American-Eurasian Journal of Scientific Research 3 (2): 153-162, 2008
ISSN 1818-6785

Application of a Coupled Simulated Annealing-Genetic Programming Algorithm to the Prediction of Bolted Joints Behavior

[1,2]A.H. Gandomi, [1]M.G. Sahab [2]A.A.R. Heshmati, [2]A.H. Alavi, [3]M. Gandomi, [1]P. Arjmandi

[1]College of Civil Engineering, Tafresh University, Tafresh, Iran
[2]College of Civil Engineering, Iran University of Science and Technology, Tehran, Iran
[3]School of Civil Engineering, College of Engineering, University of Tehran, Tehran, Iran

Abstract: This paper proposes a novel approach for the prediction of the flexural resistance and initial rotation stiffness of bolted joints using a hybrid search algorithm that couples genetic programming (GP) and simulated annealing (SA), called GP/SA. Two types of the steel bolted joints were investigated: bolted endplate joints and end bolted joints with angles, respectively. The GP/SA models are developed using experimental results collected from literature. The accuracy of the proposed models is satisfactory as compared to experimental results. The results of proposed models are further compared with Eurocode 3 reference values, as well as existing models in the literature. The results demonstrate that the proposed GP/SA models provide superior performance than other models.

Key words: Steel structure · Semi-rigid joints · Combined genetic programming and simulated annealing. Flexural resistance · Initial rotation stiffness

INTRODUCTION

A steel framed multi-story structure has three main structural components, namely, beam, column and their joint. In fact, all the joints are semi-rigid, but previous standards have always accepted joints as either totally pinned or rigid. This assumption had some advantages and disadvantages. While structural analysis and design are simplified by assumption, the actual behaviors of bolted beam-column joints still were uncertain.

Two of the main structural properties for joint designing are flexural resistance and initial rotational stiffness. Eurocode 3 [1] determines some formulations to compute these properties. According to this standard, flexural resistance and initial rotational stiffness depend on many parameters which should be computed from different formulations and tables. The real behavior of a structural joint with the main objective of determining the physical and geometric parameters that influence this behavior has been investigated through several experimental tests, [2-11].

The complex behavior of the flexural resistance and initial rotation stiffness of bolted joints and presence of nonlinear relationship between them and the influencing parameters suggest the necessity to develop comprehensive mathematical models to be able to evaluate them with high accuracy. Some investigations have concentrated on predicting the beam-column steel joints behavior using artificial neural networks (ANNs) [12] in the literature [13-16]. In spite of the successful performance of ANNs, they are black-box models that do not give a deep insight into the process they use the available information to obtain a solution.

Genetic programming (GP) [17, 18] is a developing subarea of evolutionary algorithms [19] inspired from Darwin's evolution theory. GP may be defined generally as a supervised machine learning technique that searches a program space instead of a data space [18]. GP has been successfully applied to some of the civil engineering problems [20-24].

Simulated annealing (SA) is a general stochastic search algorithm, which introduces the concept of evolution into the annealing process. SA was first presented in 1953 by Metropolis *et al*. [25] to mimic the natural process of metals annealing. This algorithm is employed to optimization problems by Kirkpatrick *et al*. [26] and Cerny [27] independently. SA is very useful for solving several types of optimization problems with

Corresponding Author: Dr. Mohammad Ghasem Sahab, College of Civil Engineering, Tafresh University, Tafresh, Iran

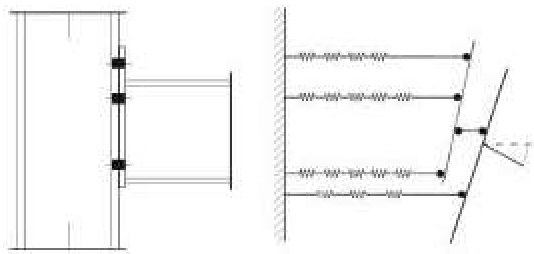

Fig. 1: Characterization of the beam-column joints components

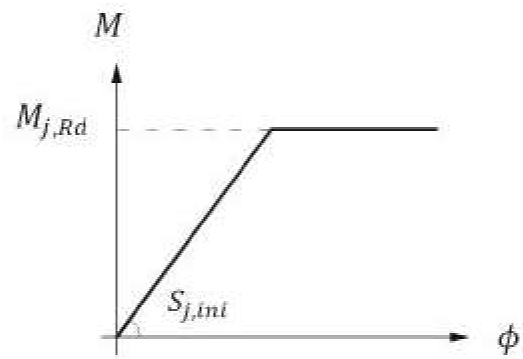

Fig. 2: Bilinear approximation of the moment versus rotation curve [1]

nonlinear functions and multiple local optima [25, 28, 29]. The ability and shortcomings of SA are well summarized by [30]. Folino *et al*. [31] combined GP and SA to make a hybrid algorithm with better efficiency. They used SA strategy to decide the acceptance of a new individual. They showed that introducing this strategy into the GP process improve the simple GP profitably.

This paper proposes an alternative GP/SA approach by utilizing the Folino's hybrid algorithm for the determination of flexural resistance and initial rotation stiffness of beam-column steel joints. To our knowledge, GP/SA technique has not been applied in the field of joints behavior prediction so far in the literature. A comparison between the results of GP/SA, Eurocode 3 and other existing models, [3], was performed. A reliable database including previously published flexural resistance and initial rotation stiffness of beam-column steel joint test results was utilized to develop the models.

Brief overview of European Committee for Standardization (Eurocode 3) model: European Committee appraises the behavior of beam-column joints by the component method. Joint components have been introduced to a simple mechanical model to predict of beam-column moment versus rotation curves [32]. Fig. 1 shows an endplate beam-column joint together with its associate mechanical model. This model is composed of springs and rigid links, for representing relevant joint components. A comprehensive description of the joint components is presented by Silva and Coelho [33]. The spring model depicted in the Fig. 1 can be simplified by altering each series of springs by an equivalent elasto-plastic spring, which keeps the related characteristics. By this procedure, a non-linear equivalent model for the analysis of beam- column joints can be obtained too [14]. After defining the equivalent elastic model, the design process continues with a post-buckling stability analysis by an energy-based formulation [33]. Since these procedures are still to be appraised, this study uses the bilinear approximation of the moment versus rotation curve relevant to the joint suggested in Eurocode 3, Fig. 2.

Hybrid Genetic Programming-simulated Annealing Algorithm (GP/SA): In this paper, a GP with a SA based selection strategy is employed for developing mathematical models to be able to predict the flexural resistance and initial rotation stiffness of beam-column steel joints. In fact in this coupled algorithm, the SA strategy for selection of new individuals is used. Before explaining the main steps of the coupled GP/SA algorithm, an overall view of SA and GP is presented.

Annealing is a process in which a metal is heated to a high temperature and then is gradually cooled to relieve thermal stresses. During the cooling process, each atom takes a specific position in the crystalline structure of the metal. By changing the temperature this crystalline structure changes to a different configuration. An internal energy, E, can be measured and assigned to each state of crystalline structure of the metal which is achieved during the annealing process.

In each temperature within the annealing process, if the temperature does not decrease quickly the atoms are allowed to adjust to a stable equilibrium state of least energy. It is evident that changing of the crystalline structure of a metal, through the annealing, is associated with a changing of the internal energy as ?E. However, as the metal temperature drops down gradually, the overall trend of changing internal energy follows a decreasing process but sometimes the energy may increase by chance. The probability of acceptance an increase in internal energy by ?E is given by Boltzmann's probability distribution function as follows:

$$P(\Delta E) = e^{\frac{-\Delta E}{KT}} \tag{1}$$

where T is the temperature of the metal in Kelvin's temperature scale and K is the Boltzmann's constant. As this expression shows the probability of higher energy is larger at higher temperatures and there is some chance of high energy as the temperature drops. An algorithm is proposed by Metropolis *et al*. [25] to simulate the annealing process. The metropolis algorithm is applied to optimization problems by Kirkpatrick *et al* [26] and Cerny [27] independently. SA based on the analogy between the way which the crystalline structure of a metal achieves near global minimum energy states during the process of annealing and the way which a function may reach minimum during a statistical search of the design space. The objective function corresponds to the energy state and moving to any new set of design variables corresponds to a change of the crystalline structural state.

The GP creates an initial population of computer programs at random with a tree structure. Then the fitness value for each computer program is calculated. The fitness value is usually calculated using a function named fitness function. This function is defined so that its value reflects how good the result of a computer program in the population can match with the experimental data. According to fitness values of the individual computer programs, in the population, some of them are copied into the mating pool with a probability, proportion to their fitness. This operation called reproduction. The crossover operator generates two new individuals (child program) by crossing two trees at randomly chosen nodes and exchanging sub trees. The two individuals participating in the crossover operations are also selected in proportion to their fitness. The mutation operator replaces one of the nodes with a new randomly generated sub tree. Through above steps a new generation of computer programs is created. The fitness value for all of the individuals in the new generation is calculated. If one of the termination or convergency conditions is satisfied the process is terminated. Otherwise another round of evaluation using genetic operators is repeated. Considering the above explanation, the main steps of the coupled GP/SA algorithm utilized in this research can be mentioned as follows:

A. A single program called "Parent Program" is initially created at random.
B. For the first run, another parent program is created at random, as a second parent, for mating. But for the other round of runs the best program to date in the entire run is considered, as the second parent.
C. A child using genetic operators, crossover and mutation, is created. In contrasts with GP algorithm in this coupled GP/SA algorithm one child of two created children is selected as a child program to transfer to the next generation. Which of the two children is used depends on the value of the offspring choice parameter.
D. The fitness value of the both parent and child program is calculated.
E. Based on the fitness value of the child and parent program, the SA algorithm decides whether to replace the parent program with the child program. If the child has better fitness than the parent, the child always replaces its parent. If the child has worse fitness than the parent, the child replaces the parent probabilistically. The probability of replacement depends on how much worse the fitness of the child is than the parent and also what is the SA temperature, T. as the run continues the annealing temperature, T, is reduced. This means for the program that the probability of replacing a worse child to a better parent gets lower and lower as the run continues. If the child program replaces the parent program then the child program becomes the new parent for the next cycle. Alternatively if the parent program is not replaced by the child, it remains as the parent program for the next cycle.
F. If the termination or convergency conditions are satisfied the process is terminated, otherwise the process is continued going step C.

Model Development: Four different models are developed for the prediction of flexural resistance and initial rotation stiffness of two kinds of beam-column joints (bolted endplate joints and bolted joints with angles) using GP/SA method. In all the models, the input parameters are geometrical characteristics and mechanical properties. The input and output parameters entering the models have been normalized before the learning process using the following formula:

$$X_n = \frac{0.9X_i - 0.05X_{i,\min} + 0.95X_{i,\max}}{X_{i,\max} - X_{i,\min}} \tag{2}$$

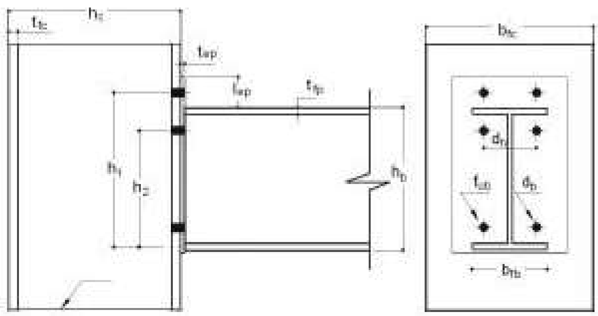

Fig. 3: Extended endplate joint layout

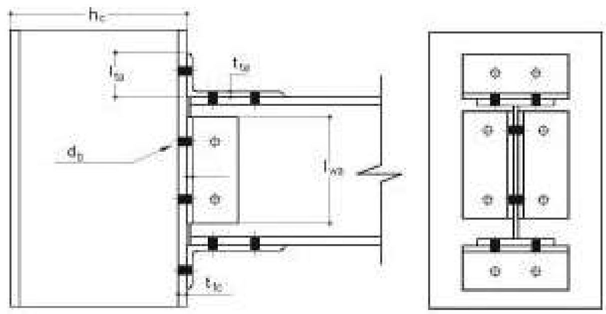

Fig. 4: Bolted angle joint

so as to lie between 0.10 and 0.90 where $X_{i,min}$ and $X_{i,max}$ are respectively the minimum and maximum values of X_i and X_n is the normalized value. These models use 80% of the total data for training and the remaining 20% for testing which were chosen randomly. The other details of the models development including the database description are presented in the following subsections.

Bolted Endplate Joints: The required data was collected for the development of two GP/SA models to predict the flexural resistance and initial rotation stiffness of this type of joint. The collected experimental data included 26 bolted endplate joints which are obtained from literature [2,4,7-10]. Sixteen variables are used as input parameters to the GP/SA predictive models as follows: column flange width (b_{fc}), column flange thickness (t_{fc}), column height (h_c), column yield stress (f_{yc}), beam flange width (b_{fb}), beam flange thickness (t_{fb}), beam height (h_b), beam yield stress (f_{yb}), 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) and horizontal distance between bolts (d_h) (as shown in Fig. 3).

Bolted Joints with Angles: Chance For bolted joints with angles, the data used to calibrate and validate the GP/SA models are obtained from the literature [5,6]. The following six variables are used as input parameters to the constructed models: column flange thickness (t_{fc}), beam height (h_b), angle thickness (t_{ta}), top and seat angle length (L_{ta}), top and seat angle length (L_{ta}) and bolt diameter (d_b). All these variables are illustrated in Fig. 4.

Table 1: Parameter settings for GP/SA

Parameter	Settings
Number of temperature levels	5000-12000
Number of iterations per temperature level	1000
Start temperature	5
Stop temperature	0.01
Crossover rate (%)	50, 95
Homologous crossover (%)	95
Probability of randomly generated parent in crossover (%)	99
Mutation rate (%)	90
Block mutation rate (%)	30
Instruction mutation rate (%)	30
Data mutation rate (%)	40
Offspring choice rate (%)	50
Replacement scaling factor	1
Maximum program size	256
Initial program size	80
Function set	+, -, *, /, v, sin, cos, tan

Model Development Using GP/SA Model: In order to develop GP/SA models to be able to predict the flexural resistance and initial rotational stiffness of beam-column steel joints the available database was used. Two separate models for single output have been developed, one for flexural resistance and the other for initial rotational stiffness, for each type of joint. Various parameters are involved in GP/SA predictive algorithm such as number of temperature levels, number of iterations per temperature level, start and stop temperatures, crossover rate and homologous crossover, mutation rate and its different types (block mutation rate, instruction mutation rate and data mutation rate), function set, program size. The parameter selection will affect the model generalization capability of GP/SA. They were selected after trial and error approach. The parameter settings are shown in Table 1.

Discipulus software [34] working based on the GP/SA algorithm is used for the analysis. The programs evolved by GP/SA are automatically written in C or inline assembler code that can be compiled in many C compilers, including Visual C++. In order to evaluate the capabilities of the GP/SA models, the coefficient of determination (R) and mean absolute error (MAE) are used as the criteria between the actual and predicted values and given in the form of formulas as follows:

$$R = \frac{\sum_{i=1}^{n}\left(h_i - \overline{h_i}\right)\left(t_i - \overline{t_i}\right)}{\sqrt{\sum_{i=1}^{n}\left(h_i - \overline{h_i}\right)^2 \sum_{i=1}^{n}\left(t_i - \overline{t_i}\right)^2}} \quad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|h_i - t_i\right| \quad (4)$$

where h_i and t_i are respectively the actual output and the calculated output value for the i^{th} output, $\overline{h}$ and $\overline{t_i}$ are the average of the actual and calculated outputs, respectively and n is the number of sample.

RESULTS AND DISCUSSION

Fig. 5(a)-(b) displays the predicted flexural resistances versus the experimental flexural resistances of all type of joints obtained by GP/SA models. A comparison of the ratio between predicted flexural resistance values by the GP/SA, as well as those obtained from European design code [1] and experimental values are shown in Figs. 6 and 7. As mentioned previously, R and MAE are selected as the target statistical parameters to evaluate the performance of the models. Considering the R and MAE values for flexural resistance, presented in Table 2, it can be seen that for the prediction of flexural resistance of all type of joints the best performance is obtained by GP/SA models for training, testing and all element test data.

The results of GP/SA for the prediction of initial rotation stiffness are shown in Fig. 8(a)-(b). A comparison of the ratio between predicted flexural resistance values by the GP/SA models and likewise those obtained from the European design code and Kishi *et al*. [3] model are illustrated in Figs. 9 and 10 for the bolted endplate joints and bolted joints with angles, respectively.

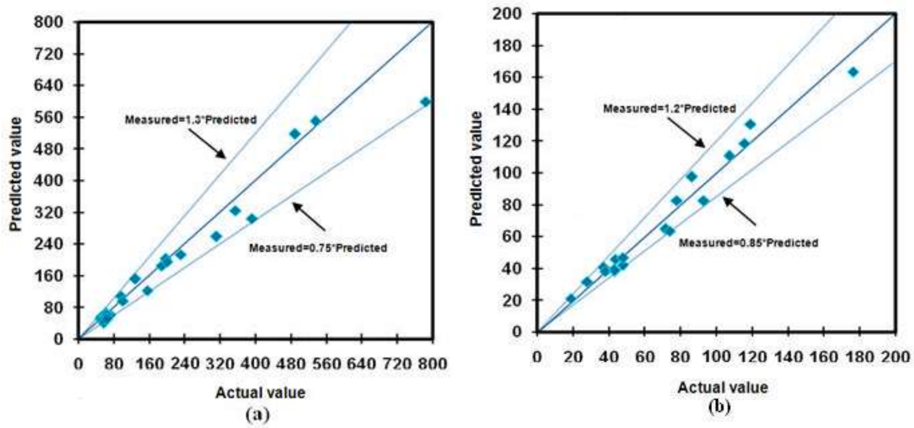

Fig. 5: Results of GP/SA prediction and actual flexural resistance in kN.m for (a) Endplate joints. (b) Bolted joints with angles

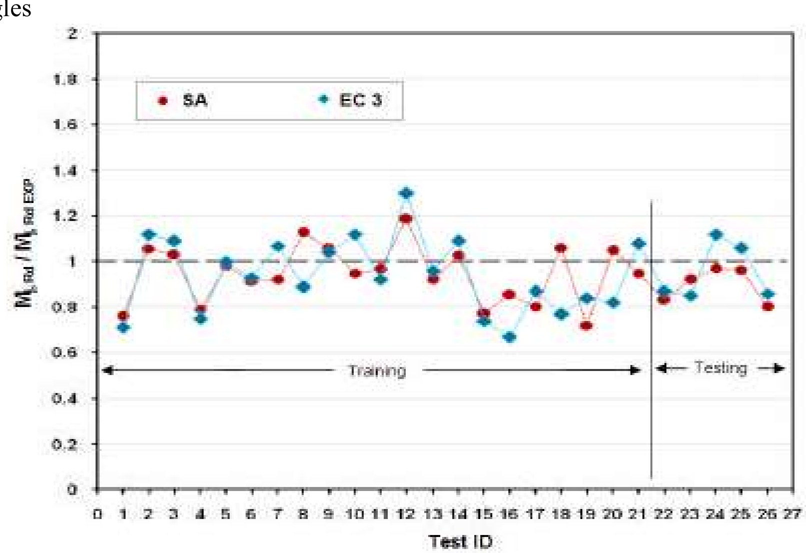

Fig. 6. Comparison of results of various methods prediction and actual flexural resistance for endplate joints

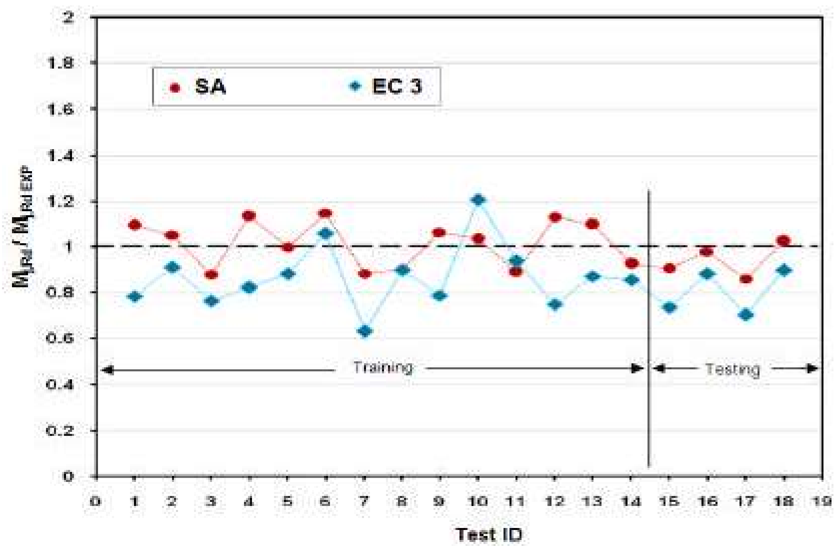

Fig. 7. Comparison of results of various methods prediction and actual flexural resistance for bolted joints with angles

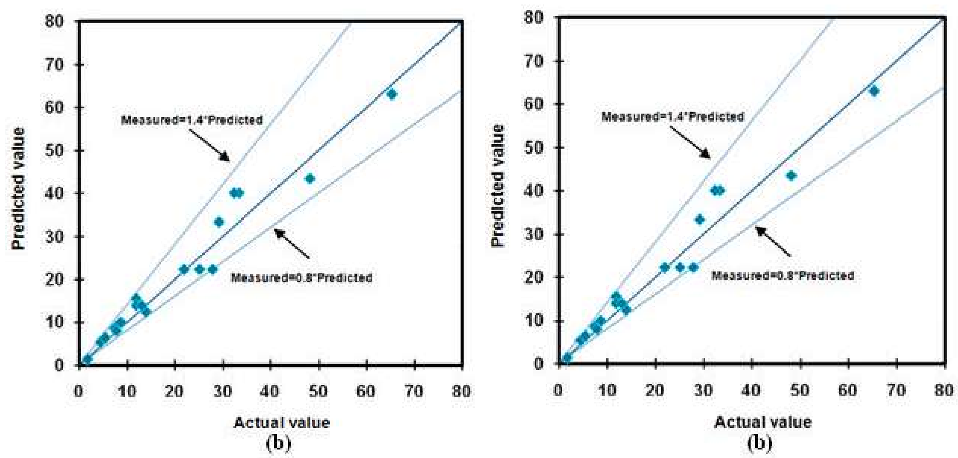

Fig. 8: Results of GP/SA prediction and actual initial stiffness in MN.m for (a) Endplate joints. (b) Bolted joints with angles

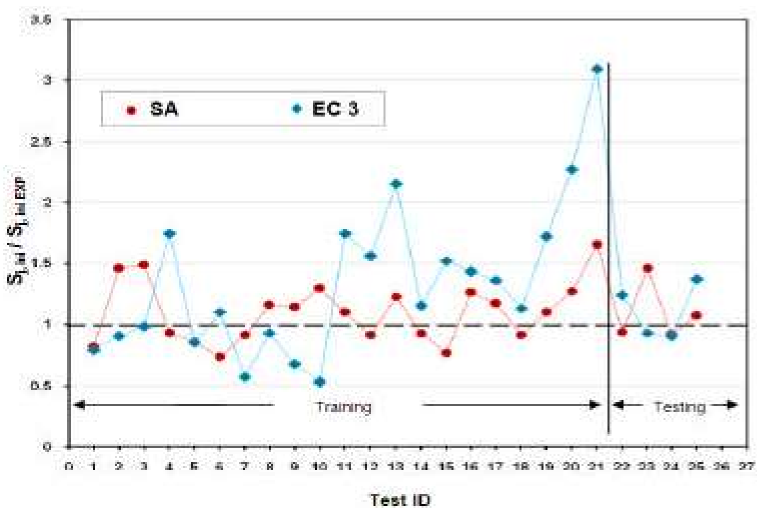

Fig. 9: Comparison of results of various methods prediction and actual initial stiffness for endplate joints

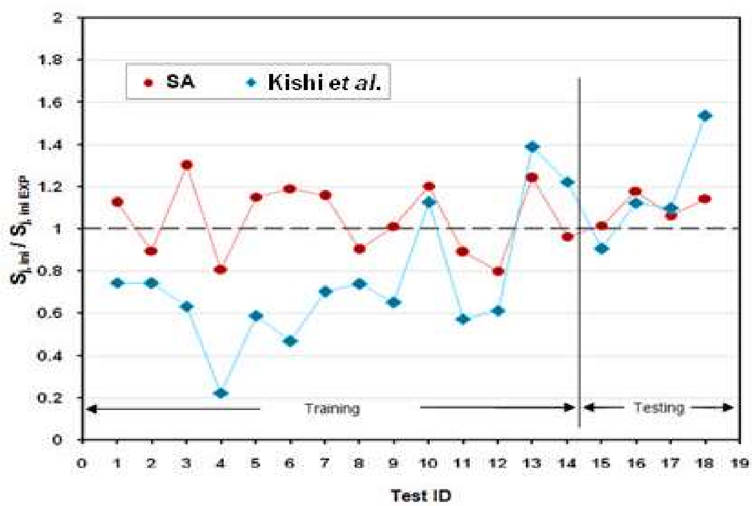

Fig. 10: Comparison of results of various methods prediction and actual initial stiffness for bolted joints with angles

Table 2: Performance statistics of models for flexural resistance prediction

		Training		Testing		All Elements	
Type of Joint	Model	R	MAE	R	MAE	R	MAE
Bolted Endplate Joint	GP/SA	0.9787	24.00	0.9924	15.45	0.9793	23.12
	Eurocode 3	0.9593	31.55	0.9798	17.15	0.9604	29.94
Bolted Joints with Angles	GP/SA	0.9852	6.04	0.9896	4.56	0.9846	5.71
	Eurocode 3	0.9633	11.61	0.9793	12.68	0.964	11.85

Table 3: Performance statistics of models for initial rotation stiffness prediction

		Training		Testing		All Elements	
Type of Joint	Model	R	MAE	R	MAE	R	MAE
Bolted Endplate Joint	GP/SA	0.9831	15.31	0.9970	3.62	0.9836	9.56
	Eurocode 3	0.9788	16.53	0.9678	7.01	0.9778	14.95
Bolted Joints with Angles	GP/SA	0.9781	2.83	0.9998	1.31	0.9784	2.55
	Kishi *et al.*	0.9409	6.56	0.9986	4.77	0.9271	6.16

Performance statistics of models for initial rotation stiffness prediction are presented in Table 3. It can be seen from this table that GP/SA model has better performance than the other models on training, testing and all element test data for all joint types. Table A.1 and A.2 of the appendix show a comparative analysis of results of the GP/SA and other available models including experimental values of flexural resistance and initial rotation stiffness, with the name and reference source of each test.

CONCLUSIONS

In this paper, the first application of a hybrid search algorithm that combines GP and SA, called GP/SA, to the flexural resistance and initial rotation stiffness prediction of semi-rigid joints is presented along with its performance comparisons.

The GP/SA based models are developed based on experimental results collected from literature. The geometrical characteristics and mechanical properties of joints were used as inputs to the models. The results of GP/SA models were compared with the experimental results, related design code (Eurocode 3) and other existing models.

The values of performance measures for the models indicate that the proposed GP/SA models give very reliable estimates of target values. The results demonstrate that for the prediction of flexural resistance and initial rotation stiffness of beam- column steel joints, GP/SA based models produce better results than the other models. In addition to acceptable accuracy, GP/SA, unlike most of available models such as ANNs, is a white-box model that provides the transparent programs of an imperative language or machine language. These programs can be easily inspected and evaluated. However, GP/SA is a very promising approach that can be utilized in order to assess the underlying relationship between the different interrelated input and output data for many of civil engineering tasks.

APPENDIX

Table A. 1: Results of GP/SA vs. experimental and other models results (Bolted endplate joint)

Test	Ref.	$M_{j,Rd\ EXP}$ (kN.m)	$M_{j,Rd\ EC3}$ (kN.m)	$M_{j,Rd\ EC3}$ / $M_{j,Rd,\ EXP}$	$M_{j,Rd\ GP/SA}$ (kN.m)	$M_{j,Rd,\ GP/SA}$/ $M_{j,Rd,\ EXP}$	$S_{j,Rd\ EXP}$ (kN.m)	$S_{j,Rd\ EC3}$ (kN.m)	$S_{j,Rd,\ EC3}$/ $S_{j,Rd,EXP}$	$S_{j,Rd\ GP/SA}$ (kN.m)	$S_{j,Rd,\ GP/SA}$ $S_{j,Rd,\ EXP}$
T110001	[9]	785.00	558.84	0.71	599.30	0.76	490.39	388.35	0.79	450.31	0.82
T110002	[9]	488.70	547.27	1.12	517.30	1.06	137.94	124.64	0.90	150.52	1.45
T110005	[9]	535.00	581.20	1.09	550.25	1.03	135.15	131.89	0.98	200.98	1.49
T109003	[10]	155.10	116.12	0.75	122.46	0.79	18.75	32.57	1.74	17.36	0.93
T109004	[10]	188.10	188.90	1.00	185.03	0.98	74.14	62.76	0.85	63.42	0.86
T109005	[10]	311.70	270.60	0.87	259.14	0.83	67.92	84.21	1.24	63.32	0.93
T109006	[10]	354.70	330.62	0.93	324.48	0.91	115.70	127.78	1.10	84.55	0.73
T101004	[4]	54.10	46.07	0.85	49.75	0.92	13.29	12.32	0.93	19.35	1.46
T101007	[4]	52.60	56.25	1.07	48.48	0.92	21.28	12.20	0.57	19.33	0.91
T101010	[4]	96.40	85.95	0.89	108.51	1.13	25.32	23.47	0.93	29.29	1.16
T101013	[4]	51.00	53.19	1.04	54.09	1.06	12.74	8.57	0.67	14.50	1.14
T101014	[4]	50.60	56.86	1.12	48.06	0.95	16.16	8.63	0.53	20.85	1.29
T839	[2]	99.20	91.71	0.92	95.92	0.97	33.10	57.43	1.74	36.25	1.10
T8310	[2]	127.80	166.01	1.30	151.68	1.19	52.22	81.30	1.56	47.36	0.91
T8311	[2]	231.30	222.70	0.96	212.94	0.92	29.38	63.08	2.15	36.01	1.23
T911	[7]	196.90	214.57	1.09	201.86	1.03	55.29	63.58	1.15	50.87	0.92
T912	[7]	200.00	223.46	1.12	194.65	0.97	72.31	65.35	0.90	66.58	0.92
T913	[7]	392.00	288.72	0.74	303.86	0.78	85.45	129.70	1.52	65.08	0.76
TC5	[8]	70.50	47.21	0.67	60.26	0.85	6.18	8.85	1.43	7.80	1.26
TC6	[8]	63.10	54.68	0.87	50.58	0.80	6.68	9.07	1.36	7.80	1.17
TC7	[8]	61.50	47.21	0.77	65.26	1.06	8.60	9.73	1.13	7.80	0.91
TC8	[8]	63.20	67.22	1.06	61.01	0.97	7.33	10.03	1.37	7.80	1.06
TC9	[8]	55.90	47.21	0.84	40.26	0.72	7.13	12.26	1.72	7.80	1.10
TC10	[8]	63.80	54.68	0.86	51.01	0.80	4.57	12.69	2.78	5.80	1.27
TC12	[8]	62.80	47.21	0.82	60.26	1.05	4.73	13.98	2.27	7.80	1.27

Bold sets are test sets

Table A.2: Results of GP/SA *vs.* experimental and other models results (Bolted Joints with Angles)

Test	Ref.	$M_{j,Rd\ EXP}$ (kN.m)	$M_{j,Rd\ EC3}$ (kN.m)	$M_{j,Rd\ EC3}$ / $M_{j,Rd,\ EXP}$	$M_{j,Rd\ GP/SA}$ (kN.m)	$M_{j,Rd,\ GP/SA}$/ $M_{j,Rd,\ EXP}$	$S_{j,Rd\ EXP}$ (kN.m)	$S_{j,Rd\ Kishi\ et\ al.}$ (kN.m)	$S_{j,Rd,\ Kishi\ et\ al.}$ / $S_{j,Rd,EXP}$	$S_{j,Rd\ GP/SA}$ (kN.m)	$S_{j,Rd,\ GP/SA}$ $S_{j,Rd,\ EXP}$
8S1	[5, 6]	37.20	29.2	0.78	40.68	1.09	7.54	5.61	0.74	8.49	1.13
8S2	[5, 6]	43.40	39.6	0.91	45.68	1.05	13.94	10.37	0.74	12.49	0.90
8S3	[5, 6]	47.70	36.4	0.76	42.03	0.88	11.83	7.48	0.63	15.38	1.30
8S4	[5, 6]	18.60	15.3	0.82	21.07	1.13	1.73	0.39	0.22	1.40	0.81
8S5	[5, 6]	38.10	33.6	0.88	38.05	1.00	8.67	5.08	0.59	9.97	1.15
8S6	[5, 6]	27.60	29.2	1.06	31.68	1.15	4.46	2.08	0.47	5.31	1.19
8S7	[5, 6]	43.00	27.1	0.63	38.05	0.88	5.42	3.81	0.70	6.27	1.16
8S8	[5, 6]	42.90	31.6	0.74	38.97	0.91	7.90	7.15	0.91	8.03	1.02
8S9	[5, 6]	47.80	42.2	0.88	46.82	0.98	11.80	13.25	1.12	12.92	1.18
8S10	[5, 6]	71.60	64.5	0.90	64.67	0.90	48.20	35.56	0.74	43.44	0.90
14S1	[5, 6]	77.70	61.3	0.79	82.60	1.06	22.03	14.37	0.65	22.30	1.01
14S2	[5, 6]	107.00	129.2	1.21	110.55	1.03	33.33	37.49	1.12	40.09	1.20
14S3	[5, 6]	73.90	52.0	0.70	63.48	0.86	13.09	14.37	1.10	13.92	1.06
14S4	[5, 6]	92.90	87.1	0.94	82.60	0.89	25.07	14.37	0.57	22.30	0.89
14S5	[5, 6]	86.20	64.5	0.75	97.56	1.13	27.90	17.13	0.61	22.30	0.80
14S6	[5, 6]	119.00	103.8	0.87	130.57	1.10	32.30	44.83	1.39	40.09	1.24
14S8	[5, 6]	176.40	150.6	0.85	163.41	0.93	65.40	79.95	1.22	63.03	0.96
14S9	[5, 6]	115.70	103.8	0.90	118.60	1.03	29.20	44.83	1.54	33.36	1.14

Bold sets are test sets

REFERENCES

1. CEN, Eurocode 3, May 2003 EN1993-1-8: Design of Joints, CEN, European Committee for Standardization, Brussels, pp: 124.
2. Zoetemeijer, P. and H. Munter, 1983. Extended Endplate with Disappointing Rotation Capacity: Test Results and Analysis. Report 6-75-20 KV-4, University of Technology, Delft.
3. Kishi, N., W.F. Chen and K.G. Matsuoka, 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.
4. Janss, J., J.P. Jaspart and R. Maquoi, 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.
5. Azizinamini, A., J.H. Bradburn and J. Radziminski, 1987. Initial Stiffness of Semi-Rigid Steel Beam-to-Column Joints. J. Constr. Steel Res., 8: 71-90.
6. Azizinamini, A. and J. Radziminski, 1989. Static and Cyclic Performance of Semi-Rigid Steel Beam-to-Column Joints. J Struct Eng-ASCE, 115, Nº 12.
7. Simek and F. Wald, 1991. Test Results on Endplate Beam-to-Column Joints. CTU, G-1121 Report. Prague.
8. Aggarwal, A.K., 1994. Comparative Tests on end Plate Beam-to-Column Joints. J. Constr. Steel Res., 30: 151-175.
9. Faella, C., V. Piluso and G. Rizzano, 1999. Structural Steel Semi-Rigid Joints - Theory, Design and Software. CRC Press, pp: 505.
10. Hummer, C. and T. Tschemmernegg, A Non-Linear Joint Model for the Design of Structural Steel Frames. Costruzioni Metalliche, No. 1.
11. Simões, R., L. Simões da Silva and P. Cruz, 2001. Behaviour of End- Plate Beam-to-Column Composite Joints Under Cyclic Loading. Steel Compos Struct, 1, No. 3: 355-376.
12. Haykins, S., 1999. Neural networks – A comprehensive foundation (2nd Ed.). Prentice Hall International Inc., Englewood Cliffs (NJ).
13. Abdala, K.M. and G.E.A. Stavroulakis, 1995. Back propagation Neural Network Model for Semi-Rigid Joints. Microcomputers in Engineering, 10: 77-87.
14. Stavroulakis, G.E. and K.M. Abdala, 1994. A systematic Neural Network Classificator in Mechanics. Application in Semi-Rigid Steel joints, International Journal of Engineering Analysis and Design, 1: 279-292.
15. Anderson, D., E.L. Hines, S.J. Arthur and E.L. Eiap, 1997. Application of Artificial Neural Networks to the Prediction of Minor Axis Joints", Computers and Structures, 63(4): 685-692.
16. de Lima, L.R.O., P.C.G. da S. Vellasco, S.A.L. de Andrade, J.G.S. da Silva and M.M.B.R. Vellasco, 2005. "Neural Networks Assessment of Beam-to-Column Joints," Journal of the Brazilian Society of Mechanical Sciences, Vol. XXVII, No. 3, pp: 314-3243.
17. Koza, J.R., 1992. Genetic programming: On the programming of computers by means of natural selection. Cambridge (MA): MIT Press.
18. Banzhaf, W., P. Nordin, R. Keller and F. Francone, 1998. Genetic Programming – An Introduction: On the Automatic Evolution of Computer Programs and Its Application. Heidelberg/San Francisco: Morgan Kaufmann.
19. Bäck, T., 1996. Evolutionary Algorithms in Theory and Practice: Evolution Strategies, Evolutionary Programming, Genetic Algorithms. USA: Oxford University Press.
20. Gandomi, A.H., A.H. Alavi, S. Kazemi and M.M. Alinia, 2008. Behavior appraisal of steel semi-rigid joints using Linear Genetic Programming. Journal of Constructional Steel Research, Submitted in the revised form.
21. Ashour, A.F., L.F. Alvarez and V.V. Toropov, 2003. Empirical modelling of shear strength of RC deep beams by genetic programming. Comput and Struc, 81(55): 331-338.
22. Alavi, A.H., AH. Gandomi, M. Gandomi, MG. Sahab, 2008. A data mining approach to compressive strength of CFRP Confined Concrete Cylinders. Computers & Structures, Submitted in the revised form.
23. Alavi, AH., A.A.R. Heshmati, A.H. Gandomi, A. Askarinejad and M. Mirjalili, 2008. Utilisation of Computational Intelligence Techniques for Stabilised Soil. In: M. Papadrakakis and BHV. Topping editors. Proceedings of the 6th International Conference on Engineering Computational Technology, Civil-Comp Press, Stirlingshire, United Kingdom, paper 175.
24. Gandomi, AH., AH. Alavi, MG. Sahab and M. Vesali, 2008. A Combined Algorithm of Genetic Programming and Simulated Annealing to obtain Tangent Elastic Modulus of concrete. The IES Journal Part A: Civil & Structural Engineering, Submitted for publication.
25. Metropolis, N., A.W. Rosenbluth, M.N. Rosenbluth, A.H. Teller and E. Teller, 1953. Equation of State Calculations by Fast Computing Mechanics. J. Chem. Physics., 21(6): 1087-1092.

26. Kirkpatrick, S., C.D. Jr. Gelatt and M.P. Vecchi, 1983. Optimization by simulated annealing. Sci., 220 (4598): 671-680.
27. Cerny, V., 1985. Thermodynamical Approach to the Traveling Salesman Problem: An Efficient Simulation Algorithm. J. Opt. Theory Appl., 45: 41-52.
28. Kita, H., 1997. Simulated Annealing. Japan Society for Fuzzy, Theory and Intelligent Informatics, 9, no. 6: 870-875.
29. Aarts, E., 1989. Simulated Annealing and Boltzmann Machines: A Stochastic Approach to Combinatorial Optimization and Neural Computing. Wiley, New York.
30. Ingber, L., 1993. Simulated Annealing: Practice versus theory. J Math Comput Model, 18(11): 29-57.
31. Folino, G., C. Pizzuti and G. Spezzano, 2000. Genetic Programming and simulated Annealing: A hybrid method to evolve decision trees. In Riccardo Poli and Wolfgang Banzhaf and William B. Langdon and Julian F. Miller and Peter Nordin and Terence C. Fogarty editors, Genetic Programming, Proceedings of EuroGP'2000, Edinburgh, Springer-Verlag, 1802: 294-303.
32. 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.
33. Silva, L.S. da and A.M.G. Coelho, 2001. Ductility Model for Steel Joints. J. Constr. Steel Res., 57: 45-70.
34. Francone, F., 2004. Discipulus Lite™ Owner's Manual, Version 4.0. Register Machine Learning Technologies.