). In existing codes like AISC 341-10 and EN1998-1 the capacity design rules may lead to underestimate the actual ultimate flexural strength of steel beams. According to AISC 341-10, the beam flexural overstrength is equal to $1.1R_y$, being 1.1 a factor accounting for strain-hardening, as well as other possible sources of overstrength, whereas R_y is ratio between the expected yield stress and the specified minimum yield stress (R_y varies in the range 1.1 to 1.5, depending on steel grade), so that it accounts for the influence of random material variability. In EN1998-1, a similar overstrength factor is given as $1.1\gamma_{ov}$, being γ_{ov} the ratio between the maximum actual yield strength $f_{y.\max}$ and the nominal yield strength f_y. However, all the current codes do not consider that the amount of strain-hardening which can be exhibited before the complete development of local buckling is generally larger than 1.1 for ductile beams (Mazzolani and Piluso 1993, D'Aniello *et al*. 2012) and is also related to several geometric and mechanical aspects, such as the width-to-thickness ratios of the plate elements constituting the cross section, the shear length, the presence of torsional restraints, the steel grade, etc. On the other hand, in thin walled or cold formed steel sections, width to thickness ratio of plate elements is often large and the flexural failure may occur by buckling and not by yielding, thus limiting the load carrying capacity of the member (Yu 2000).

This implies that an effective estimation of the level of hardening developing in such elements prior than strength degradation occurs is essential at the design stage for a safe application of capacity design rules (Grecea *et al*. 2004, Della Corte *et al*. 2007, Tortorelli *et al*. 2010, D'Aniello *et al*. 2012, Güneyisi *et al*. 2013, Della Corte *et al*. 2013) and to minimize the possibility of the brittle failure (Brooke and Ingham 2011).

In the recent years, there have been implementation of artificial intelligence technologies in modelling and optimization of the steel members and/or steel structures (Fonseca *et al*. 2003, Hayalioğlu and Değertekin 2004, Kim and Ma 2007, Gandomi *et al*. 2009, Kim *et al*. 2009a, b, Gholizadeh *et al*. 2011, Hakim and Abdul-Razak 2013, Güneyisi *et al*. 2013, D'Aniello *et al*. 2014). For example, in the study of Fonseca *et al*. (2003), neural networks (NNs) were used to forecast steel beam patch load resistance. They compared the results with preceding models and existing design formulations. It was found that the networks' percentage errors relative to the experimental results confirmed the possibility of using the unified methodology to generate new data accurately. Hayalioğlu and Değertekin (2004) proposed a genetic algorithm based on optimum design model for non-linear steel frames with semi-rigid connections. A genetic algorithm was employed as optimization method which uses reproduction, crossover and mutation operators. A polynomial model proposed by Frye and Morris (1975) was used for modeling of semi-rigid connections. They concluded that the parameters of genetic algorithm played an important role in the optimization of steel frames with semi-rigid connections. Kim *et al*. (2009a) studied on a system identification technique for a bridge deck with NNs. They trained NNs for system identification and the identified structure gave training data in return. They verified the proposed strategy with known systems and it was applied to a bridge deck with experimental data. As a result, they proved the effectiveness and applicability of the proposed method. However, no explicit formulation was presented. In the another study by Gholizadeh *et al*. (2011), finite element qtrpand soft-computing techniques, namely, back-propagation neural network and adaptive neuro-fuzzy inference system were employed in order to propose the models for estimation of the critical buckling load of the web posts of castellated steel beams.

Recently, NN has been used on the field of steel beams by D'Aniello *et al*. (2014), to estimate the available rotation capacity of cold-formed rectangular and square hollow section (RHS-SHS) steel beams. In this study, the Authors described two novel mathematical models based on both NNs and gene expression programming (GEP), showing the different level of accuracy and the relevant advantages. On the other hand, estimation of the flexural overstrength factor (s) of the steel beam through soft-computing techniques has not yet been studied comprehensively in the literature. In the recent paper by the authors of this study (Güneyisi *et al*. 2013), the formulation of s for I-H and RHS-SHS steel beams was achieved through GEP, which was originated from genetic algorithms. The developed models were compared to the existing analytical relations proposed in the literature. Güneyisi *et al*. (2013) also reported that the developed GEP based models were more accurate in terms of the prediction capability than the existing ones (D'Aniello *et al*. 2012). However, in the current study, another alternative soft-computing technique for modelling the flexural overstrength factor of the steel beam that is NN is used for the first time. The explicit form of the proposed NN based models for I-H and RHS-SHS steel beams is derived and presented as a mathematical formulation. Moreover, the prediction performance of the proposed NN models are compared with the existing GEP based models suggested by Güneyisi *et al*. (2013).

2. Definition of flexural overstrength

The flexural overstrength factor (s) is used for the characterization of the structural steel beams having ultimate bending capacity larger than the plastic bending strength due to the strain hardening that can be experienced before the complete development of local buckling or fractures (D'Aniello *et al*. 2012). It is a non-dimensional parameter expressed by the following ratio

$$s = \frac{f_{LB}}{f_y} \tag{1}$$

where f_{LB} is the stress corresponding to the complete development of local flange buckling or at the lateral torsional buckling (Rebelo *et al*. 2009, Da Silva *et al*. 2009), and f_y is the yielding stress.

Moreover, this factor can be computed through the following more practical relation

$$s = \frac{M_{\max}}{M_p} \tag{2}$$

where $M_{\max}$ is the maximum moment that can be reached by the beam, while M_p is the theoretical full plastic moment. The definition is illustrated in the generalized force displacement curve of a member able to withstand plastic deformation shown in Fig. 1.

The parameter s can be used to classify steel members. This approach has been adopted by OPCM 3274 (2003), the late Italian code for seismic design, on the basis of concept of member behavioural classes (Mazzolani and Piluso 1993). The classification criterion allowed to properly apply capacity design criteria providing the adequate overstrength to non-dissipative members. On the contrary, Eurocode 3 (CEN 2005) defines the subdivisions of cross-sections in four classes,

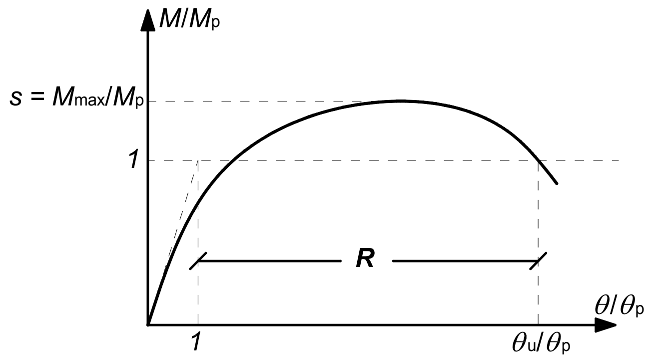


Fig. 1 Generalized moment–rotation curve for a steel beam (D’Aniello *et al*. 2012)

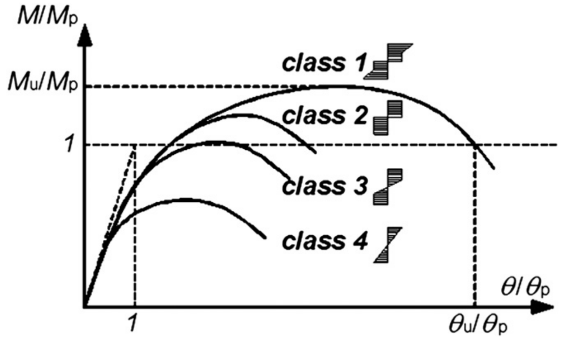


Fig. 2 EN 1993:1-1 classification criterion (D’Aniello *et al*. 2012)

depending mainly on the properties of compression elements (Fig. 2), without providing indications to quantify the rotation capacity and the flexural overstrength.

3. Description of the database used for derivation of the models

The database used for explicit neural network formulation of the flexural overstrength factor (s) for I-H and RHS-SHS steel beams were collected from the available scientific literature (Lukey and Adams 1969, Climenhaga 1970, Grubb and Carskaddan 1979, 1981, Kemp 1985, Schilling 1988, Schilling 1990, Wargsjö 1991, Dahl *et al*. 1992, Boeraeve and Lognard 1993, Suzuki *et al*. 1994, Wilkinson 1999, Zhou and Young 2005, Landolfo *et al*. 2011, D’Aniello *et al*. 2012).

The examined test configurations accounting for different load patterns (namely, bending moment distribution) and cross-sectional typologies are demonstrated in Figs. 3 and 4, respectively. The data sources presented in Table 1 contain precisely selected data samples to ensure a wide range of cross-sectional typologies under monotonic loading with different local slenderness ratios. The experimental data are reported in Tables 2 and 3 for I-H and RHS-SHS beams, respectively.

All data samples were ordered to create a consistent sequence of the inputs to be used for the derivation of the models. The input nodes include the geometric properties of the section, the mechanical properties of the material, and the shear length of the steel beams. Thus, a total of nine

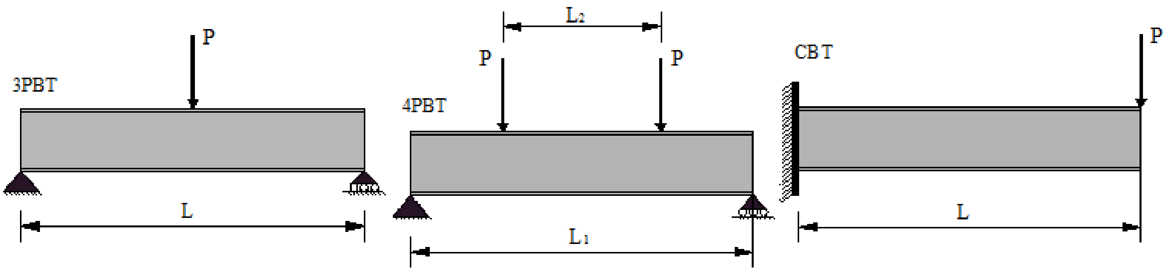


Fig. 3 Test configurations of the steel beams under investigation

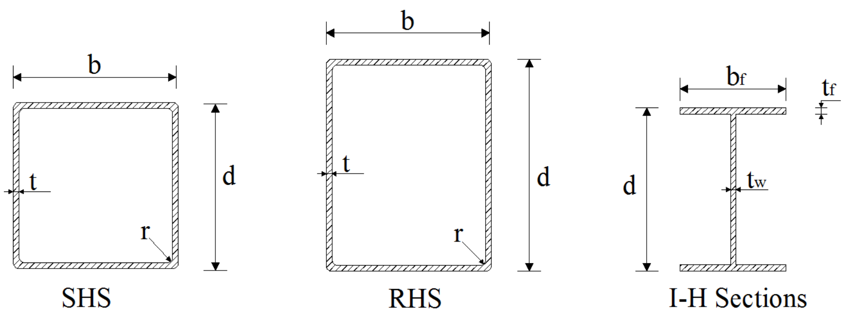


Fig. 4 Geometry of steel beam cross sections

Table 1 Details of available experimental data for the steel beams

No.	Authors	Profile type	Steel grade	Test setup	Loading history
1	Lukey and Adams (1969)	I and H hot-rolled	MCS [a]	3PBT [c]	Monotonic
2	Climenhaga (1970)	I welded	MCS	3PBT	Monotonic
3	Grubb and Carskaddan (1979, 1981)	I welded	HSS [b]	3PBT	Monotonic
4	Kemp (1985)	I and H welded + hot-rolled	MCS	3PBT	Monotonic
5	Schilling (1988, 1990)	I welded	HSS	3PBT	Monotonic
6	Wargsjö (1991)	I welded	HSS	3PBT	Monotonic
7	Dahl *et al.* (1992)	I welded	HSS	3PBT	Monotonic
8	Boeraeve and Lognard (1993)	I and H hot-rolled	MCS	3PBT	Monotonic
9	Suzuki *et al.* (1994)	I welded	MCS + HSS	3PBT	Monotonic
10	Landolfo *et al.* (2011) D'Aniello *et al.* (2012)	I and H hot-rolled	MCS	CBT [d]	Monotonic
11	Wilkinson (1999)	Cold-formed RHS + SHS	MCS	4PBT [e]	Monotonic
12	Zhou and Young (2005)	Cold-formed RHS + SHS	MCS + HSS	4PBT	Monotonic
13	Landolfo *et al.* (2011) D'Aniello *et al.* (2012)	Cold-formed RHS + SHS	MCS	CBT	Monotonic

[a] MCS: mild carbon steel; [b] HSS: high-strength steel; [c] 3PBT: 3-point bending test; [d] CBT: cantilever bending test; [e] 4PBT: 4-point bending test

and eight input parameters were utilized for the development of NN based models for the steel beams with I-H and RHS-SHS profiles, respectively.

The model generated for I-H sections consists of the following parameters: b_f (width of flange), d (depth of section), t_f (thickness of flange), t_w (thickness of web), L_v (shear length), $f_{y,flange}$ (yield stress of flange), $f_{y,web}$ (yield stress of web), E/E_h (ratio of the modulus of elasticity of steel to the hardening modulus), and $\varepsilon_h/\varepsilon_y$ (ratio of the strain corresponding to the beginning of hardening to the yield strain) (see Table 2).

The NN model for the RHS-SHS profiles covers the following input parameters: b (width of section), d (depth of section), t (wall thickness of section), r (inside corner radius), L_v (shear length), f_y (yield stress), E/E_h, and $\varepsilon_h/\varepsilon_y$ (see Table 3).

In order to generate the artificial neural network based on mathematical formulation, training data containing input and output variables have been defined. Moreover, for verification of the repeatability and robustness of the developed model, another data set containing the same number and sequence of input and output variables has been used. Therefore, in the present study, two sets of available experimental data (one for I-H and one for RHS-SHS beams) were arbitrarily divided into two parts to obtain the training and testing databases. Approximately 1/4 of the total data samples were used as the test database, while the rest were utilized as the training database, as shown in Tables 2 and 3. Thus, 57 and 49 data samples were used as the training data for I-H and RHS-SHS profiles, respectively, and the testing database contained 19 data samples for the former and 16 for the latter.

Table 2 Experimental data used for the model of I-H steel beams

Ref no.	Data no.	b_f (mm)	d (mm)	t_f (mm)	t_w (mm)	L_v (mm)	$f_{y,flange}$ (MPa)	$f_{y,web}$ (MPa)	E/E_h	$\varepsilon_h/\varepsilon_y$	s
Lukey and Adams (1969)	1	203.5	256.7	10.8	7.65	1740	283	308	42.8	11	1.38
	2	176	256.7	10.8	7.65	1473	283	308	42.8	11	1.41
	3	102.6	201.86	5.28	4.45	777	371	395	48.2	9.8	1.11
	4	73.9	201.86	5.28	4.45	518	371	395	48.2	9.8	1.15
	5	86.1	201.86	5.28	4.45	627	371	395	48.2	9.8	1.13
	6	94	201.86	5.28	4.45	698	371	395	48.2	9.8	1.05
	7	96.8	201.82	5.26	4.45	724	371	395	48.2	9.8	1.04
	8	101.9	251.72	5.26	4.6	686	371	350	48.2	9.8	1.11
	9	73.7	251.72	5.26	4.6	480	371	350	48.2	9.8	1.26
	10	85.9	251.72	5.26	4.6	584	371	350	48.2	9.8	1.16
	11	93.5	251.72	5.26	4.6	648	371	350	48.2	9.8	1.12
	12	88.9	251.72	5.26	4.6	640	371	350	48.2	9.8	1.14
Climenhaga (1970)	13	135	201	8	5.7	1956	315	344	48.2	9.8	1.09
	14	134	204	9.5	6	1956	293	310	42.8	11	1.22
	15	104	305.8	6.9	6	1956	357	412	48.2	9.8	0.89
	16	128	352	8	6	1956	324	363	48.2	9.8	0.86
	17	141	398.2	7.6	6.2	1956	303	379	42.8	11	0.92
	18	135	201	8	5.7	1346	315	344	48.2	9.8	1.06

Table 2 Continued

Ref no.	Data no.	b_f (mm)	d (mm)	t_f (mm)	t_w (mm)	L_v (mm)	$f_{y,flange}$ (MPa)	$f_{y,web}$ (MPa)	E/E_h	$\varepsilon_h/\varepsilon_y$	s
Climenhaga (1970)	19	134	204	9.5	6	1346	293	310	42.8	11	1.26
	20	104	305.8	6.9	6	1346	357	412	48.2	9.8	0.97
	21	128	352	8	6	1346	324	363	48.2	9.8	0.92
	22	105	308.6	10.3	6.2	1346	319	384	48.2	9.8	0.97
Grubb and Carskaddan (1979,1981)	23	156	406.4	9.7	6.7	914	383	345	48.2	9.8	1.04
	24	156	406.4	9.7	6.7	1829	383	345	48.2	9.8	1.00
	25	156	406.4	9.7	6.7	2743	383	345	48.2	9.8	0.96
	26	157	308.4	11.2	8.3	1219	370	337	48.2	9.8	1.31
	27	150	374.4	11.2	8.4	1524	370	337	48.2	9.8	1.15
	28	130	404.4	11.2	8.4	1524	370	337	48.2	9.8	1.10
	29	158	407.4	11.2	8.4	1524	370	337	48.2	9.8	1.08
Kemp (1985)	30	150	217.8	8.09	6.65	1830	340	358	48.2	9.8	1.12
	31	145	217.4	10.57	6.82	1830	285	329	42.8	11	1.14
	32	106	273.9	7.05	5.85	1830	332	388	48.2	9.8	1.03
	33	149	217.9	8.56	6.78	915	340	358	48.2	9.8	1.27
	34	149	217.1	8.44	6.78	915	294	300	42.8	11	1.22
	35	140	209.5	10.77	6.76	915	288	329	42.8	11	1.27
	36	145	366.3	8.33	5.96	1830	375	403	48.2	9.8	1.01
Kemp (1985)	37	154	120.3	9.83	7.44	1830	313	300	48.2	9.8	1.22
	38	146	217.9	9.03	6.35	1830	340	358	48.2	9.8	1.09
	39	105	282.2	6.92	5.82	1830	332	388	48.2	9.8	1.00
	40	104	277.5	6.76	5.59	2179	317	351	48.2	9.8	1.05
	41	145.54	402.2	11.11	6.84	1830	285	329	42.8	11	1.11
	42	180	210	8.05	6.11	1830	332	326	48.2	9.8	1.18
	43	180	210	8	6	1816	332	326	48.2	9.8	1.26
Schilling (1988, 1990)	44	127	611	7	5.3	1067	410	450	48.2	9.8	0.68
	45	229	622	12.5	5.3	1981	401	450	48.2	9.8	0.81
	46	311	945.4	15.7	5.3	2895.5	342	450	48.2	9.8	0.89
Wargsjö (1991)	47	131	500.8	9.9	4	1910	370	335	48.2	9.8	0.91
	48	130	501.8	9.9	4	2860	370	335	48.2	9.8	0.89
	49	131	457	10	4	1760	370	335	48.2	9.8	0.92
	50	131	458.8	9.9	4	2640	370	335	48.2	9.8	0.95
	51	132	414.6	9.8	4	1610	370	335	48.2	9.8	0.94
	52	130	422	10	4	2400	370	335	48.2	9.8	0.92
	53	131	379.8	9.9	4	1460	370	335	48.2	9.8	0.99
	54	131	379.8	9.9	4	2160	370	335	48.2	9.8	0.97
	55	131	336	10	4	1310	370	335	48.2	9.8	1.02

Table 2 Continued

Ref no.	Data no.	b_f (mm)	d (mm)	t_f (mm)	t_w (mm)	L_v (mm)	$f_{y,flange}$ (MPa)	$f_{y,web}$ (MPa)	E/E_h	$\varepsilon_h/\varepsilon_y$	s
Wargsjö (1991)	56	131	339.6	9.8	3.9	1920	370	335	48.2	9.8	0.98
Dahl *et al.* (1992)	57	202	200	15	9.5	1500	428	456	48.2	9.8	1.36
	58	202	200	15	9.5	1500	428	456	48.2	9.8	1.30
	59	280	280	18	10	1500	982	984	48.2	9.8	1.09
	60	280	280	18	10	1500	864	813	48.2	9.8	1.06
	61	280	280	18	10	1500	468	536	48.2	9.8	1.06
	62	280	280	18	10	1500	278	323	48.2	9.8	1.24
Boeraeve and Lognard (1993)	63	200.7	183.3	14.1	8.8	1500	303	342	42.8	11	1.14
	64	200.2	183.3	14.7	9.5	1500	375	421	48.2	9.8	1.15
	65	201.5	184.6	15.1	9.5	1500	445	462	48.2	9.8	1.16
	66	200.4	185.8	14.6	9.6	1500	261	291	37.5	12.3	1.13
	67	199.9	189.3	14.9	9.4	1500	409	426	48.2	9.8	1.15
Suzuki *et al.* (1994)	68	150	132	9	6	600	291	340	42.8	11	1.25
	69	150	132	9	6	900	291	340	42.8	11	1.23
	70	150	132	9	6	600	526	509	48.2	9.8	1.26
	71	150	132	9	6	600	527	340	48.2	9.8	1.20
	72	150	132	9	6	600	291	509	42.8	11	1.15
	73	150	132	9	6	900	291	686	42.8	11	1.14
Landolfo *et al.* (2011) D’Aniello *et al.* (2012)	74	160	152	9	6	1875	275	275	42.8	11	1.30
	75	240	240	17	10	1875	275	275	42.8	11	1.36
	76	150	300	10.7	7.1	1875	275	275	42.8	11	1.22

Table 3 Experimental data used for the model of RHS-SHS steel beams

Ref no.	Data no.	b (mm)	d (mm)	t (mm)	r (mm)	L_v (mm)	f_y (MPa)	E/E_h	$\varepsilon_h/\varepsilon_y$	s
Wilkinson (1999)	1	50.25	151.04	4.92	9.9	450	441	48.2	9.8	1.23
	2	50.41	150.92	4.9	10.7	450	441	48.2	9.8	1.17
	3	50.27	150.43	3.92	6.8	450	457	48.2	9.8	1.27
	4	50.4	150.44	3.87	7.3	450	457	48.2	9.8	1.19
	5	50.11	150.42	3.89	7.3	450	457	48.2	9.8	1.24
	6	50.16	150.21	3.89	5.4	450	423	48.2	9.8	1.17
	7	50.22	150.47	2.97	5.9	450	444	48.2	9.8	1.15
	8	50.01	150.79	2.95	5.8	450	444	48.2	9.8	1.16
	9	50.34	150.8	2.96	5.7	450	444	48.2	9.8	1.13
	10	50.15	150.43	2.6	4.6	450	446	48.2	9.8	1.02
	11	50.41	150.39	2.57	4.6	450	446	48.2	9.8	1.00

Table 3 Continued

Ref no.	Data no.	b (mm)	d (mm)	t (mm)	r (mm)	L_v (mm)	f_y (MPa)	E/E_h	$\varepsilon_h/\varepsilon_y$	s
Wilkinson (1999)	12	50.23	150.4	2.59	4.8	450	446	48.2	9.8	1.10
	13	50.4	150.31	2.64	5.3	450	440	48.2	9.8	1.11
	14	50.64	150.65	2.25	4.6	450	444	48.2	9.8	0.98
	15	50.57	150.51	2.28	4.2	450	444	48.2	9.8	1.01
	16	50.7	150.37	2.26	4.8	450	444	48.2	9.8	0.98
	17	50.7	100.45	2.06	3.8	450	449	48.2	9.8	1.07
	18	50.55	100.49	2.07	3.9	450	449	48.2	9.8	1.01
	19	50.24	100.46	2.04	4.7	450	449	48.2	9.8	1.07
	20	50.22	100.45	2.04	3.4	450	423	48.2	9.8	1.08
	21	50.1	75.48	1.94	4.4	400	411	48.2	9.8	1.04
	22	50.31	75.63	1.95	4.4	400	411	48.2	9.8	1.02
	23	25.28	75.31	1.98	3.7	400	457	48.2	9.8	1.11
	24	25.23	75.33	1.95	4	400	457	48.2	9.8	1.13
	25	25.12	75.24	1.54	3.1	400	439	48.2	9.8	1.08
	26	25.2	74.9	1.54	3.4	400	439	48.2	9.8	1.13
	27	25.08	74.98	1.56	3.9	400	439	48.2	9.8	1.09
	28	25.12	75.27	1.55	3.4	400	422	48.2	9.8	1.03
	29	25.25	75.19	1.56	3.4	400	422	48.2	9.8	1.00
	30	50.13	150.46	3	6.2	450	370	48.2	9.8	1.21
	31	50.19	150.5	2.96	6.5	450	370	48.2	9.8	1.15
	32	50.51	150.45	3	6.8	450	382	48.2	9.8	1.18
	33	50.51	150.38	3	6.3	450	382	48.2	9.8	1.21
	34	50.43	100.91	2.06	3.6	450	400	48.2	9.8	1.00
	35	50.52	100.83	2.05	3.8	450	400	48.2	9.8	1.00
	36	75.84	125.56	2.92	6.6	450	397	48.2	9.8	1.03
	37	75.74	125.4	2.93	6.9	450	397	48.2	9.8	1.04
	38	75.56	125.4	2.91	7.1	450	397	48.2	9.8	1.03
	39	75.1	125.4	2.53	3.9	450	374	48.2	9.8	1.06
	40	100.27	100.43	2.88	5.2	450	445	48.2	9.8	1.02
	41	100.33	100.53	2.91	5	450	445	48.2	9.8	0.95
	42	100.25	100.53	2.86	5.2	450	445	48.2	9.8	1.03
	43	50.21	150.32	3.9	7.9	450	349	48.2	9.8	1.28
	44	50.57	150.39	3.85	7.5	450	410	48.2	9.8	1.19
Zhou and Young (2011)	45	40.1	40.1	1.96	2	480.7	447	48.2	9.8	1.29
	46	40	40.1	3.88	4	480.3	565	48.2	9.8	1.31
	47	80.5	80.4	1.91	4	480.7	398	48.2	9.8	0.98
	48	79.9	79.8	4.77	7.5	481	448	48.2	9.8	1.49

Table 3 Continued

Ref no.	Data no.	b (mm)	d (mm)	t (mm)	r (mm)	L_v (mm)	f_y (MPa)	E/E_h	$\varepsilon_h/\varepsilon_y$	s
Zhou and Young (2011)	49	49.8	99.9	1.97	2	480	320	48.2	9.8	1.51
	50	49.6	99.7	3.88	4	479.7	378	48.2	9.8	1.71
	51	59.9	120.2	1.84	2.5	480.7	361	48.2	9.8	1.14
	52	59.7	120	3.89	5.5	480.7	392	48.2	9.8	1.80
	53	40.2	40	1.94	2	414.3	707	48.2	9.8	1.21
	54	50.1	50.3	1.54	1.5	414	622	48.2	9.8	1.05
	55	150.6	150.7	2.78	4.8	546.7	448	48.2	9.8	0.78
	56	150.7	150.5	5.87	6	550	497	48.2	9.8	1.23
	57	80.5	140.3	3.09	6.5	480	486	48.2	9.8	1.19
	58	80.9	160.6	2.9	6	480	536	48.2	9.8	1.07
	59	109.1	197.7	4	8.5	548	503	48.2	9.8	1.07
Landolfo *et al*. (2011) D'Aniello *et al*.(2012)	60	100	150	5	10	1875	275	42.6	11	1.29
	61	80	160	4	8	1875	275	42.6	11	1.25
	62	100	250	10	20	1875	275	42.6	11	1.44
	63	160	160	6.3	12.6	1875	355	48.2	9.8	1.05
	64	200	200	10	20	1875	355	48.2	9.8	1.28
	65	250	250	8	16	1875	355	48.2	9.8	1.14

4. Overview of artificial neural networks (NNs)

Soft-computing is defined as a collection of methodologies aiming to exploit the tolerance for imprecision and uncertainty to achieve tractability, robustness and low solution cost. Fuzzy logic, genetic programming, artificial neural networks and probabilistic reasoning are the main components of soft-computing (Zadeh 1994). Soft-computing plays a critical role in various fields of application. Human mind is the basic model for soft-computing.

Neural network (NN) is a functional simulation of the biological neural structures of the central nervous system (Aleksander and Morton 1993, Arbib 1995, Anderson 1995, Gao *et al*. 2011). It can exhibit a number characteristic of human brain, such as learn from experience and generalize from previous cases to new problems. In NNs, there are many cells and connections between inputs and outputs. These connections between neurons get a transmission value as for the relation and this is called weight. The weights can be renewed for every new data. After realizing the weights, a present database teaching system is easily updated with the data to be obtained later (Mukherjee and Biswas 1997, Topçu and Sarıdemir 2008). The NNs are systems composed of many simple processing elements operating in parallel whose functions are determined primarily by the pattern of connectivity. These systems are capable of high level functions, such as adaptation or learning, and lower level functions such as data pre-processing for different kinds of inputs. The NNs have been inspired both by biological nervous systems and mathematical theories of learning, information processing, and control (Gao *et al*. 2011).

In this study, neural network fitting tool (nftool) provided as a soft-computing tool in MatlabV.R2012a was utilized to perform neural network modeling. In fitting problems, a neural network was used to map between a data set of numeric inputs and a set of numeric targets. The nftool helps create and train a network, and evaluate its performance using mean square error and regression analysis. A two-layer feed-forward network, with sigmoid hidden neurons and linear output neurons, can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. The network was trained with Levenberg-Marquardt (Levenberg 1944) back propagation algorithm.

An artificial neuron consists of three main components, namely weights, bias, and an activation function. Each neuron receives inputs I_1, I_2, . . . ,I_n attached with a weight w_i which shows the connection strength for that input for each connection. Each input is then multiplied by the corresponding weight of the neuron connection. A bias can also be defined as a type of connection weight with a constant nonzero value added to the summation of weighted inputs, as given in Eq. (3). Generalized algebraic matrix operation is provided in Eq. (4) to clearly indicate the mathematical operations in an artificial neuron

$$U_k = Bias_k + \sum_{j=1}^{n}\left(w_{j,k} I_k\right) \tag{3}$$

$$U_k = \begin{bmatrix} w_{11} & w_{12} & \cdot & \cdot & \cdot & w_{1n} \\ w_{21} & & & & & \cdot \\ \cdot & \cdot & & & & \cdot \\ \cdot & & \cdot & & & \cdot \\ \cdot & & & \cdot & & \cdot \\ \cdot & & & & \cdot & \cdot \\ w_{m1} & & & & & w_{mn} \end{bmatrix}_{m\times n} \begin{bmatrix} I_1 \\ I_2 \\ \cdot \\ \cdot \\ \cdot \\ I_n \end{bmatrix}_{n\times 1} + \begin{bmatrix} Bias_1 \\ Bias_2 \\ \cdot \\ \cdot \\ \cdot \\ Bias_m \end{bmatrix}_{m\times 1} = \begin{bmatrix} U_1 \\ U_2 \\ \cdot \\ \cdot \\ \cdot \\ U_m \end{bmatrix}_{m\times 1} \tag{4}$$

Since nftool uses the normalized values in the range of [–1, 1], the input parameters are normalized by means of Eq. (5) in order to get the prediction results after execution of the training process of the NN. Since the obtained results are also in the normalized form, considering the Eq. (5) and the normalization coefficients *a* and *b* for outputs, de-normalization process is applied and the results are monitored.

$$\beta_{normalized} = \alpha\beta + b \tag{5}$$

where β is the actual input parameter or output values given in Tables 2 and 3. $\beta_{normalized}$ is the normalized value of input parameters or outputs ranging between [–1,1]. *a* and *b* are normalization coefficients given in the following equations (Eqs. (6)-(7)).

$$a = \frac{2}{\beta_{\max} - \beta_{\min}} \tag{6}$$

$$b = \frac{\beta_{\max} + \beta_{\min}}{\beta_{\max} - \beta_{\min}} \tag{7}$$

Table 4 The normalization coefficients for the I-H data given in Table 2

Normalization Parameters	Input and output variables									
	b_f (mm)	d (mm)	t_f (mm)	t_w (mm)	L_v (mm)	$f_{y,flange}$ (MPa)	$f_{y,web}$ (MPa)	E/E_h	$\varepsilon_h/\varepsilon_y$	s
β_{max}	311	945.4	18	10	2895.5	982	984	48.2	12.3	1.41
β_{min}	73.7	120.3	5.26	3.9	480	261	275	37.5	9.8	0.68
a	0.00843	0.00242	0.15699	0.32787	0.00083	0.00277	0.00282	0.18691	0.8	2.73972
b	1.62116	1.29160	1.82575	2.27869	1.39743	1.72399	1.77574	8.00934	8.84	2.86301

Table 5 The normalization coefficients for the RHS-SHS data given in Table 3

Normalization Parameters	Input and output variables								
	b (mm)	d (mm)	t (mm)	r (mm)	L_v (mm)	f_y (MPa)	E/E_h	$\varepsilon_h/\varepsilon_y$	s
β_{max}	250	250	10	20	1875	707	48.2	11	250
β_{min}	25.08	40	1.54	1.5	400	275	42.6	9.8	25.08
a	0.00889	0.00952	0.23641	0.10811	0.00136	0.00463	0.35714	1.66667	0.00889
b	1.22301	1.38095	1.36407	1.16216	1.54237	2.27315	16.21429	17.3333	1.22301

where β_{max} and β_{min} are the maximum and minimum actual values of either input or output, respectively. The normalization coefficients for both input and output variables are given in Tables 4 and 5.

5. Proposed NN models

In order to select the optimum number of the nodes in hidden layer, a preliminary study was conducted. The mean square errors (MSE) and correlation coefficients (R) were evaluated for training and testing databases. The trials between 3 to 25 nodes indicated that the lowest MSE values associated with the highest R values were obtained at 20 nodes for both datasets formed for I-H and RHS-SHS beams. Based on this preliminary result, NN models of 9-20-1 and 8-20-1 NN architectures were used for I-H and RHS-SHS steel beams, respectively. The structure of the networks are graphically depicted in Fig. 5 for the former and Fig. 6 for the latter, where it can be noted that the number of nodes for the input layer is different from each other, while the nodes in the hidden layer were kept constant as a result of trial and error process. Single node in the output layer corresponds to the flexural overstrength factor. It should be noticed that all variables were normalized to a range of [–1, 1] before being introduced to the NN. Therefore, the normalized values must be entered in the mathematical operations given for NN model within the maximum and minimum limits specified in Tables 4 and 5. The developed NN models are given in Eqs. (8) and (9) for I-H and RHS-SHS steel beams, respectively. U_m values in these equations are calculated according to the matrix operation given in Eq. (4). The Eq. (4) uses input weights (w_{mn}) and input bias values ($Bias_m$) given in Tables 6 and 7 for I-H and RHS-SHS beams, respectively. In Eqs. (8) and (9), s is the flexural overstrength of steel beam in normalized form, and the activation function in these equations is hyperbolic tangent ($\tanh(U_m)$). Since the obtained results

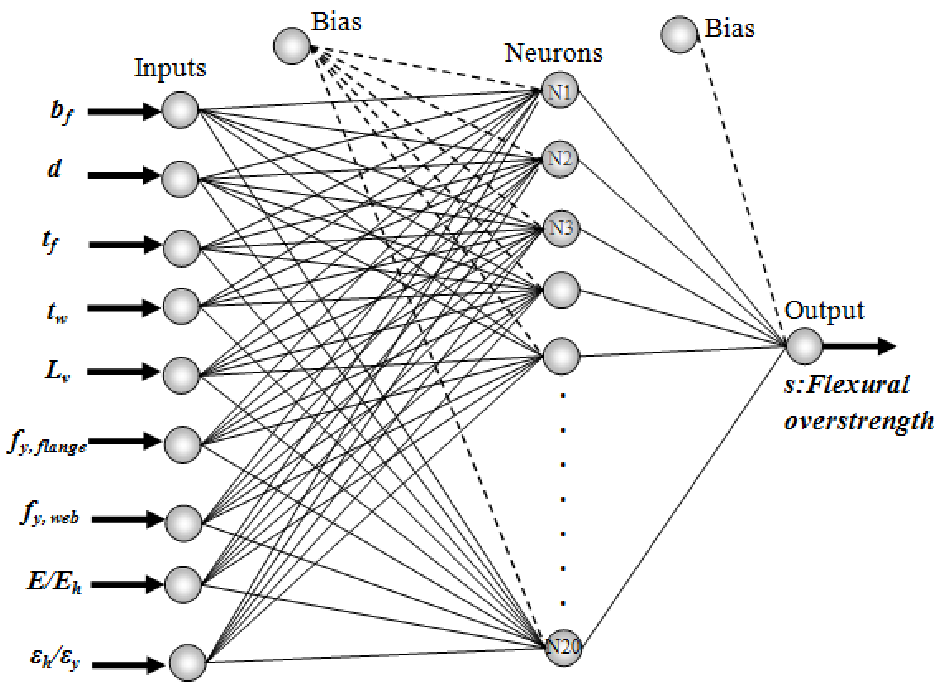


Fig. 5 Structure of the proposed NN model to predict the flexural overstrength of I-H steel beams

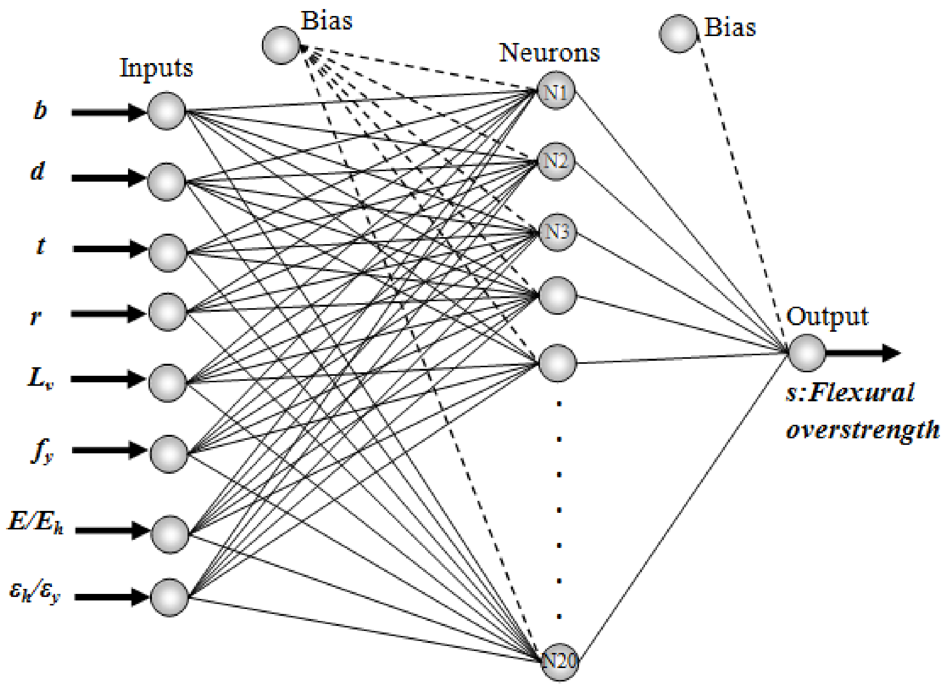


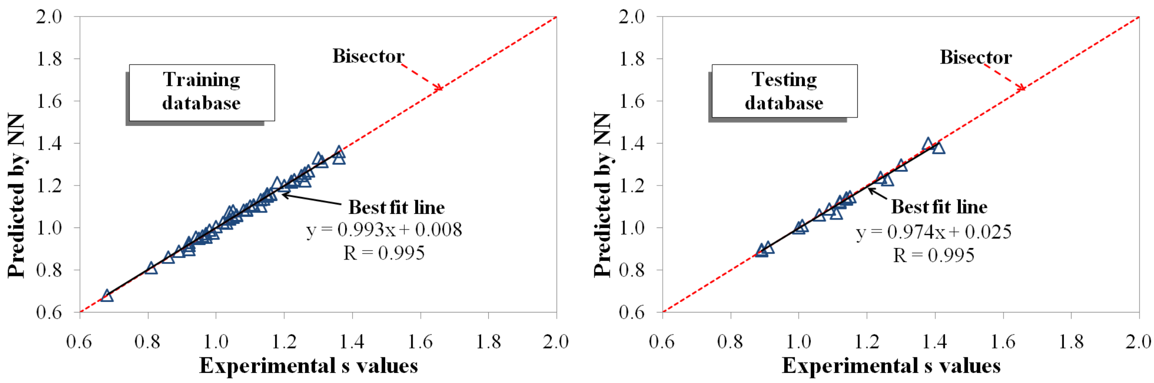
Fig. 6 Structure of the proposed NN model to predict the flexural overstrength of RHS-SHS steel beams

in Eqs. (8) and (9) are in the normalized form, they need to be de-normalized according to Eq. (5) and normalization coefficients given in Tables 4-5.

$$
\begin{aligned}
s_{I-H} = {} & 0.1776 - 0.35456\tanh(U_1) + 1.0759\tanh(U_2) - 1.61662\tanh(U_3) \\
& + 0.08575\tanh(U_4) + 0.2597\tanh(U_5) - 1.4881\tanh(U_6) - 1.4204\tanh(U_7) \\
& - 0.50917\tanh(U_8) + 1.2314\tanh(U_9) + 138787\tanh(U_{10}) + 0.62399\tanh(U_{11}) \\
& - 1.1774\tanh(U_{12}) - 0.90339(U_{13}) + 1.6306\tanh(U_{14}) - 0.6112\tanh(U_{15}) \\
& + 1.5976\tanh(U_{16}) - 3.5834\tanh(U_{17}) + 2.0509\tanh(U_{18}) - 1.7404\tanh(U_{19}) \\
& + 0.078951\tanh(U_{20})
\end{aligned} \tag{8}
$$

$$
\begin{aligned}
s_{RHS-SHS} = {} & 0.023914 + 0.97814\tanh(U_1) + 1.0828\tanh(U_2) + 2.6554\tanh(U_{3.}) \\
& - 1.3594\tanh(U_4) + 2.1175\tanh(U_5) - 0.6534\tanh(U_6) - 0.1893\tanh(U_7) \\
& - 1.0503\tanh(U_8) + 1.22027\tanh(U_9) - 1.1343\tanh(U_{10}) - 0.76416\tanh(U_{11}) \\
& + 1.1236\tanh(U_{12}) + 0.0079831(U_{13}) - 1.8346\tanh(U_{14}) + 0.99942\tanh(U_{15}) \\
& - 0.18454\tanh(U_{16}) - 1.6382\tanh(U_{17}) - 1.7617\tanh(U_{18}) + 0.50816\tanh(U_{19}) \\
& - 0.72806\tanh(U_{20})
\end{aligned} \tag{9}
$$

The comparison between the experimental and predicted overstrength factors for I-H section and RHS-SHS steel beams are graphically illustrated in Figs. 7 and 8. The correlation is demonstrated via the correlation coefficient "*R*" (Eq. (10)), which defines the fit of the model's output variable approximation curve to the actual test data output variable curve. Higher R coefficients indicate a model with better output approximation capability.



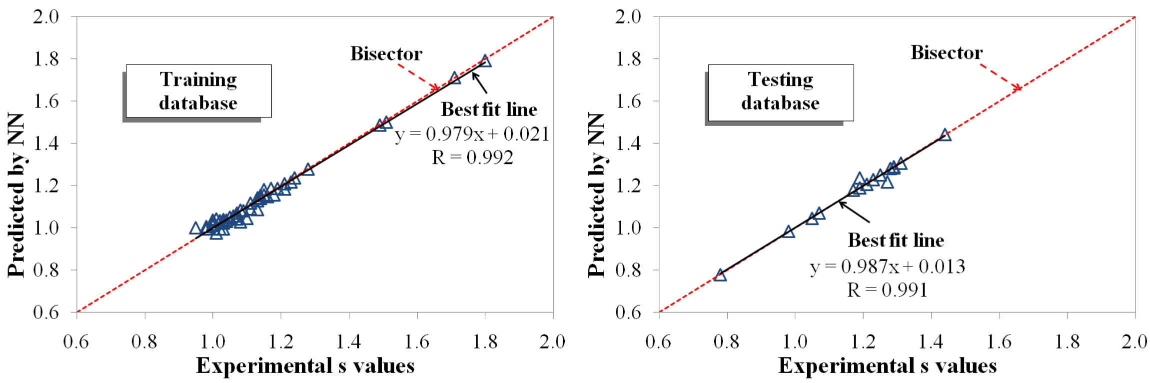
(a) (b)

Fig. 7 Performance of the proposed NN model for I-H beams: (a) train set; and (b) test set

Table 6 Weight values and biases for the proposed NN model of I-H steel beams

Input weights *									Input *Bias* **
0.041657	-0.90154	-1.0866	-0.94637	-0.39161	0.13773	-0.42352	0.56915	-0.2423	2.0249
1.6859	-0.54162	-1.1497	-1.6087	0.39812	-0.88377	-0.04785	-0.79379	0.42555	-1.4617
-2.3032	1.6864	-0.57757	-0.6147	0.45779	0.43369	-0.27217	0.18581	0.41933	0.66585
-0.28665	-1.3649	-0.1111	-0.61298	0.72778	-0.73832	-0.03057	-0.00327	-0.63737	1.6282
-0.9583	-0.79403	0.44856	0.43979	0.75513	-0.37764	-0.2402	-0.15523	-1.1497	1.1957
1.3844	0.56091	1.1142	-0.46406	-1.3896	1.9486	-0.35268	0.99487	-0.31188	-0.78386
-1.1721	-0.73018	0.12399	0.68655	-0.3997	-0.8356	0.37759	0.28531	0.31213	0.38886
0.18385	-0.71209	0.78371	-1.245	-0.12173	-0.4008	-0.67795	-0.14643	-1.7585	-0.20061
0.026684	-0.51626	-0.13029	-1.0956	0.57925	-0.07661	1.9422	-0.98027	0.46407	-0.80835
0.42153	-0.83027	-1.1412	1.7517	-0.8373	-1.4284	0.054601	-0.26967	-0.97369	0.70776
-1.4394	-0.57849	-1.4776	-2.1018	0.26219	0.89764	-0.2169	0.99349	-0.29114	-0.2548
1.702	-0.8268	-1.0168	0.32446	-1.0136	-0.21416	0.51016	-0.57122	0.035776	0.05775
-0.37871	-0.51883	-1.3641	0.19538	2.6559	0.020797	0.093415	0.46335	-0.67929	-0.3706
-0.59323	1.24	0.99135	0.7448	0.93057	0.055864	-1.3544	-0.25385	1.3514	0.59234
0.2604	-2.576	-0.00313	0.84301	0.90486	0.78172	0.97406	-0.56116	1.568	-0.91773
-1.3106	-0.50056	-1.6593	0.012347	-0.42598	2.6055	0.25507	0.45708	-0.75461	-0.35207
1.2329	-1.9208	-1.6012	-2.1951	0.030366	-0.94574	-1.1289	0.37469	0.75439	0.49444
-0.49615	2.0711	-2.4371	-0.03646	-0.5021	-1.9122	-0.15914	0.16786	0.25537	2.4053
-2.2362	3.257	-1.3274	2.4596	1.1411	-1.3176	0.88908	-0.7693	-0.72177	-1.2384
0.5074	0.50908	-0.33472	0.54841	-0.01365	0.41063	-0.44725	-0.22524	-0.07511	2.824

* Weight matrix with dimension of 20 × 9 in Eq. (4)
** Bias matrix with dimension of 20 × 1 in Eq. (4)



(a) (b)

Fig. 8 Performance of the proposed NN model for RHS-SHS beams: (a) train set; and (b) test set

Table 7 Weight values and biases for the proposed NN model of RHS-SHS steel beams

Input weights *								Input *Bias* **
1.4371	-0.6966	1.1441	0.87245	0.16689	0.25051	0.21754	-0.38116	-2.0913
0.12168	-2.164	0.8206	0.96659	0.93793	-1.1317	0.48383	1.23	1.9637
-0.99876	1.453	1.105	1.202	3.0054	-0.51489	0.75842	-0.032	2.4677
1.4739	-0.72638	-0.16866	1.3323	0.52427	-1.443	1.0522	-0.38292	-0.86367
1.3832	-1.2802	-1.4574	-1.028	0.030363	0.2247	0.63666	0.72227	-1.4952
-0.27406	-1.111	-1.211	-0.98338	-0.08354	-0.37516	-0.00648	-0.25804	1.2168
0.26259	2.1929	0.88772	0.82825	-0.15923	-2.5098	1.2825	-1.3526	0.20848
0.10092	-1.0093	-1.3078	-0.39398	-0.1231	-1.426	-0.87251	1.7508	0.054752
-0.38372	-1.5667	-0.21441	-1.6534	0.20193	0.83785	-1.1318	-0.7997	0.29624
0.11806	-0.53034	0.71511	-0.27177	-1.6241	1.0442	-1.1232	-0.15105	-0.7559
-0.04135	-1.0881	-0.54399	1.5707	0.21348	-1.1648	0.048174	0.55675	-0.12949
0.24856	-2.2743	1.1574	2.0344	-0.06197	0.98297	-0.84237	-0.63722	0.99472
-0.48477	0.043324	-0.33926	1.4309	-0.88885	-1.1258	-0.2084	-1.3935	-0.055261
0.98772	-1.4566	0.25477	-0.79961	1.4398	0.89651	-0.91906	-0.33111	0.94382
-1.1277	1.1023	0.1829	-1.7934	-0.30382	0.96667	0.58786	-0.66188	-1.4683
0.93953	1.6584	-0.40056	-0.31274	-0.43015	-0.80886	0.55026	-2.2802	-0.36972
-2.3609	2.479	2.3218	0.95136	-0.62959	-1.0651	-0.32484	-0.39974	-1.4977
-0.39601	0.046466	-1.1181	-0.15761	-1.333	3.1105	-1.1098	0.41319	1.5804
-0.68124	0.1594	-0.91027	0.48644	0.39971	-0.80434	-1.0165	1.1397	-1.6838
0.54603	0.18214	0.54405	0.091099	0.30832	-1.5864	0.11351	-1.078	2.5421

* Weight matrix with dimension of 20 × 8 in Eq. (4)
** Bias matrix with dimension of 20 × 1 in Eq. (4)

$$R = \frac{\sum (m_i - m')(p_i - p')}{\sqrt{\sum (m_i - m')^2 (p_i - p')^2}} \tag{10}$$

where *m*' and *p*' are mean values of measured (m_i) and predicted (p_i) values, respectively.

As shown in Figs. 7 and 8, there is strong correlation between actual and predicted values for both train and test dataset. The correlation coefficients (*R*) are very close to 1, which indicates the perfect correlation. Close values of the correlation coefficients may be considered as a proof for the consistency and good fitness of the proposed models. Moreover, the best fit lines and bisector lines drawn in Figs. 7 and 8 are almost coincident, which demonstrates the accuracy of the prediction capability of the proposed models.

6. Performance of the proposed model

Even though NN and GEP methods are both originated from artificial intelligence philosophy to develop simulations for the real life problems, the two methods substantially differ. Indeed, the main peculiarity of the GEP method is to create an analytical model comprising of various mathematical operations to provide the best fitness. On the contrary, the NN model proposed in this study uses a fixed mathematical procedure with the aid of assigned weights to the input parameters and hidden layers.

The proposed NN based formulation for *s* values proved to be more accurate than the GEP based formulations presented by Güneyisi *et al*. (2013), where the correlation coefficients obtained for testing and training datasets for steel beams ranged between 0.909 and 0.929, depending mainly on the section typology. In order to compare the prediction performances of the proposed NN models and the GEP models by Güneyisi *et al*. (2013), the normalized values were calculated by dividing predicted results by actual ones, as shown in Figs. 9 and 10.

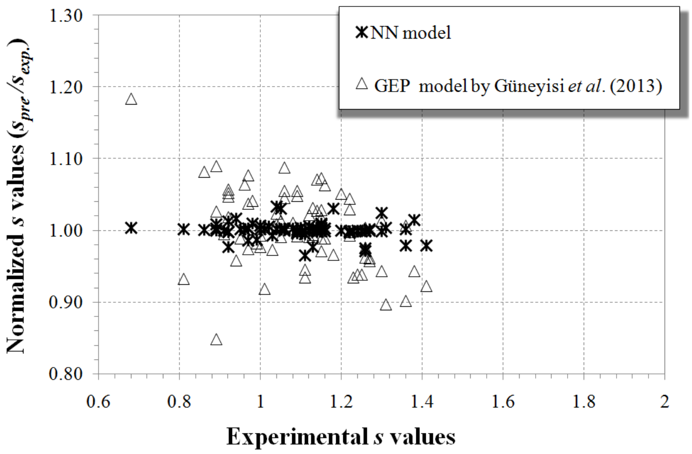


Fig. 9 Comparison of the prediction accuracy of the proposed NN model and GEP model by Güneyisi *et al*. (2013) for the flexural overstrength of I-H steel beams

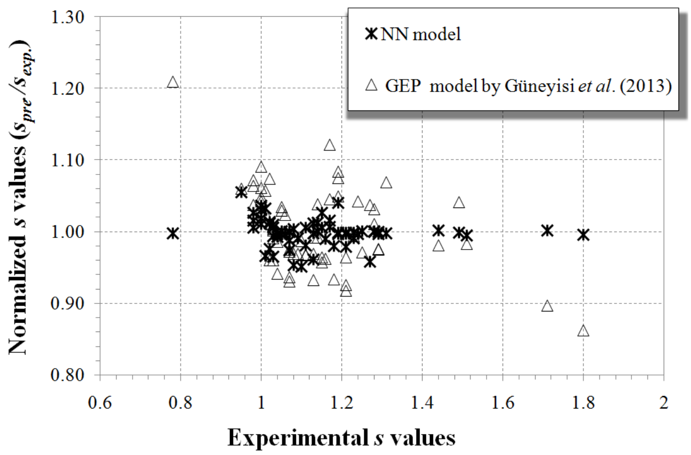


Fig. 10 Comparison of the prediction accuracy of the proposed NN model and GEP model by Güneyisi *et al*. (2013) for the flexural overstrength of RHS-SHS steel beams

According to the normalized values ($s_{\text{predicted}}/s_{\text{experimental}}$), the perfect estimation performance is equal to 1. Figs. 9 and 10 show that the closest trend in variation of the normalized values around 1 was observed for the NN model. The normalized *s* values of I-H sections ranged between 0.85 and 1.18 for the GEP model and 0.99 and 1.03 for NN model. However, when considering the normalized s values of RHS-SHS, these ranges were observed as 0.86-1.18 and 0.99-1.03 for the former and latter, respectively. Thus, it can be pointed out that the performance of NN models is better than that of GEP models for both types of sections. Moreover, the fluctuation of the normalized data seems to be irregular for the GEP model since there is an irregular scatter of underestimated and overestimated data. However, the normalized values obtained from the proposed NN model for I-H sections revealed almost uniform distribution with very low fluctuations around 1 while the NN data for RHS-SHS demonstrated slightly underestimation between actual *s* values of 1.0-1.2.

The input parameters used for derivation of the proposed models are thoroughly representative of both geometrical and mechanical properties of steel beams. Any variations in those parameters significantly affect the value of *s*. Therefore, the physical effectiveness of these parameters can

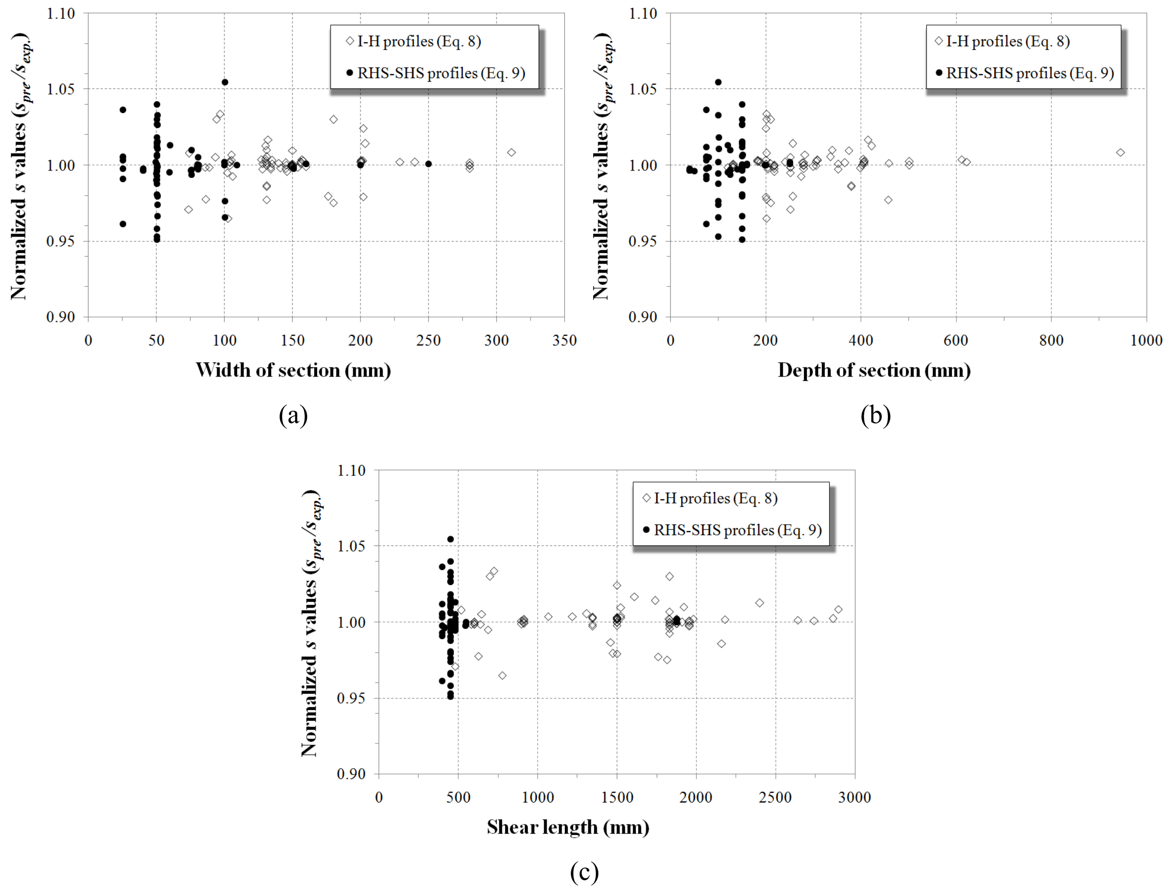


Fig. 11 Interaction between prediction capability of the proposed models and (a) width of sections; (b) depth of sections; and (c) shear length of the beams

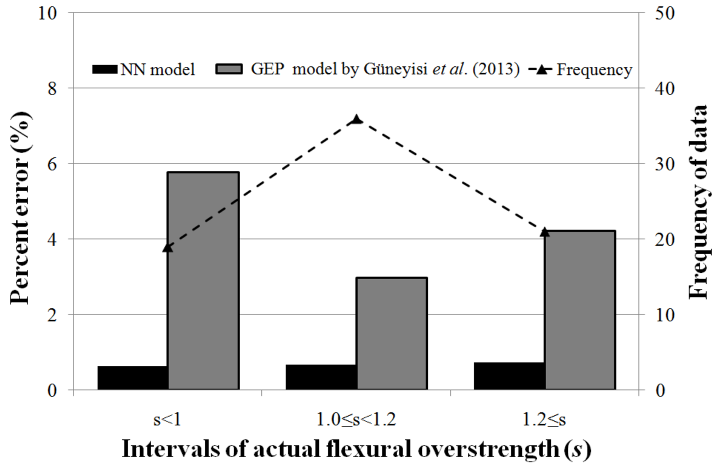


Fig. 12 Variation in absolute errors of the proposed NN model and GEP model by Güneyisi *et al*. (2013) with respect to the actual flexural overstrength values of I-H steel beams

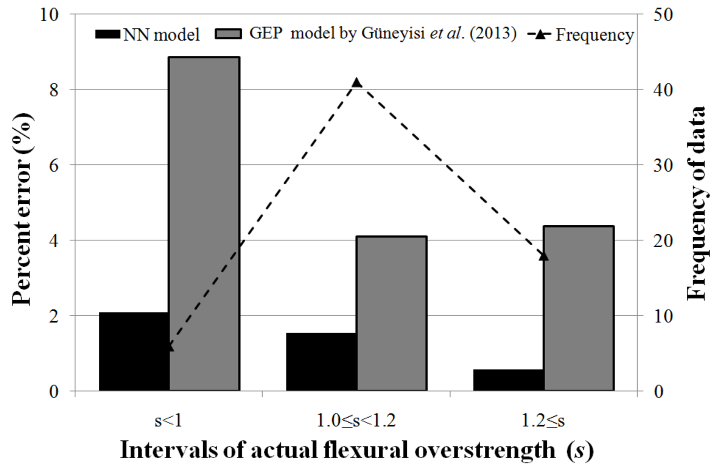


Fig. 13 Variation in absolute errors of the proposed NN model and GEP model by Güneyisi *et al*. (2013) with respect to the actual flexural overstrength values of RHS-SHS steel beams

also be observed from the models. In order to highlight the interaction between the input parameters and the proposed models, Fig. 11 is plotted to demonstrate the fluctuation of prediction performance against the variation of some input parameters.

For further comparison of the proposed models, the estimation errors are graphically shown in Figs. 12 and 13. The frequency of the data in the specified intervals is also given in these figures. By this way, more detailed analysis of the prediction performances of the proposed NN models and GEP models can be observed through examining the absolute errors presented in these figures. The errors for the predicted values obtained from NN model for I-H section seems to be very close to each other for the specified intervals of actual *s* values. However, for the RHS-SHS, the errors have a tendency of decrease as the actual *s* value increases. As seen from Figs. 12 and 13, the majority of *s* values fall between 1.0 and 1.2. The lowest errors for the GEP model occurred in this interval. However, the highest error observed from the GEP model were for the actual *s* values of smaller than 1.0.

7. Conclusions

A novel prediction model through explicit formulation of flexural overstrength of the steel beams is presented in this study. The proposed formulations are derived by means of artificial neural network (NN). To generate the model, the available experimental data presented in the existing literature were used. Based on the analysis of the results, the following conclusions can be drawn:

- It was proved that NN technique can be profitably used to develop empirical mathematical formulations of the flexural overstrength of the steel beams with various cross-sectional properties, boundary and loading conditions. No invalid results were obtained from the prediction models. Therefore, it can be inferred that the developed models can be considered as handful tools with satisfactory prediction capability of the whole data set when the proposed mathematical relation is transferred to the computer.
- The proposed NN model was compared with an available formula derived from Gene expression programming (GEP). Considering the whole data set for I-H and RHS-SHS beams, the performance of the proposed NN model is noticeably more accurate than the GEP model.
- Based on the statistical evaluation, the accuracy of the proposed models can be considered fully satisfactory to be utilized for estimation of the *s*. The correlation coefficients for training and testing databases are higher than 0.99 for all of the databases considered in this study. Even though the database for testing data set were not used for training, a high level of prediction was obtained for both training and testing data sets associated with low mean absolute percentage of error and high coefficients of correlation. This can be considered as the proper robustness of the developed models.
- Unlike the GEP model, the NN model requires the data to be normalized between [–1, 1]. Although the GEP model can be considered as a more user friendly than the NN model, when the accuracy of the prediction possesses more significance, the utilization of the NN model becomes more critical. However, by means of properly computerization of the proposed NN models, they can easily be exploited.

The proposed models for I-H and RHS-SHS steel beams in this study have been developed from existing experimental data presented in the literature. It is worth noting that the further use of both models in different datasets to validate results and/or comparison with results from other authors would noticeably increase the interest of the work. Indeed, increasing the number of data samples used for training the models by generating data through new experimental work may provide more robust models as well as increasing the generalization capability of such models.

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