Automated Design of Steel Columns Under Axial Compression Using Genetic Algorithm

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Abstract. This paper is concerned with the automated design of steel columns with W or I cross section geometry, using Genetic Algorithm optimization. Provided with basic design parameters, the algorithm automatically search for the optimal cross section shape and deliver the most suitable solution, constrained or not by the commercial shapes available. In order to show the efficiency and reliability of the algorithm, some benchmark examples were provided. Based on the results and the analysis, the automated design algorithm proved to be a faster and reliable alternative for designing steel columns with equal load carrying capacity of conventional methods, under the Brazilian and international standards.

Keywords: Steel design, Columns, Genetic Algorithm and NBR8800.

1 Introduction

The high competitive market of the construction sector require from companies and edge over their competitors, mainly sought by providing more economical designs or higher productivity. The economical design can be easily implemented on steel elements, since its production is highly standardized and more suitable to optimization procedures.

In the optimization of structural elements, regardless of the material, a common design objective is the minimization of self-weight while satisfying load capacity and serviceability constraints. The optimization procedure can be based on formal mathematical programming, such as the works of Templeman and Yates [1] and Zhu [2]; or based on principles of stochastic search, like the works of Seaburg and Salmon [3] and Tran and Li [4]. The stochastic search can be easily applied to discrete problems as a main tool of the Genetic Algorithm.

A number of researches have proposed applying optimization methods to shape selection and design in general, most of them considering evolutionary algorithms. Lee et al. [5] used genetic algorithms to search for optimal channel cross section dimensions for cold-formed steel columns under axial compression and Lee et al. [6] applied the same approach for beams under uniformly distributed loads. Penalties were employed in the objective function for violating constraints from the AISI specification [7]. Leng et al. [8] assumed a more complex approach, coupling of optimization algorithms with Direct Strength Method (DSM) and open source software package CUFSM for the design of cold-formed steel columns. The results were promising although not well suited for design automation, since unpractical shapes are obtained.

Therefore, there is a clear need for efficient optimization procedures following the Brazilian standards, mainly for steel structures, in order to help Brazilian engineers to efficiently design steel columns under basic design premises.

This paper aims to optimize steel columns designated shapes by adjusting the size of the W or I cross section (depth, width and thickness) subjected to basic design constraints, in order to obtain a minimum cross section area and thus minimized the weight and consequently the cost. Empowered with the Genetic Algorithm capabilities, the approach can rapidly design columns and select the most suitable available cross section from the commercial design tables, on an automated fashion.

2 Design of steel columns under axial load

This section follows the Brazilian design code for laminated steel structures [9], which is very similar to USA design code ANSI/AISC 360-05 [7]. Hence, a similar approach can be used for both codes. The design procedure will be programmed into a MATLAB routine and used later for optimization. Only the Ultimate Limit State is considered on the routine. The slenderness ratio is given by

$$\lambda = \frac{l_{ef}}{r} \ , \tag{1}$$

where l_{ef} effective length accounting for buckling and r is radius of gyration. the stress due to the applied axial compression load

$$\sigma_{cd} = \frac{N_c}{QA_g} \ , \tag{2}$$

in which Q is the reduction factor for local compression buckling, A_g is the cross-sectional area and N_c is the factored axial compression load. The reduction factor Q is 1 when local buckling is absent. Although, when $b/t > (b/t)_{lim}$, where b is the width and t is thickness of the element, Q assume different values and can be obtained on NBR8800 [9], also implemented in the design code. The effective non dimensional slenderness ratio

$$\lambda_0 = \lambda\sqrt{\frac{Qf_y}{\pi^2 E}} \ , \tag{3}$$

in which f_y specified minimum yield stress and E is the modulus of elasticity of steel. The reduction factor for axial compression for $\lambda_0 \geq 1.5$ is given by

$$\chi = \frac{0.877}{{\lambda_0}^2} \ , \tag{4}$$

and for $\lambda_0 < 1.5$

$$\chi = 0.688^{{\lambda_0}^2} \ . \tag{5}$$

Lastly, the design strength for axial compression

$$f_{cd} = \frac{\chi f_y}{\gamma_{a_1}} \tag{6}$$

can be used to perform a capacity check, where γ_{a_1} is the resistance factor to account for material uncertainties; usually $\gamma_{a_1} = 1.1$ in most cases.

3 Formulation of optimization problem

The aim of the numerical problem optimization is to minimize the objective function using the column design routine, by finding the optimal geometrical parameters b_f, t_f, t_w and h, for W sections, as show in Figure 1, such that the design capacities and limits are satisfied. This paper presents an optimization scheme which is based on optimal W cross section dimensions, although can be easily extended for other geometrical cross sections.

3.1 Objective function

The appropriate definition of objective functions has a considerable impact on the overall performance of the optimization process. This Section presents the objective functions considered in this paper, for the optimization of steel columns under axial compression load.

The defined objective function

$$\phi = \left| \frac{\sigma_{cd}}{f_{cd}} - 1 \right| \ , \tag{7}$$

in which σ_{cd} is the stress due to the axial load and f_{cd} is the design compression strength. Therefore, ϕ is always very close to zero, when optimal geometric values are obtained in the optimization. The routine, based on this objective function, is always searching for the closest cross sectional area presented in commercial design tables, leading to optimal section choices.

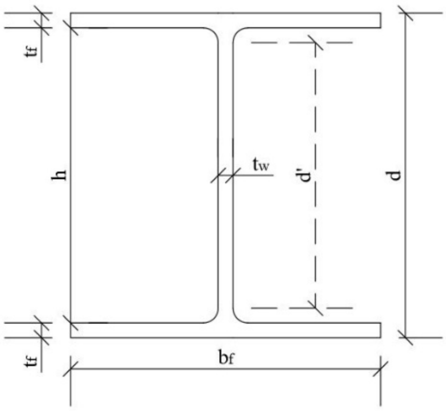

Figure 1. Geometrical parameters b_f, t_f, t_w and h of a W section.

3.2 Mathematical formulation

The mathematical formulation of the single-objective optimization scheme is defined as follows

$$
\begin{aligned}
\text{minimize} \quad & \phi(b_f, t_f, t_w, h) \\
\text{subject to} \quad & b_f = {b_f}^{min} \leq b_f \leq {b_f}^{max} \\
& t_f = {t_f}^{min} \leq t_f \leq {t_f}^{max} \\
& t_w = {t_w}^{min} \leq t_w \leq {t_w}^{max} \\
& h = h^{min} \leq h \leq h^{max} \\
\text{where} \quad & b_f = ({b_f}_1, {b_f}_2, ..., {b_f}_n) \in \boldsymbol{b_f} \\
& t_f = ({t_f}_1, {t_f}_2, ..., {t_f}_n) \in \boldsymbol{t_f} \\
& t_w = (t_{w1}, t_{w2}, ..., t_{wn}) \in \boldsymbol{t_w} \\
& h = (h_1, h_2, ..., h_n) \in \boldsymbol{h} \ ,
\end{aligned}
\tag{8}
$$

in which ϕ is the resulting geometrical parameter, as presented in subsection 3.1. For the single-objective optimization, the fitness function, that is the routine containing the design and capacity check for steel columns, should accept scalar values, and return a scalar (ϕ), the objective function. Although the routine follow the Brazilian design standards, the same approach could be easily applied to other codes, as seen in Lee et al. [6] and Lee et al. [5].

Genetic Algorithm (GA) optimization parameters, such as population size, selection function, scaling function and etc, are different in each optimization scheme and will be properly addressed in section 3.3.

3.3 GA implementation

Genetic Algorithm (GA) is part of evolutionary algorithms and are an optimization technique that is considered as a non-derivative global search heuristic. GA perform a search and optimization scheme that is motivated by the principles of natural genetics and natural selection, originally proposed by [10]. They are a robust and flexible approach that can be applied to a wide range of optimization problems, as seen in Kelner and Leonard [11], McCall [12] and more recently Oliveira et al. [13].

The approach of the automatic optimization of steel columns under axial compression requires initial data in order to run, named the axial compression (N_c) in kN, the steel yield stress (f_y) in MPa, the Modulus of elasticity of steel (E) in MPa and the effective length accounting for buckling (l_{ef}) in meters. The algorithm follows the scheme presented in Figure 2. The geometrical parameters of the W section b_f, t_f, t_w and h are optimized in a single-objective optimization process, considering the column design routine to evaluate ϕ as an objective function. In the end, the routine chooses the closest commercial W cross section between the ones available in the excel spreadsheet provided, based on the generic design variables obtained. The solution is unique for each problem depending on the initial input provided by the user.

The initial population is set to 400 individuals and is randomly generated. Then, the fitness function is calculated for each member of the population and scaled using a rank process, which is used in the selection. A

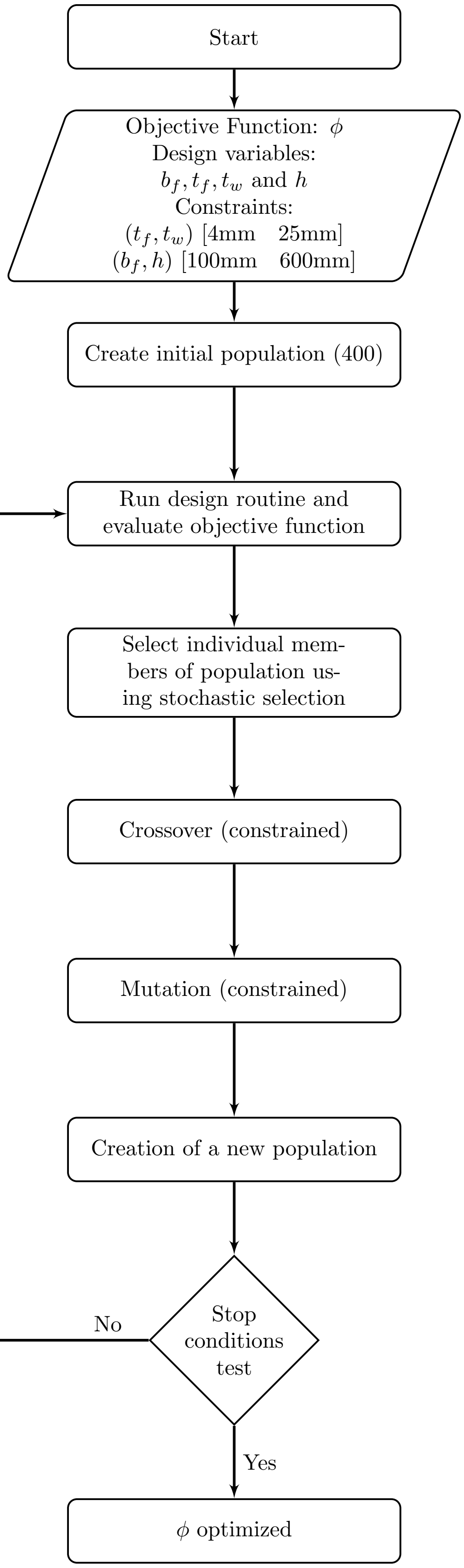

Figure 2. Flowchart of the routine defined for the fully automated column steel design. The optimization routine can be found at GitHub.

stochastic uniform selection is chosen as the reproduction operator. Both mutation and crossover are constraint dependent. Finally, the optimization process is terminated if the number of generations exceeds the predefined maximum number of 800, or if the average change in fitness function is less than 1×10^{-6}.

It is quite important to stress that the accuracy and the efficiency of the proposed algorithm are presented in a single and fully automated routine that can optimize a steel column and select the best W section without the need of any manual calculation or additional design parameter. The level of automation can be defined in the beginning of the algorithm, where you can select if you want individual scalar values for geometrical parameters, stiffened of unstiffened sections and even if you want to limit for specific sections; or the recommended option, fully automated results, yielding only the final selected section. Even faster results can be obtained with this routine by using the MATLAB parallel environment, which performs multiple analyses simultaneously.

4 Numerical results

This section presents numerical results to illustrate the accuracy and efficiency of the automated design routine, considering practical examples presented by Pfeil and Pfeil [14] and Geschwindner et al. [15]. All applications were performed using MATLAB 2019a on an Intel Core I7-4700MQ computer with CPU of 2.4GHz and 16 GB of RAM.

4.1 Example 5.8.1

Consider a W150 X 37.1 kg/m section of ASTM A36 steel ($E = 2.0 \times 10^4 kN/cm^2$ and $f_y = 25kN/cm^2$). Both extremities are simply supported (fixed) and the column is 3 meters tall. No buckling is allowed on y direction. The results obtained with the analysis are presented in Table 1 and Figure 3; where Pfeil are the results obtained by Pfeil and Pfeil [14], GA Generic are the results obtained by the design routine with generic design variables, GA Table are the results obtained by the design routine considering commercial tables (89 registered sections) and the column ”sections” represent the selected section by the authors or the algorithm.

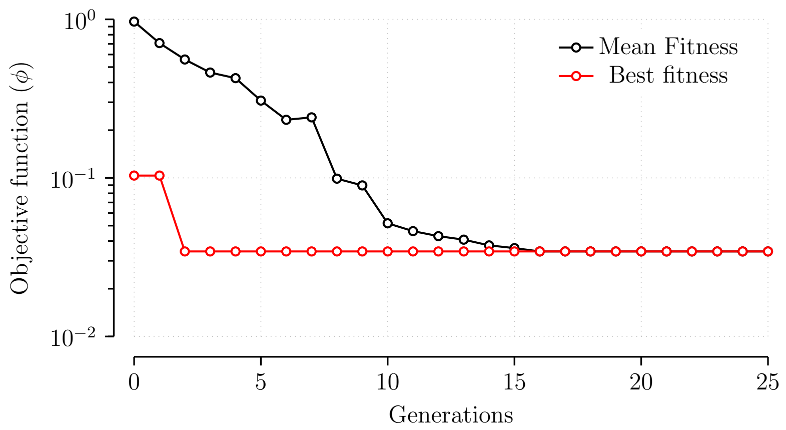

Figure 3. Performance of GA design routine for example 5.8.1. 400 individuals per iteration and 25 generations are considered.

Table 1. Comparison between the algorithm and the practical problem for example 5.8.1.

Method	Section	b_f (mm)	t_f (mm)	t_w (mm)	h (mm)	A_g (cm^2)	ϕ
Pfeil [14]	W150 X 37.1	154	11.6	8.1	139	48.85	0.022
GA Generic	Custom	239.41	6.11	4.46	209.64	38.6	3.05×10^{-8}
GA Commercial	W200 x 35.9 (H)	165	10.2	6.2	181	45.7	0.0176

The results show that all approaches obtained a satisfactory load carrying capacity, always very close to the maximum capacity, ensuring an efficient design. As expected, GA with generic values approach obtained the best result among all options.

The cross section area (A_g) was also close between different approaches, resulting in 26.55% more area for Pfeil and 18.4% for GA with commercial tables, when compared to GA with generic values. Moreover, not only the section selected by the GA with commercial tables is smaller than the section selected by Pfeil, it is also closer to the maximum capacity (1.7%) and therefore more accurate under the same problem conditions.

Figure 3 show that the optimization algorithm obtained the best fitness on the third generation. Also, convergence between mean fitness and best fitness was obtained after 16 generations, which is a good metric for well performed optimizations. The routine takes 4 seconds to get the best fitness and 28 seconds to finish 25 generations using parallel processing. The reduced computational effort highlight the improved performance of the automated routine when compared to traditional design methods.

4.2 Example 5.4

Lastly, consider a W10 X 49 lb/ft section of ASTM A992 steel ($E = 2.0 \times 10^4 kN/cm^2$ and $f_y = 34.5 kN/cm^2$). For y direction, one end is pinned and the other end is fixed and for x direction both ends are pinned. The results obtained with the analysis are presented in Table 2 and Figure 4; where Geschwindner are the results obtained by Geschwindner et al. [15], GA Generic are the results obtained by the design routine with generic design variables, GA Table are the results obtained by the design routine considering commercial tables and the column sections represent the selected section by the authors or the algorithm.

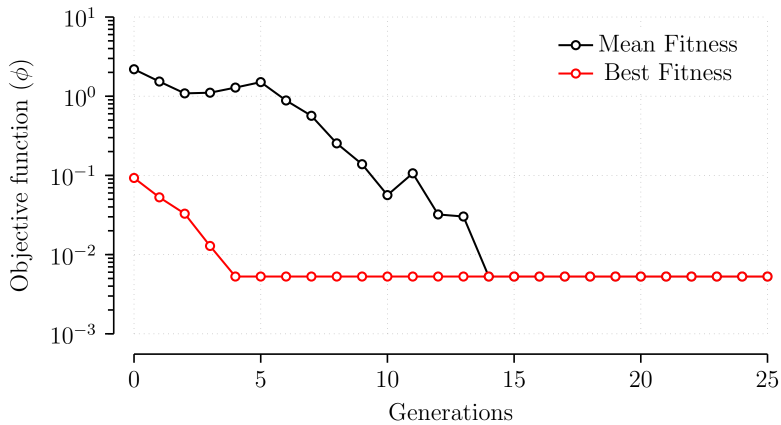

Figure 4. Performance of GA design routine for example 5.4. 400 individuals per iteration and 25 generations are considered.

Table 2. Comparison between the algorithm and the practical problem for example 5.4.

Method	Section	b_f (mm)	t_f (mm)	t_w (mm)	h (mm)	A_g (cm^2)	ϕ
Geschwindner [15]	W10 X 49	254	14.224	8.636	225.044	92.9	0.269
GA Generic	Custom	231.079	11.251	8.589	349	91.486	6.87×10^{-8}
GA Commercial	W 250 X 73 (H)	177	10.9	7.5	381	67.16	0.0053

Similar results are obtained with both routines, even when different design codes (NBR8800 [9] and ANSI/AISC 360-16 [7]) are considered, where all approaches obtained a satisfactory load carrying capacity. As expected, the only difference between the results are the standardized commercial sections available, since the design code is also similar. This result is of paramount importance and highlight the efficiency of the routine for Brazilian and international standards, requiring only changes in commercial tables for each region.

The best fitness was obtained on the fourth generation, as seen in Figure 4. Furthermore, convergence between mean fitness and best fitness was obtained after 14 generations, which is a good metric for well performed optimizations. The routine takes 8 seconds to get the best fitness and 49 seconds to finish 25 generations using parallel processing.

5 Conclusion

The automated design of steel columns with W or I cross section geometry, using Genetic Algorithm optimization was presented on this paper. When provided with basic design parameters for particular design problems, the algorithm automatically search for the optimal cross section shape and deliver the most suitable solution, constrained or not by the commercial shapes provided by the user.

Benchmark examples were provided to show the efficiency and reliability of the algorithm. In all examples and iterations a satisfactory load carrying capacity was achieved. Really accurate results were obtained using the optimization routine, both constrained and not constrained by commercial tables; getting the same or even better results than the original design. The efficiency was measure though computational effort during the optimization process. The automated design routine obtained really fast results, requiring only 3 to 4 generations to obtain the best values for b_f, t_f, t_w, h and also choosing the best section between 89 options available. The last example show the minimum difference between the Brazilian design code (NBR8800 [9]) and the USA design code (ANSI/AISC 360-16 [7]), which could greatly increase the scope of the automated routine.

All in all, based on the results and the analysis presented, the automated design algorithm proved to be a faster and reliable alternative for designing steel columns, with equal load carrying capacity of conventional methods and proven efficiency, under the Brazilian standards.

The MATLAB routine and design tables developed during this paper are available at GitHub.

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