Analysis of optimization algorithm models for the design of prestressed steel beams

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Abstract. Prestressing in steel beams offers significant benefits in terms of structural efficiency and material savings. The aim of this study is to present a comparative analysis of the design results of prestressed steel beams obtained through three optimization algorithms: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and its variant, including a craziness operator for performance enhancement (CRPSO). These algorithms were used to minimize CO_2 emissions and cost in the structural design process, while adhering to the constraints imposed by ABNT NBR 8800:2008. The implementation was carried out using MATLAB (2016). The validation of the methodology was conducted using examples from the literature, comparing the CO_2 emissions and cost values obtained from experimental work and those derived from GA, PSO, and CRPSO. The results indicate that, although the Genetic Algorithm is widely used in optimization, more optimized results are achieved using PSO. Furthermore, the improvement obtained by CRPSO showed no significant deviation from those obtained by PSO, nor did it affect the convergence speeds of the results. It was also observed that all three implemented models yielded more optimized values of emissions and costs compared to those reported in the literature.

Keywords: Optimization algorithms; prestressed steel beams; CO_2 emissions; cost; structural design.

1 Introduction

In structural design, whether involving of reinforced or prestressed concrete or steel adhering to current standards is essential for ensuring user safety and comfort, in addition to delivering more economical and efficient solutions. Simultaneously, environmental impacts have been widely debated in all economic fields, including civil construction, both at the execution stage – with actions such as waste reduction, team training, and better material selection – and at the design stage, impacting the design of structures and leading to the search for more sustainable systems. In this context, optimization using metaheuristic algorithms has proven to be an effective strategy for achieving optimal outcomes that balance financial costs and environmental impacts.

Studies such as those by Santoro and Kripka [1], Tormen et al. [2], Payá-Saforteza et al. [3], Camp and Huq [4], Park et al. [5], Yepes et al. [6], and Yu et al. [7] indicate that optimizations focused only on financial cost may not be sufficient, necessitating an evaluation of the environmental impact throughout the material's life cycle. Among the various environmental effects caused by civil construction, CO_2 emissions stand out, with cement – the main material in civil construction – being the primary emitter (Oliveira et al. [8]).

Studies on externally prestressed steel and concrete composite beams, such as those by Nie et al. [9], Chen et al. [10], El-Sisi et al. [11], and Hassanin et al. [12], show that prestressing improves the performance of composite beams. Due to this superior performance, with the aim of reducing cement consumption and consequently CO_2 emissions, externally prestressed steel beams have become an alternative to steel and concrete composite beams for spanning large distances. These elements, besides not using concrete in their constitution, have facilitated maintenance as the tendons can be positioned externally to the element's cross-section. Regarding the structural efficiency of prestressed steel beams. Lou et al. [13] state that external prestressing is effective in reducing tension at the bottom of the central section of a simply supported steel beam. Meanwhile, Lou et al. [14] observe that external prestressing improves short-term structural behavior but has little effect in the long term.

The application of optimization techniques in structural elements has increased in recent decades, as observed in studies by Senouci and Al-Ansari [15], Erdal et al. [16], Hare et al. [17], Breda et al. [18], Arpini et al. [19], and Mousavi et al. [20]. Among these works, Tormen et al. [2] studied the minimization of CO_2 in steel and concrete composite beams, analyzing the concrete's compressive strength and the interaction between the slab and the steel beam. Santoro and Kripka [1] highlight that the use of high-strength concrete reduces CO_2 emissions for reinforced concrete columns but has less effect on beams. Abbas et al. [21] compared the optimization of prestressed and non-prestressed steel beams, noting that prestressed beams require a smaller cross-section. Aydin [22] optimized the costs of prestressed steel trusses using the Jaya algorithm, showing that prestressing reduced project costs.

Fiorotti et al. [23] implemented in the Matlab platform the optimization problem aimed at generating the design of prestressed steel beams according to ABNT NBR 8800:2008 [24], which produce the least environmental impact (lowest CO_2 emission) and lowest cost. In the mentioned work, beams with straight or polygonal tendons, as well as steel beams with monosymmetric and doubly symmetric sections, were implemented. It was concluded that the Genetic Algorithm provided more optimized results compared to literature results.

This work aims to enhance the program implemented by Fiorotti et al. [23] for the design of prestressed steel beams, which already featured the Genetic Algorithm (GA) for optimizing cost and emissions. The Particle Swarm Optimization (PSO) algorithm and its CRPSO variant were implemented to evaluate the efficiency of these additional algorithms in structural design and provide a comparative analysis between these three algorithms.

2 Methodological approach

In the program created by Fiorotti et al. [23], some data, such as the thickness of the flanges, were optimized as a continuous variable, which could take any value between 1.6 and 4.44 cm, while the thickness of the web of the profile was an input and was not being optimized. In this update, the web is also being optimized, and these thicknesses are now discrete variables, based on commercial plate thicknesses that can take the following values: 0.63, 0.8, 0.95, 1.25, 1.6, 1.9, 2.24, 2.5, 3.15, 3.75, 4.445, 5.0, 6.3, 7.5, 8.89, 10.0.

Another change is that for doubly symmetric profiles, the thickness of the flanges, which was also an input, has now become an optimized variable, making the entire cross-section optimal: width and thickness of the flanges, height, and thickness of the web.

Due to this update, the beam analysis by Abbas et al. [21] was repeated with the same Genetic Algorithm used by Fiorotti [23], and even more optimal values were obtained than before. These two methods are identified below as GA for the new analysis and GA-F for Fiorotti's [23] previous results.

In addition to these improvements, the PSO optimization method was added to the program, requiring the readjustment of objective functions and constraints. After this implementation, the algorithm was enhanced with the craziness coefficient, giving rise to CRPSO. This craziness coefficient is introduced to prevent the "particles" from getting stuck in local minima by making them exhibit "crazy" behavior, jumping to a new random position in the search space, which might be neglected by traditional PSO. This helps avoid the problem of premature convergence and increases the chances of finding the global optimal solution.

3 Results and discussions

To validate the new routines implemented, the model by Abbas et al. [21] was recalculated using the GA, PSO, and CRPSO algorithms. The beam tested by Abbas is simply supported, with input data from Table 1 and loading shown in Figure 1.

Table 1 – Input data for the example by Abbas et al. [21].

Span length L	22 m
Unbraced distance	0 m
Distance between stiffeners	22 m
Cable position	-5 cm
Cable support positioning	-10 cm
C_b	1
Profile cost	R$10.00/kg
Steel type	ASTM A36
Tendons diameter	9.5 mm
Tendons type	CP 190

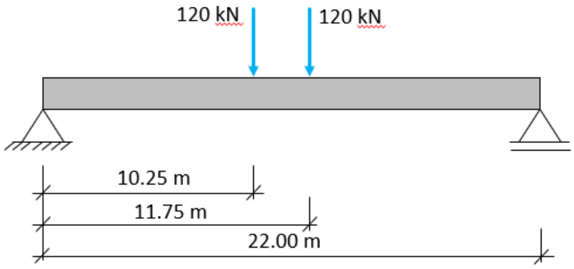
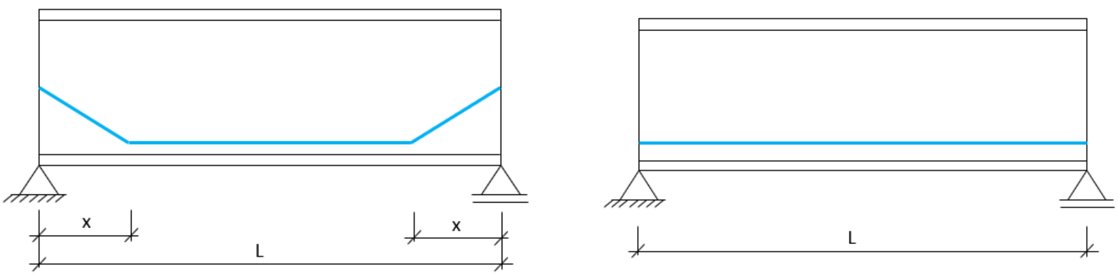


Figure 1 - Loads for Abbas example. Source: Fiorotti et al. [23]

These pieces of information served as the database for performing calculations, where the profile type varied between Monosymmetric (M) and Doubly symmetric (D), the tendons geometry, which could be Polygonal (P) or Straight (R), as exemplified in Fig. 2, and three values were adopted for prestressing losses: 0% (P0), 10% (P10), and 20% (P20), as done by Fiorotti et al. [23]. Thus, each combination has a code that defines the profile type (M or D), cable geometry (P or R), and the adopted value for prestressing losses (P0, P10, or P20), where the profile DR-P10, for example, represents the doubly symmetric profile, straight cable, with 10% prestressing loss. All these variations were calculated to optimize CO_2 emissions and cost.



(a) Polygonal cable (b) Straight cable

Figure 2 - Cable geometry. Source: Fiorotti et al. [23]

The obtained results were presented in the graphs of Figures 3 and 4 for CO_2 emission optimization results and cost optimization results, respectively. Results from Fiorotti et al. [23] and Abbas et al. [21] were also included, allowing us to conclude that all implemented models, for all combinations of geometries formed, generated more optimized results than those found by Abbas et al. [21]. Furthermore, it is possible to observe that the values Fiorotti et al. [23] used for the web and flange thicknesses in the design of doubly symmetric profiles (variables that were not optimized in their version) prevented the cost and emission results from being fully optimized. When comparing Fiorotti's [23] results indicated by the acronym AG-F and the results obtained by the altered genetic algorithm indicated by the acronym AG, it becomes evident that even more optimized values can be found.

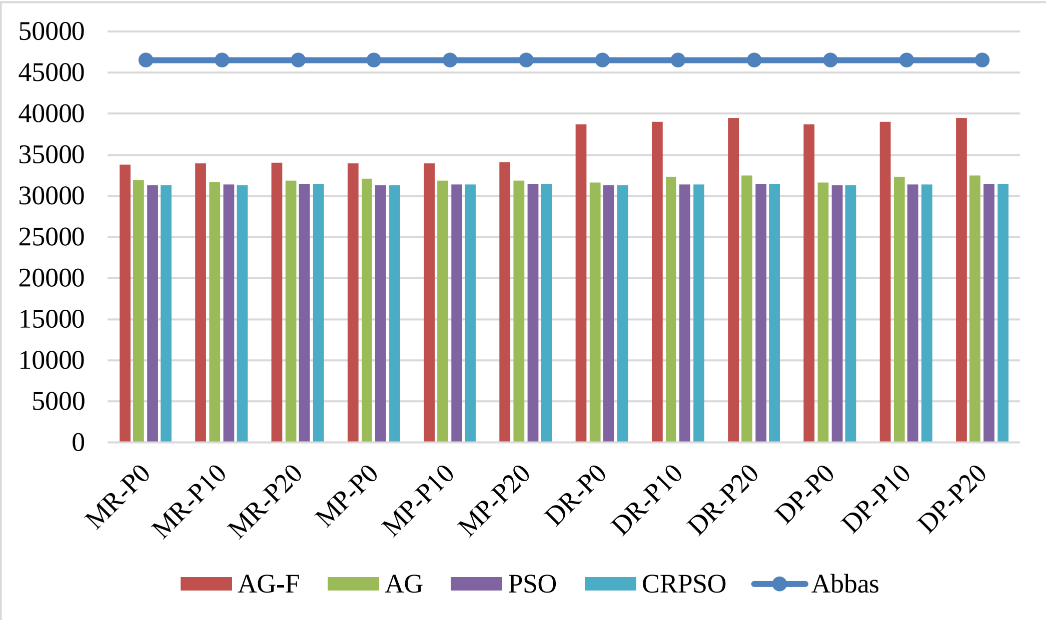


Figure 3 - Cost comparison results.

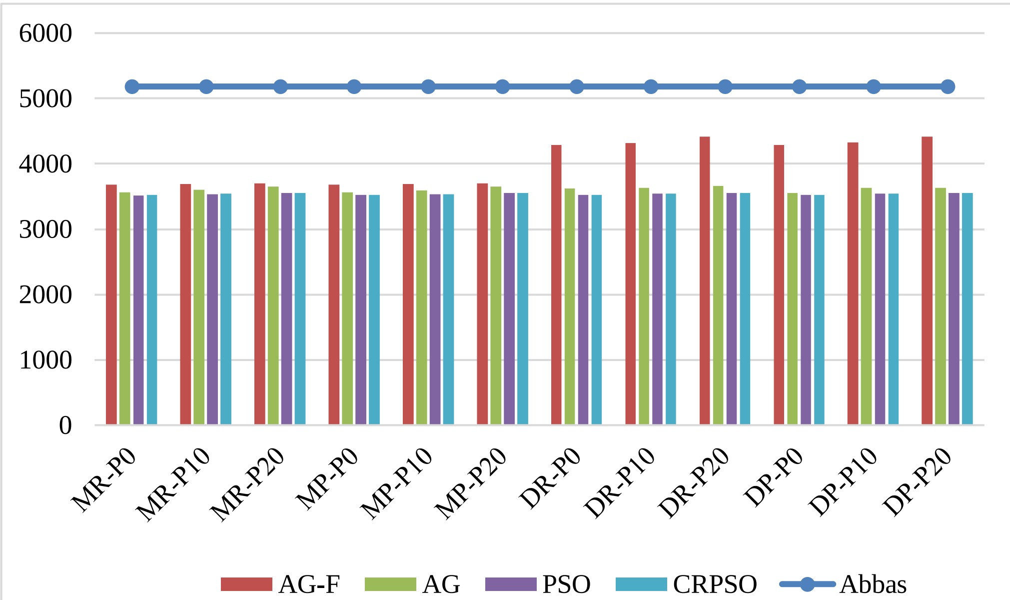


Figure 4 - Emission comparison results.

For all cases presented, it can be observed that particle swarm optimization algorithms, PSO and CRPSO, provided even better results than those obtained through genetic algorithms. With the graphs in Figures 5 and 6, it is noticeable that the largest variation found between the two methods is 0.17%. In the case of doubly symmetric profiles, which have 2 fewer variables, both methods converged. Therefore, it can be concluded that either of the two models has the potential to provide the same result.

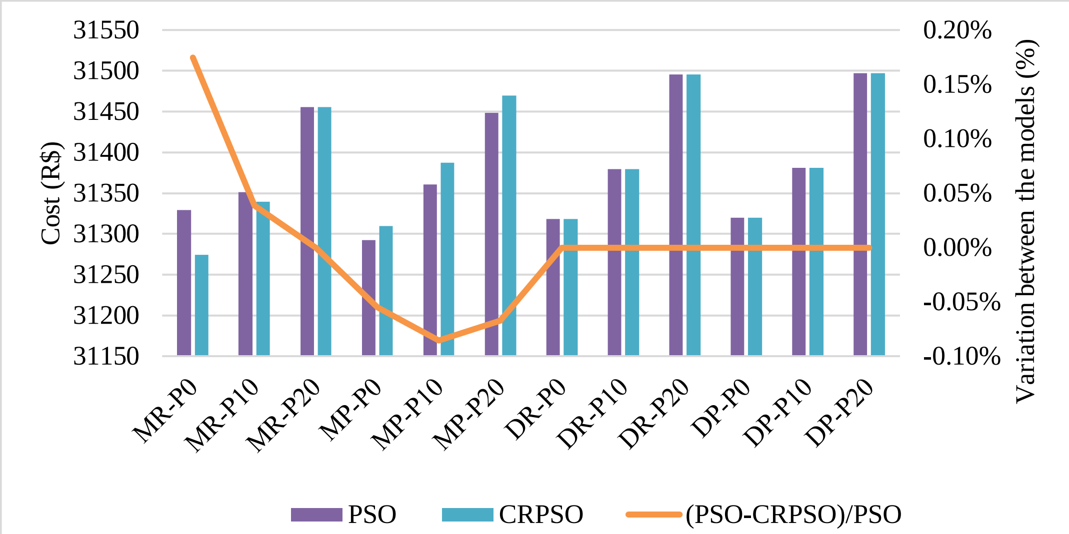


Figure 5 - Comparison between PSO and CRPSO models for cost analysis.

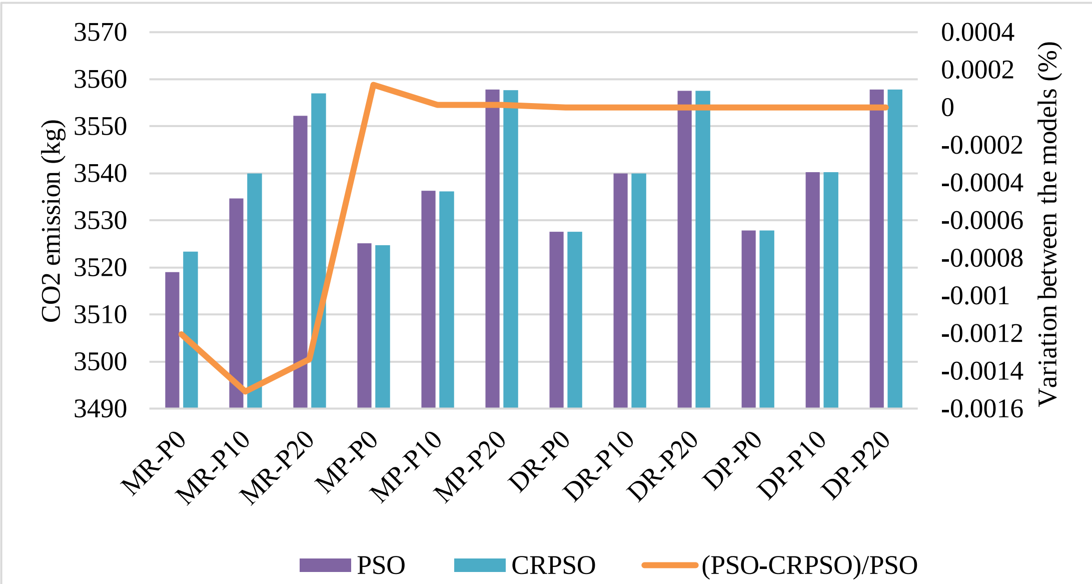


Figure 6 - Comparison between PSO and CRPSO models for emission analysis.

In the implementation of PSO and CRPSO algorithms, it was observed that the results did not always converge to the same value. Therefore, a strategy was adopted to perform 15 iterations and select the smallest value. Table 4 presents the example of cost optimization for beam MR-P10 using the two mentioned algorithms, where it is possible to observe the lack of convergence in values, but their proximity.

Upon performing the analysis of variance (ANOVA) on the results in Table 4, it was found that the value F = 1.25, while the critical F value (Fcritical) = 4.2. This indicates that the variation in the obtained results is insignificant and can be disregarded. Since our goal is to minimize cost or emissions, it is reasonable to select the smallest value.

Table 4 - Cost results for beam MR-P10 using PSO and CRPSO algorithms.

Iteration	PSO	CRPSO
1	R$ 31 577.36	R$ 31 351.50
2	R$ 31 577.73	R$ 31 370.49
3	R$ 31 386.04	R$ 31 414.53
4	R$ 31 386.04	R$ 31 616.65
5	R$ 31 406.76	R$ 31 914.93
6	R$ 31 549.73	R$ 31 601.19
7	R$ 31 637.80	R$ 31 386.04
8	R$ 31 401.23	R$ 31 358.40
9	R$ 31 351.50	R$ 31 462.02
10	R$ 31 386.04	R$ 31 571.40
11	R$ 31 547.57	R$ 31 386.04
12	R$ 31 597.22	R$ 31 395.53
13	R$ 31 571.31	R$ 31 386.04
14	R$ 33 042.86	R$ 31 339.41
15	R$ 31 601.11	R$ 31 561.38
Minimum cost	R$ 31 351.50	R$ 31 339.41

4 Conclusions

This study presented a detailed comparative analysis of optimization algorithms for the design of prestressed steel beams aiming at minimizing cost and/or CO_2 emissions. Using Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and a variant of PSO with chaos operator (CRPSO), was evaluated the efficiency of these algorithms in structural optimization, adhering to ABNT NBR 8800:2008 standards to ensure correct sizing.

The Genetic Algorithm remains a very useful optimization tool, as correctly introducing problem variables and constraints can yield reliable results. However, these results were surpassed by particle swarm optimization algorithms PSO and CRPSO, which provided more optimized values than GA. The introduction of random variables and the chaos function within the PSO code, forming the CRPSO algorithm for the applied example, did not significantly improve performance, with both demonstrating comparable convergence speeds.

Although the results obtained by PSO and CRPSO do not converge to the same outcome in 100% of cases, statistically, the variations can be considered negligible by adopting the minimum value from a series of predefined iterations. All implemented optimization tools provided more optimized values than the example collected from the literature, demonstrating their potential to reduce CO_2 emissions and costs in structural projects. The updated approach, which included optimizing additional variables such as web and flange thicknesses as discrete values, further enhanced the efficiency of the design process.

Finally, the efficiency of meta-heuristic optimization algorithms in addressing environmental and economic concerns in structural engineering was confirmed for the optimizes design of prestressed steel beams. Future studies could explore additional refinements of these algorithms and their application to a broader range of structural elements and materials.

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