Optimal Design of Prestressed Steel and Concrete Composite Beams

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Abstract. The application of prestressing techniques is typically associated with concrete structures and has been relatively underexplored in the context of concrete-steel composite beams. The objective of this study is to propose a formulation for the optimal design of prestressed steel and concrete composite beams. The objective function will analyze the costs and final CO_2 emissions of the beam. As constraints, the guidelines outlined in NBR 8800:2008 for steel structures and NBR 6118:2021 for prestressing in concrete structures will be adhered to. To solve the optimization problem, the Ant Colony Algorithm (ACO) will be employed. Additionally, a parametric analysis will be conducted and compared with examples proposed in the literature, aiming to identify the key factors that impact the final solution.

Keywords: Steel and Concrete Composite Beam, Prestressing, Ant Colony Algorithm, Cost, CO_2 Emission.

1 Introduction

Technological advances in civil construction have allowed the increase of spans in concrete and steel beam structures, thanks to the adoption of prestressing techniques. This innovation, although common in concrete structures, is less explored in steel elements and in steel-concrete composite structures, revealing a gap in studies applied to these configurations, as discussed by Ayyub, Sohn and Saadatmanesh [1]. External prestressing in steel beams is notable for its robustness and lower environmental impact, due to the reduction of CO_2 emissions, compared to concrete beams (Lou et al., [2]). However, the optimization of these prestressed beams, especially the use of bioinspired algorithms to solve structural problems, is an emerging field, with significant contributions from Abbas et al. [3] and recent advances by Mageveske et al. [4] and Fiorotti et al. [5], which explore the application of bioinspired algorithms, such as the Genetic Algorithm and Particle Swarm Optimization Algorithm. This work aims to contribute to this field by applying the Ant Colony Optimization Algorithm (ACO) to find optimal solutions for composite steel and concrete prestressed beams, marking an important step toward greener and more efficient civil construction.

Optimizing structures through prestressing enhances structural efficiency and significantly reduces environmental impact. By reducing material usage while maintaining strength and durability, the carbon footprint of buildings is substantially lowered. Optimized structures use fewer natural resources and less energy, promoting sustainability in construction. Bioinspired algorithms, like the Ant Colony Algorithm (ACO), further enhance this by minimizing waste and maximizing material efficiency. This work aims to contribute to this field by applying ACO to find optimal solutions for prestressed steel and concrete composite beams, advancing greener and more efficient construction practices.

In this context, this research aims to propose optimal solutions for prestressed steel and concrete composite beams using the ACO algorithm. The optimization problem solution was compared with the results proposed by Fiorotti [5].

2 ACO – Ant Colony Optimization

The ACO algorithm, originally proposed by Dorigo [6], was inspired by the behavior of ants in constructing the optimal path to food sources through the emission of pheromones. In nature, ants find the shortest path between their colony and food sources by depositing pheromones, which then serve as a guiding trail for other ants. Inspired by this behavior, ACO employs a simulation approach where agents, acting as virtual ants, roam the problem space. These agents deposit virtual pheromones, which subsequently guide other virtual ants toward higher-quality solutions. Figure 1 schematically demonstrates how the ACO functions.

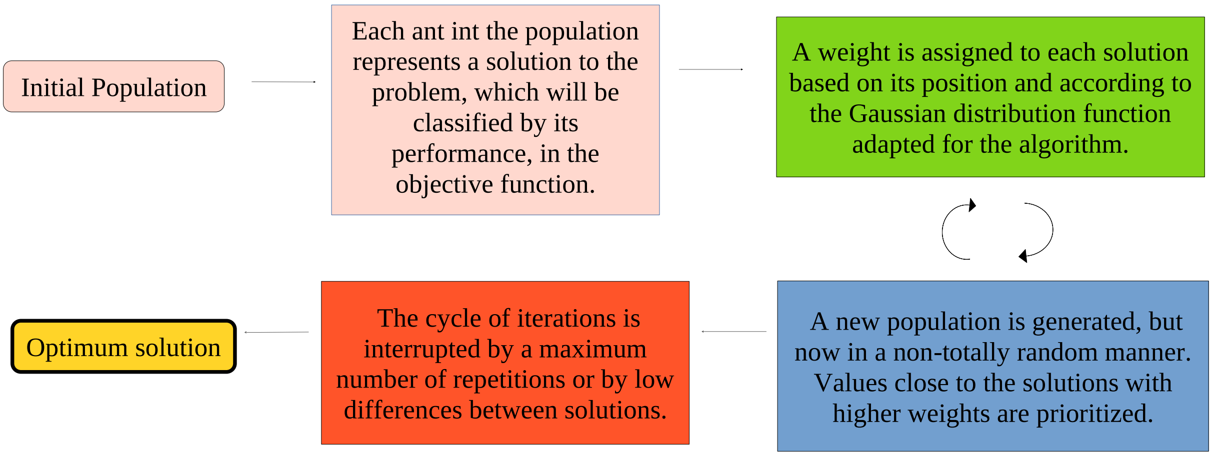
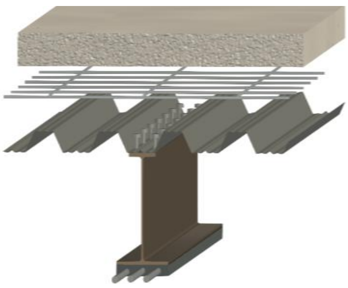


Figure 1 – ACO operating flowchart.

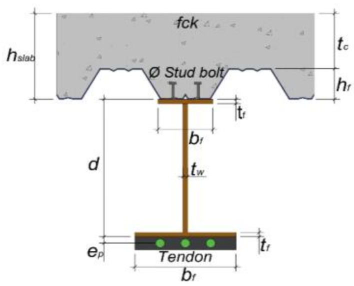
Several studies have effectively applied ACO to solve optimization problems, including the works of Luh and Lin [7] and Babaei and Sanaei [8], among others. Serra and Venini [9] demonstrated the application of ACO in optimizing flat trusses under static constraints. Their study concluded that the proposed formulation is efficient for the various problems analyzed.

3 Optimization Problem Formulation

To formulate the optimization problem, the variables were adopted as discrete and are presented in Fig. 2(a) and 2(b). The lower and upper bounds of these variables are defined in Table 1.



(a) Transversal Section (3D)



(b) Transversal Section (2D)

Figure 2 – Design Variables Definition

Table 1 -Lower and Upper bounds of design variables.

Profile height (d)	50 mm ≤ d ≤ 1000 mm
Upper flange (b_f^{top})	50 mm ≤ b_f^{top} ≤ 600 mm
Lower flange (b_f^{bot})	50 mm ≤ b_f^{bot} ≤ 600 mm
Upper flange thickness (t_f^{top})	4 mm ≤ t_f^{top} ≤30 mm
Lower flange thickness (t_f^{bot})	4 mm ≤ t_f^{bot} ≤ 30 mm

Web thickness (t_w)	4 mm ≤ t_w ≤ 30 mm
Slab concrete compressive strength (f_{ck})	20 Mpa ≤ f_{ck} ≤50 MPa, with a step of 5 MPa.
Number of tendons	0 ≤ No.Tendons ≤ 20.
Stud bolt	Diameter of 19 mm and 22 mm.

Slab concrete thickness (t_c) and steel deck form-work height (h_f) were selected from the options in the Metform steel form-work catalog.

3.1 Objective Function

In this work, the optimization performance of two objective functions was analyzed: one focused on reducing emissions (Equation 1), and the other on minimizing costs (Equation 2).

$$CO_2 = CO_{2,S}V_S\rho_S + CO_{2,TR}V_{TR}\rho_S + CO_{2,Slab} + CO_{2,Studbolt} \tag{1}$$

$$Cost = Cost_{(formwork)} + Cost_{(concrete)} + Cost_{(add.pos.reinf)} + Cost_{(mesh)} + Cost_{(crack.reinf)} \tag{2}$$

Each parameter of Eq. (1) and (2) are described in Table 2.

Table 2 – Parameters detailed.

$CO_{2,X}$	Emission constant
V_X	Element volume
ρ_X	Specific mass

In Table 2, an X marks the material identifiers: S for steel profile, TR for tendons, CS for the composite slab (steel and concrete), and Stud bolt for Stud bolts. The same principle was used in the cost reduction objective function. Table 3 shows the unit values of CO_2 emissions and costs used in the analysis.

Table 3 - Coefficients used in both functions

Component			Strength	***CO₂ Emission (kgCO₂/m³)***	***Source***	***Cost (R$/m3)***	***Source***
Concrete			20 MPa	129.85	Santoro e Kripka (2020)[10]	463.14	SINAPI (2023)[11]
			25 MPa	142.71		474.87	
			30 MPa	153.68		491.01	
			35 MPa	163.25		504.22	
			40 MPa	171.73		518.15	
			45 MPa	189.6		532.09	
			50 MPa	199.72		546.02	
Steeldeck formwork	MF50	esp.0.8mm	280 MPa	2.638kgCO_2/kg	Worldsteel Association (2020)[12]	90.5R$/m^2	Local Supplier (2024)
		esp.0.95mm				107.64 R$/m^2	
		esp.1.25mm				141.64 R$/m^2	
	MF75	esp.0.8mm				99 R$/m^2 R$/m^2	
		esp.0.95mm				117 R$/m^2	
		esp.1.25mm				154 R$/m^2	
Reinforcement mesh Wire mesh			600 MPa	1.924 kgCO_2/kg		10.48R$/kg	SINAPI (2023)[10]
Tendons				1.924 kgCO_2/kg		15.60R$/kg	

To address the constraints of the problem, the guidelines from NBR 8800:2008 [13] and NBR 6118:2021[14], as proposed in Fiorotti [5], were utilized.

4 Numerical Results

This section presents the results of applying the Ant Colony Optimization Algorithm (ACO) to the design of prestressed steel and concrete composite beams. The analysis compares CO_2 emissions and costs, contrasting ACO results with those from Fiorotti [5], who used the Self-adaptive Bonobo Optimizer (SaBO) algorithm. Additionally, it highlights CO_2 emissions and costs for different spans, emphasizing their interrelationships in structural optimization.

4.1 Validation of results

This study analyzed spans of 30, 35, and 40 meters. Considerations included the beam's self-weight, a construction load of 1kN/m², a live load of 5kN/m², and a dead load of 2kN/m². A beam spacing of 3 meters and the use of a steel deck slab were factored in, with the structure considered unshored. Prestressing cables were straight and positioned 50mm below the lower flange, with an unbraced beam length of 5 meters. The best results for each span, from both optimizations, were compared with Fiorotti [15] in Table 4. For the prestressing cables, steel CP190 with a 15.2mm diameter was used, and for the profile, ASTM Gr52 steel with a yield strength of 345MPa and Elastic Modulus of 200GPa was used.

Table 4 – Comparison of results between the Author and Fiorotti [5].

Span (m)	**CO_2 Emission (kg): Authors**	**CO_2 Emission SABO (kg): Fiorotti [15]**	**Cost (R$) Authors**	**Ratio CO_2 (Authors/Fiorotti [15])**
30.0	10660.28	10917.0	75892.31	-2.4 %
35.0	16084.43	16080.7	123807.74	+0.04%
40.0	22664.83	22682.3	186848.74	-0.08 %

From this comparison, it is clear that the results obtained by the Ant Colony Optimization (ACO) algorithm align well with those reported by Fiorotti [5]. This alignment validates the problem configuration and indicates it accurately reflects real-world conditions. While some differences exist due to the distinct optimization strategies, these discrepancies are reasonable.

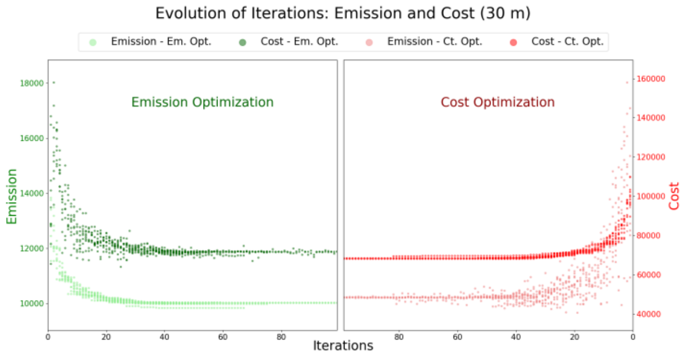
4.2 Results Analysis

To evaluate the beam's performance in terms of cost efficiency and emission reduction, 10 rounds of tests were conducted for three different spans. Each test began with an initial population of 200 individuals, an evaporation factor of 0.1, and ran for 100 iterations or until a stopping criterion was met. Often, the process halted early, indicating convergence before reaching the maximum number of iterations.

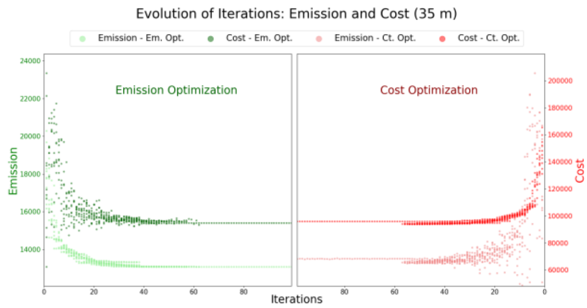
This approach enabled us to understand the behavior of the optimized functions (Eq. 1 and Eq. 2), correlate them, and analyze the structure's performance. The first analysis revealed a clear correlation between cost and emissions, as weight, a key parameter for both calculations, significantly influences both functions.

However, optimizing the cost function resulted in solutions with slightly higher emissions than those obtained by directly optimizing the emissions function. Similarly, optimizing the emissions function led to slightly higher costs than optimizing the cost function. This discrepancy can be attributed to the fact that the cost and emission coefficients are not directly proportional, as other factors, such as technology investment in different materials, also influence the cost.

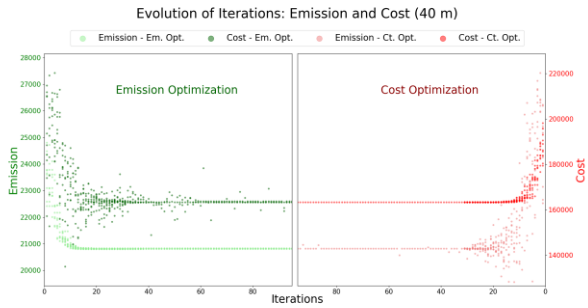
From this analysis, it can be concluded that for this type of problem, it is possible to achieve both cost savings and sustainability through the optimization of structures and the cost and CO_2 emission functions are not concurrent functions to apply a multiobjective optimization.



(a) 30 m



(b) 35 m



(c) 40 m

Figure 3 – Iterations carried out in the three spans for emissions and costs.

By plotting the solution points in a 3D graph that relates costs, emissions, and algorithm iterations, as shown in Figure 4, it was observed that the three analyzed spans exhibited very similar behavior, with differences primarily in the final amount of emissions and costs.

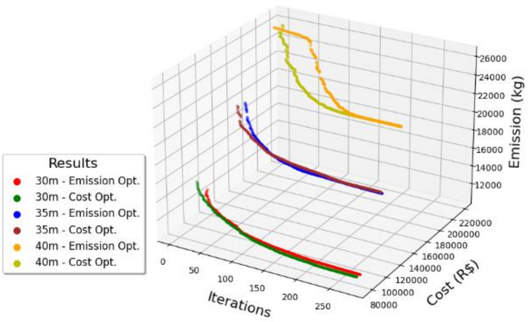


Figure 4 – 3D graph of iterations, costs and emissions.

Figures 5(a), (b), and (c) show the optimized profiles for each span. These figures illustrate the necessity of increasing the cross-sectional area as the span lengthens and a distinct difference between profiles optimized for emissions (Em – Opt.) and those optimized for cost (Cs- Opt.). When optimizing for emissions, the algorithm favors solutions with lower f_{ck} values, leading to slightly larger profiles. In contrast, this tendency is not observed when optimizing for cost. The images cited also compare the optimized profiles with those proposed by Fiorotti[5]. Table 3 supports this observation, showing that the emissions coefficient for concrete increases more significantly than the cost as f_{ck} increases.

Table 5 – Final Geometries

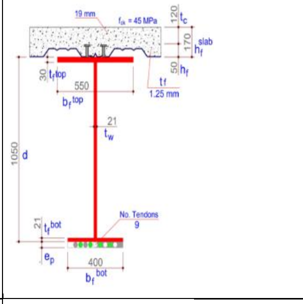
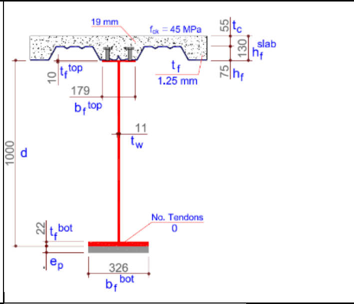
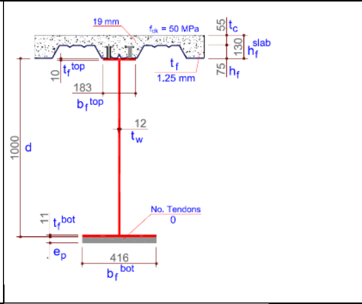
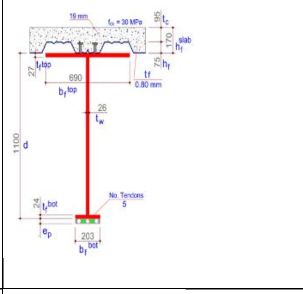
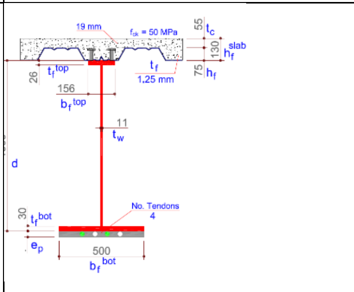
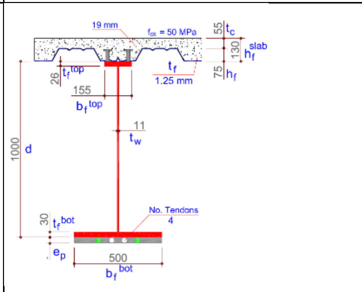
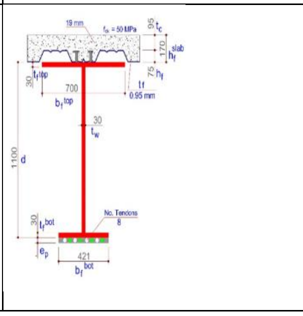
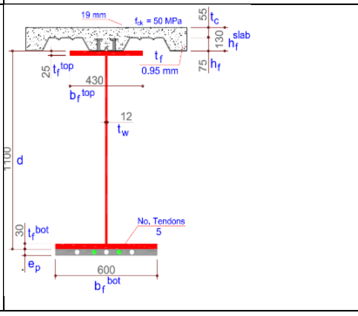
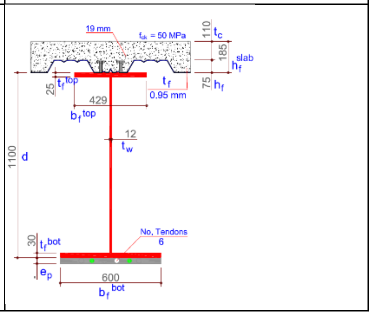
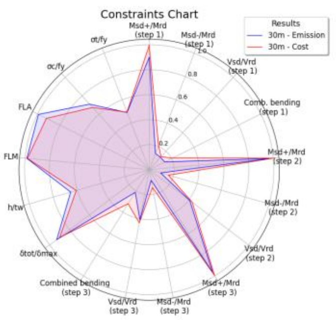
Span (m)	Fiorotti [15]	Authors (CO_2)	Authors Cost
30.0			
35.0			
40.0			

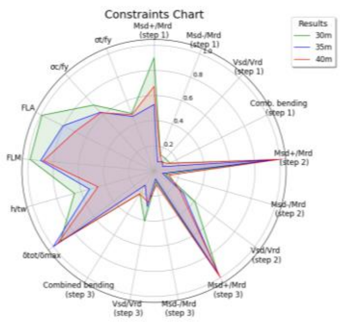
Figure 5 – Profiles found by the algorithm for each span.

A gradual increase in the profile determined by the algorithm is observed also in Figure 5. This trend is attributed to the dynamics of the standard constraints analyzed during the iterative process. Fiorotti's [5] constraints were adopted for various stages in the execution of the prestressed composite beam. Figure 6 (a) illustrates the convergence of these constraints in both cost and emissions optimization, using a 30-meter span as an example. The constraints are pushed to their critical values, indicating that within normative specifications, the algorithm achieved the optimal solution. Notably, the behavior observed is consistent across other spans as well. The different stages mentioned above are as follows: Stage 1 – prestressed steel beam subjected to its own weight; Stage 2 – prestressed steel beam subjected to its own weight plus the weight of the slab and construction loads; Stage 3 – analysis of the composite steel and prestressed concrete section with live load; Step 4 – verification of the limit state of use in infinite time.

Figure 6 (b) compares the constraints for each span, revealing that the limiting constraints are consistent across all spans. This demonstrates that for large spans, moment and deformation become the critical factors, overshadowing other considerations such as shear.



(a) Constraints of each optimization



(b) Constraints for each span (Emission Optimization)

Figure 6 – Result of constraints.

5 Conclusions

Comparison with Fiorotti's [15] results showed that the ACO achieved consistent CO_2 emissions, validating its representation of reality, as Fiorotti's [15] work is widely regarded as reliable. The results demonstrated that the ACO is capable of finding efficient solutions in terms of both costs and CO_2 emissions.

Additionally, the cost analysis indicated that the ACO can generate more economical solutions, reinforcing its viability for application in real-world projects. The observed correlation between emissions reduction and cost reduction highlights the possibility of combining savings and sustainability through structural optimization.

In summary, the application of ACO in the design of prestressed steel and concrete composite beams shows great promise, contributing to greener and more efficient civil construction. Future research could explore the application of other bioinspired algorithms, expand the analysis to different types of structures, and even use ACO for multi-objective analyses, aiming to further improve sustainable construction practices.

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