

## Optimization of the cross section of car lift column under pressure load using genetic algorithms

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### Abstract

Car elevators are responsible for lifting car to specific height. These sets are so necessary for firms which are related to manufacturing, servicing and mending of cars. In this article, two columns elevators under the pressure load were investigated and optimization process with respect to the forces and momentums to the column was performed based on Genetic Algorithms and the optimum parameters of the cross section have been obtained. After offering the optimum parameters, the effects of these parameters on the column maximum pressure tolerance has been investigated. In the optimization process, the cross section was assumed to be with lips. Results of numerical calculations for optimization are presented in tables and figures.

**Keywords:** Car elevator, compressive force, genetic algorithms

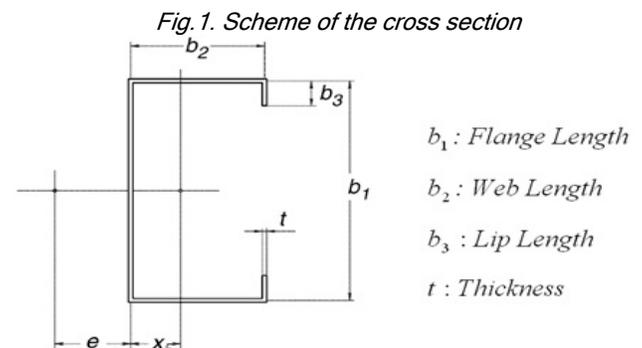
### Introduction

Car elevators play very important role in industry. Different kinds of these elevators have been planed and built and two-column elevators are the most widely used. In this case, after locating the car between two columns, jack arms locate on the floor of the car and by controlling the arms in vertical side, the car can be retain in a suitable height. The length of arms in these elevators is different. This length discrepancy is due to weight difference on the front and rear axle. The front axle weight of car that is usually heavier, places on the small arm and rear axle weight that is less, places on the big arm. In this situation, the side torque due to column length discrepancy, is very minimal and negligible. Important parts of the double column jacks are: columns, arms and power supply systems. In this kind of elevators, columns bear compression, bending or bending-compression. For every kind of elevators, one of these forces might be used. Arm is responsible to place under the car and supply power for raising the car. Lift power used in two-column jacks can be hydraulic or cable type. Each kind of these systems, forces different loading on column. In two-column elevators, the weight of car forces on the arm. The arm is attached to the jugular that has sliding motion within the column. Because of this the cross section of column should be open. This open section is different in various elevators, but what is nearly common in all elevators is the open shape of the column.

Vinot *et al.* (2008) presented a methodology for optimizing the shape of thin-walled structures. Magnucki (2002) studied optimization of an open cross-section of a thin-walled beam with flat web and circular flange analytically and numerically. Knowledge-based global optimization of cold-formed steel columns under pure axial compression was presented by Liu *et al.* (2009). In result of the study, five anti-symmetrical open cross-

sections were proposed. Theoretical and experimental study on the minimum weight of cold-formed channel thin-walled beams with and without lips were analyzed by Tian and Lu (2004). Optimum design of cold-formed steel channel beams under uniformly distributed load using micro Genetic Algorithm was presented by Lee *et al.* (2005). Global optimization of cold-formed steel thin-walled beams with lipped channel sections were described by Tran and Li (2006). Optimal design of open cross sections of cold-formed thin-walled beams with respect to the dimensionless objective function as the quality measure was presented by Magnucki and Ostwald, (2005a), Magnucki *et al.* (2006a,b), Kasperska *et al.* (2007), Ostwald *et al.* (2007), Manevich and Raksha, (2007) described bicrite- rial optimal design of open cross-sections of cold-formed beams. Strength, global and local buckling and optimization problems of cold-formed thin-walled beams with open cross-sections were collected and described by Magnucki and Ostwald, (2005b).

In the present article, the optimization using genetic algorithms was carried out and the cross section's parameters were obtained. Fig. 1 shows the cross section of the column which was considered in this paper.



### Modeling for optimization of the column under compressive force

There are many relationship to survey columns with ideal fulcrum condition in engineering sciences, but this condition never exist in practice, so the designing of column is done according to the relations that are fully accepted in laboratory results.

Following equation was presented about buckling of columns by Euler in 1757 where  $P$  is critical load (Tian and Lu, 2004):

$$\frac{\pi}{2} = \frac{L}{2} \sqrt{\frac{P}{EI}} \quad (1)$$

According to Fig.1, an open cross section of elevator column was considered. The weight of the section and normal stress were obtained as below:

$$w = ptL(b_1 + 2b_2 + 2b_3) \quad (2)$$

$$\sigma = \frac{P}{(b_1 + 2b_2 + 2b_3)t} \quad (3)$$

In order to yield didn't occur in cross section, normal stress should be less than yielding stress ( $\sigma \leq \sigma_y$ ). The range of  $\sigma_y$  for steel is relatively broad ( $100MPa \leq \sigma_y \leq 350MPa$ ). here  $\sigma_y = 280MPa$  is considered. For a long column with open section, flexural buckling force,  $P_e$ , can be obtained along two directs  $x$  and  $y$  by Euler equation:

$$P_{ex} = \frac{\pi^2 EI_x}{(KL)^2} \quad (4)$$

$$P_{ey} = \frac{\pi^2 EI_y}{(KL)^2} \quad (5)$$

In these equations,  $K$  is effective length coefficient. For simple fulcrum  $K=1$  and for tangly fulcrum  $K=0.7$ .  $I_x$  and  $I_y$  are the surface torque respectively. By calculating and putting  $I_x$  and  $I_y$  in above equations, normal stress constrain in Euler equation is obtained as follow:

$$\sigma \leq \sigma_{ex} = \frac{\pi^2 E}{(KL/r_x)^2} \quad (6)$$

$$\sigma \leq \sigma_{ey} = \frac{\pi^2 E}{(KL/r_y)^2} \quad (7)$$

Where  $r_x$  and  $r_y$  are radius of gyration around  $x$  and  $y$  axes. According to the Fig. 1, the distance between center of surface and central line was obtained as below:

$$x_c = \frac{b_2(b_2 + 2b_3)}{b_1 + 2b_2 + 2b_3} \quad (8)$$

The distance between shear center and central line is given as following equation:

$$e = \frac{tb_2b_3b_1^2}{I_x} \left( \frac{1}{2} + \frac{b_2}{4b_3} - \frac{2b_3^2}{3b_1^2} \right) \quad (9)$$

Critical force of bending-torsion buckling for an open section column which is shown in Fig. 1 is given as follow:

$$P_{tf} = \frac{1}{2\beta} \left[ (P_{ex} + P_t) - \sqrt{(P_{ex} + P_t)^2 - 4\beta P_{ex} P_t} \right] \quad (10)$$

Where  $\beta = 1 - \left( \frac{x_0}{r_0} \right)^2$  and  $r_0 = \sqrt{r_x^2 + r_y^2 + x_0^2 + y_0^2}$

is polar radius of gyration around shear center ( $x_0, y_0$ ) and  $P_t$  is shear buckling force that can be obtained by following equation:

$$P_t = \frac{1}{r_0^2} \left[ GJ + \frac{\pi^2 EC_w}{(K_t L)^2} \right] \quad (11)$$

In this equation,  $J = \left( \frac{t^3}{3} \right) (b_1 + 2b_2 + 2b_3)$  is Saint-

Venant constant and  $G = \frac{E}{2(1+\nu)}$  is shear modulus.

$C_w = b_2^2 t (4b_3^3 + 3b_1^2 b_3 + 6b_1 b_3^2 + b_2 b_1^2) / 6 - I_x e^2$  is warping constant resulting from torque and  $K_t=1$  is effective length for torsional buckling.

Design constrains for minimization of the weight of the column that is under bending-torsion buckling were expressed as follows:

$$\sigma \leq \sigma_{tf} = \frac{\sigma_t \sigma_{ex}}{\sigma_t + \sigma_{ex}} \quad (12)$$

In this equation,  $\sigma_t = \frac{E}{\lambda}$  is critical stress obtained from torsion buckling.

Local buckling for an open cross section in three columns with same length  $L$  and different widths  $b_1, b_2$  and  $b_3$  have been investigated. To prevent local buckling, normal stress should be less than the minimum stress:

$$\sigma \leq \min(\sigma_{lb1}, \sigma_{lb2}, \sigma_{lb3}) \quad (13)$$

Where  $\sigma_{lbi} = \frac{k_i \pi^2 E (t/b_i)^2}{12(1-\nu^2)}, i = 1, 2, 3$

$K$  is the surface buckling coefficient. The optimization problem for compression condition can be modeled as follow:

$$w = ptL(b_1 + 2b_2 + 2b_3) \quad (14)$$

$$1 - \frac{P}{EL^2} \frac{E}{\sigma_y} \frac{L^2}{A} \geq 0 \quad (15)$$

$$1 - \frac{P}{EL^2} \frac{L^4}{I_y} \left( \frac{K}{\pi} \right)^2 \geq 0 \quad (16)$$



$$1 - \frac{P}{EL^2} \frac{L^2}{r_x^2} \left( \frac{K}{\pi} \right)^2 \frac{(G/E)(J/L^4) + (\pi/K)^2 (C_w/L^6) + (\pi/K)^2 (r_x^2 A r_0/L^6)}{(G/E)(J/L^4) + (\pi/K)^2 (C_w/L^6)} \geq 0 \quad (17)$$

$$1 - \frac{12(1-\nu^2)}{K_1 \pi^2} \frac{P}{EL^2} \frac{L^2}{A} \left( \frac{b_1}{t} \right)^2 \geq 0 \quad (18)$$

$$1 - \frac{12(1-\nu^2)}{K_2 \pi^2} \frac{P}{EL^2} \frac{L^2}{A} \left( \frac{b_2}{t} \right)^2 \geq 0 \quad (19)$$

$$1 - \frac{12(1-\nu^2)}{K_3 \pi^2} \frac{P}{EL^2} \frac{L^2}{A} \left( \frac{b_3}{t} \right)^2 \geq 0 \quad (20)$$

In this optimization,  $b_1$ ,  $b_2$ ,  $b_3$  and  $t$  are taken as decision variables and should be optimized.

### Genetic algorithms

A genetic algorithm (GA) is a search technique used in computing to find exact or approximate solutions to optimization and search problems (Konak *et al.*, 2006). This method is a particular class of evolutionary algorithms (EA) that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover (Deb, 2001). In nature, weak and unfit species within their environment are faced with extinction by natural selection. The strong ones have greater opportunity to pass their genes to future generations via reproduction. In the long run, species carrying the correct combination in their genes become dominant in their population. Sometimes, during the slow process of evolution, random changes may occur in genes. If these changes provide additional advantages in the challenge for survival, new species evolve from the old ones and unsuccessful changes are eliminated by natural selection (Konak *et al.*, 2006). In GA terminology, a solution vector  $x \in X$  is called an individual or a chromosome and chromosomes are made of discrete units called genes. Each gene controls one or more features of the chromosome. In the original implementation of GA by Holland, genes are assumed to be binary digits (Deb, 2001). In later implementations, more varied gene types have been introduced. Normally, a chromosome corresponds to a unique solution  $x$  in the solution space. This requires a mapping mechanism between the solution space and the chromosomes. This mapping is called an encoding. In fact GA works on the encoding of a problem, not on the problem itself. GA operates with a collection of chromosomes, called a population. The population is normally randomly initialized. As the search evolves, the population includes fitter and fitter solutions, and eventually it converges, meaning that it is dominated by a single solution. Holland also presented a proof of convergence (the schema theorem) to the global optimum where chromosomes are binary vectors. GA uses two operators to generate new solutions from existing ones: crossover and mutation. The crossover operator is the most important operator of GA. In crossover, generally two chromosomes, called parents, are combined together to form new chromosomes, called

offspring. The parents are selected among existing chromosomes in the population with preference towards fitness so that offspring is expected to inherit good genes which make the parents fitter. By iteratively applying the crossover operator, genes of good chromosomes are expected to appear more frequently in the population, eventually leading to convergence to an overall good solution. The mutation operator introduces random changes into characteristics of chromosomes. In typical GA implementations, the mutation rate (probability of changing the properties of a gene) is very small and depends on the length of the chromosome. Therefore, the new chromosome produced by mutation will not be very different from the original one. As discussed earlier, crossover leads the population to converge by making the chromosomes in the population alike. Mutation reintroduces genetic diversity back into the population and assists the search escape from local optima. Reproduction involves selection of chromosomes for the next generation. In the most general case, the fitness of an individual determines the probability of its survival for the next generation. Proportional selection, ranking, and tournament selection are the most popular selection procedures. The procedure of a generic GA is given as follows (Konak *et al.*, 2006):

Step 1: Set  $t = 1$ . Randomly generate  $N$  solutions to form the first population,  $P_1$ . Evaluate fitness of solutions in  $P_1$ .  
Step 2: Crossover: Generate an offspring population  $Q_t$  as follows:

2.1. Choose two solutions  $x$  and  $y$  from  $P_t$  based on the fitness values.

2.2. Using a crossover operator, generate offspring and add them to  $Q_t$ .

Step 3: Mutation: Mutate each solution  $x \in Q_t$  with a predefined mutation rate.

Step 4: Fitness assignment: Evaluate and assign a fitness value to each solution  $x \in Q_t$  based on its objective function value and infeasibility.

Step 5: Selection: Select  $N$  solutions from  $Q_t$  based on their fitness and copy them to  $P_{t+1}$ .

Step 6: If the stopping criterion is satisfied, terminate the search and return to the current population, else, set  $t = t+1$  go to Step 2.

### Optimization results and discussion

Optimization by means of genetic algorithms was performed in this section. The alloy used in column assumed to be steel with  $E = 207Gpa$ ,  $\nu = 0.3$  and

$\sigma_y = 60Mpa$ . The objective functions and constraints are modeled in equations 14-20 and decision variables are taken as  $b_1$ ,  $b_2$ ,  $b_3$  and  $t$ . In this work, axial force  $F$  is taken as  $26000N$ . The results of optimization based on genetic algorithms for cross section with lips are summarized in Table 1.

Stages of genetic algorithm to find optimal parameters are given in the Fig.2-Fig.5.

Fig 2. Optimized parameter  $b_1$

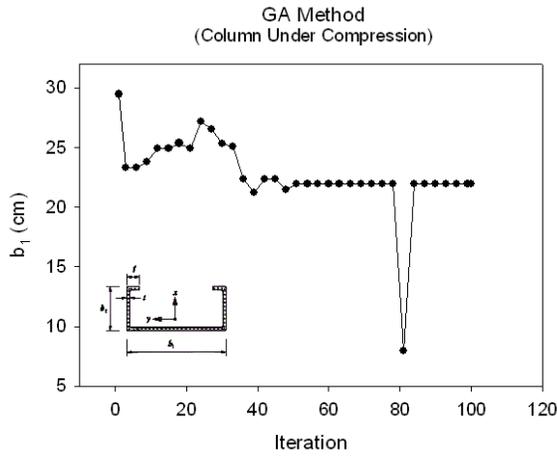


Fig 3. Optimized parameter  $b_2$

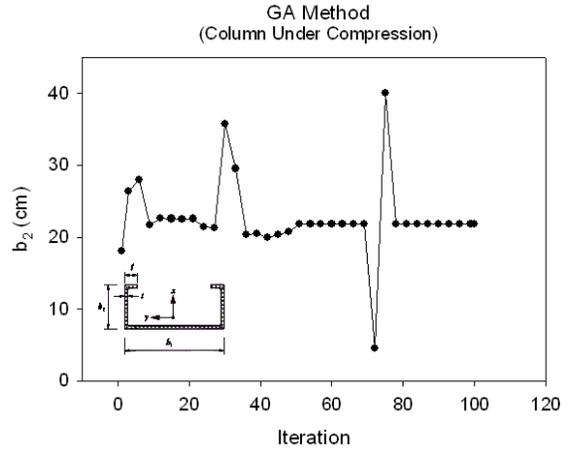


Fig 4. Optimized parameter  $b_3$

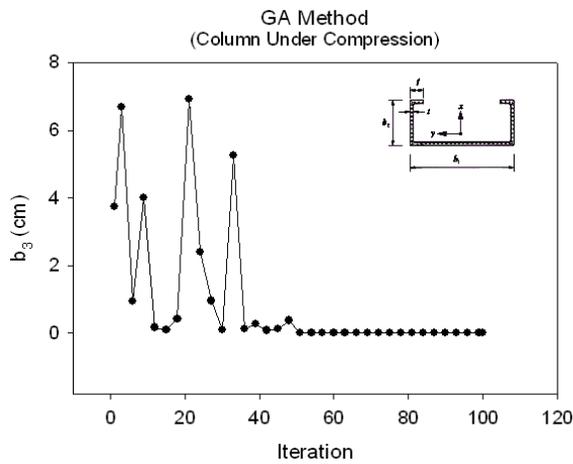


Fig 5. Optimized parameter  $t$

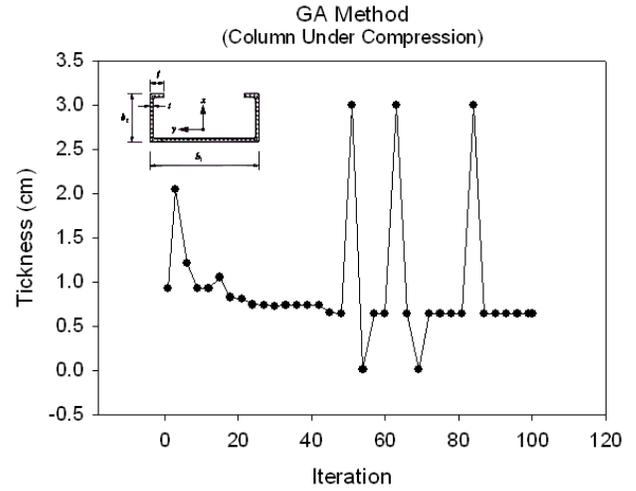


Fig 6. Optimized area of cross section

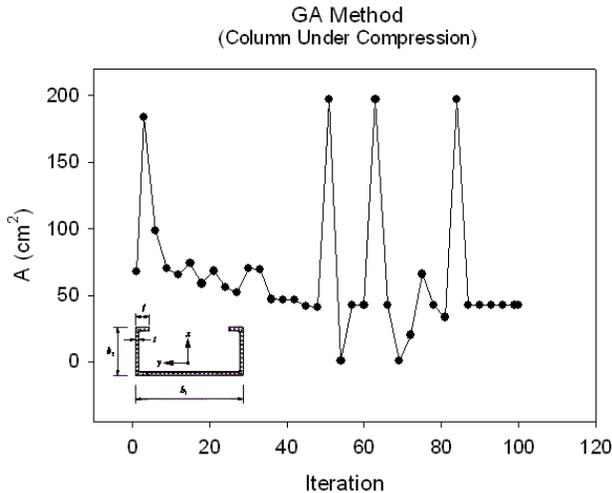


Fig 7. Critical axial force for variation in the cross section parameters

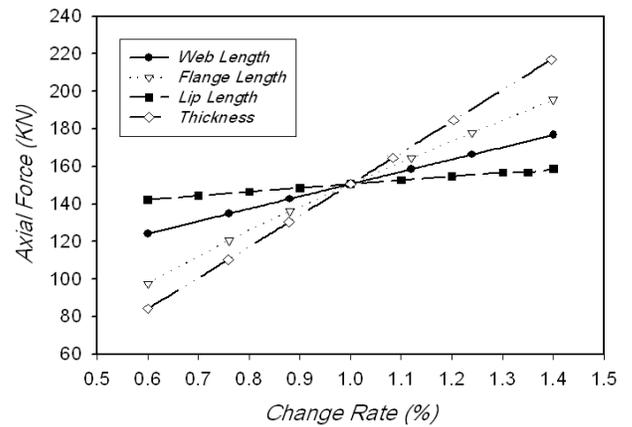


Table.1 optimized parameters in each iteration

Iteration	b <sub>1</sub>	b <sub>2</sub>	b <sub>3</sub>	t	A
1	29.4647	18.0825	3.737	0.9241	67.55513
3	23.3383	26.4255	6.6895	2.0482	183.4538
6	23.3104	27.9752	0.9306	1.2179	98.79848
9	23.8371	21.6914	3.997	0.9318	70.08431
12	24.925	22.6066	0.1664	0.9318	65.66488
15	24.925	22.5725	0.0896	1.0527	73.95133
18	25.37	22.4499	0.4041	0.8259	58.70332
21	24.9101	22.5766	6.9209	0.812	68.13094
24	27.1632	21.456	2.4083	0.7437	55.69703
27	26.542	21.3315	0.9578	0.7325	52.09584
30	25.3477	35.8005	0.1003	0.726	70.53039
33	25.1161	29.5229	5.2543	0.7324	69.33667
36	22.3911	20.3641	0.1268	0.7395	46.86426
39	21.215	20.5299	0.2648	0.7355	46.19264
42	22.3563	19.9063	0.0786	0.7397	46.10262
45	22.3911	20.3641	0.1268	0.6564	41.59797
48	21.5078	20.8108	0.3716	0.6452	41.2106
51	21.9819	21.895	0.0126	3	197.3913
54	21.9819	21.895	0.0126	0.01	0.657971
57	21.9819	21.895	0.0126	0.6452	42.45229
60	21.9819	21.895	0.0126	0.6452	42.45229
63	21.9819	21.895	0.0126	3	197.3913
66	21.9819	21.895	0.00001	0.6452	42.43604
69	21.9819	21.895	0.0126	0.01	0.657971
72	21.9819	4.5	0.0126	0.6452	20.00578
75	21.9819	40	0.0126	0.6452	65.81498
78	21.9819	21.895	0.0126	0.6452	42.45229
81	8	21.895	0.0126	0.6452	33.43117
84	21.9819	21.895	0.0126	3	197.3913
87	21.9819	21.895	0.0126	0.6452	42.45229
90	21.9819	21.895	0.0126	0.6452	42.45229
93	21.9819	21.895	0.0126	0.6452	42.45229
96	21.9819	21.895	0.0126	0.6452	42.45229
99	21.9819	21.895	0.0126	0.6452	42.45229
100	21.9819	21.895	0.0126	0.6452	42.45229

Next, the influence of the cross section parameters on the critical compressive force in column was investigated. Increase in the cross section parameters causes an increase in the critical axial force. Also the change in the thickness has the most influence of all the other parameters and lip length has a little effect on the column bearing pressure. Fig. 7 shows the axial bearing force for variation in cross section parameters.

### Conclusion

Optimization has been successfully performed for a cross section of a column in a two-column elevator using genetic algorithms principles and the optimized parameters of the cross section have been obtained. Change in the thickness has the most influence of all the

other parameters and lip length has a little effect on the column bearing pressure.

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### References

1. Deb K (2001) Multi objective optimization using evolutionary algorithms. NY, Wiley.
2. Kasperska R, Magnucki K and Ostwald M (2007) Bicriteria optimization of cold-formed thin-walled beams with monosymmetrical open cross-sections under pure bending. *Thin-Walled Structures*. 45, 563-572.
3. Konak A, Coit DW and Smith AE (2006) Multi- objective optimization using genetic algorithms: A tutorial. *Reliability Engineering and System safety*. 919, 992-1007.
4. Lee J, Kim SM, Park HS and Woo BH (2005) Optimum design of cold- formed steel channel beams using micro Genetic Algorithm. *Engineering Structures*. 27, 17-24.
5. Liu H, Igusa T and Schafer BW (2009) Knowledge-based global optimization of cold-formed steel columns, *Thin-Walled Structures*. 42, 785-801.
6. Magnucki K and Ostwald M (2005a) Optimal design of open cross-sections of cold-formed thin-walled beams. *Proc. 4th Intl. Conf. on Advances in Steel Structures*, Shanghai, China, Elsevier. pp:1311-1316.
7. Magnucki K, Maćkiewicz M and Lewiński J (2006a) Optimal design of a mono-symmetrical open cross-section of a cold-formed beam with sinusoidally corrugated flanges. *Thin-Walled Structures*. 44, 554-562.
8. Magnucki K, Rodak M and Lewiński J (2006b) Optimization of mono and anti-symmetrical I-section of cold-formed thin-walled beams. *Thin-Walled Structures*. 44, 832-836.
9. Manevich AI and Raksha SV (2007) Two-criteria optimization of H-section bars-beams under bending and compression. *Thin-Walled Structures*. 45,898-901.
10. Magnucki K and Ostwald M (2005b) *Optimal Design of Selected Open Cross-Sections of Cold-Formed Thin-Walled Beams*. Publishing House of Poznan University of Technology, Poznań.
11. Magnucki K (2002) Optimization of open cross-section of the thin-walled beam with flat web and circular flange, *Thin-Walled Structures*. 40, 297-310.
12. Ostwald M, Magnucki K and Rodak M (2007) Bicriteria optimal design of open cross-sections of cold-formed beams. *Steel & Composite Structures*. 7, 53-70.
13. Tian YS and Lu TJ (2004) Minimum weight of cold formed steel sections under compression. *Thin-Walled Structures*. 42, 515-532.
14. Tran T and Li L (2006) Global optimization of cold-formed steel channel sections. *Thin-Walled Structures*. 44, 399-406.
15. Vinot P, Cogan S and Piranda J (2008) Shape optimization of thin-walled beam-like structures. *Thin-Walled Structures*. 39, 611-630.