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Optimization of Steel Structures Using Meta-Heuristic Methods

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The paper explores the significance of optimal design in ensuring the robustness, service life, and structural integrity of civil engineering projects, particularly focusing on large and inherently complex steel structures. Meta-heuristic methods are lauded for their effectiveness in improving the functionality and architecture of steel structures, offering advantages such as adaptability to dynamic and uncertain environments, escape from local optima, and parallel processing capabilities. The paper displays real-life examples and case studies demonstrating their application in enhancing the efficiency and performance of different steel structures. The challenges associated with integrating meta-heuristic Genetic Algorithm "GA" methods into the development and optimization of steel constructions is discussed, along with potential approaches. The paper details the optimization technique, problem formulation, and objective function, using the total construction cost constrained by stress and displacement as an illustrative example. In conclusion, the paper asserts that employing meta-heuristic methods Genetic Algorithm" for steel structure optimization offers a practical means of reducing costs, enhancing structural performance, and fostering ecologically friendly designs.
Keywords: Genetic algorithm; meta-heuristics; method of optimization; objective function; steel structures.

1. Introduction

Optimizing the overall design process for steel structures therefore entails anticipating construction difficulties early in the design phase, resulting in an optimization process centered on minimizing, the structure's cost of construction. The typical technique for optimizing steel construction is to lower the structure's weight. However, connections seldom account for more than 5%[1] of a structure's overall weight. In practice, this low share conceals a large cost, which can exceed 30% of the whole structure's manufacturing cost [2,3]. In reality, the cost of labor, which is determined mostly by the intricacy of the assembly, determines the price of a framework. As a result, an optimized structural definition based simply on weight requirements may result in construction arrangements that are not optimal. In terms of building costs, it is far from perfect. As a result, we developed an optimization approach aimed at lowering the structure's construction costs. This cost includes the steel superstructure's material, fabrication, and assembly expenses, as well as the foundation systems' material and production costs. This ideal optimization approach additionally considers the component's dimensional attributes [4], the type of the supports, and the design of the connections [5].

To achieve our objectives, we must take a methodical approach, Fig1, beginning with formulating the optimal design problem in order to resolve the optimization issue by providing an overview of the different optimization criteria, namely the design variables, which are the cross-sections of the load-bearing elements. The optimization limitations are drawn from the Steel construction code requirements Eurocode 3 (EC3) [6]. Then, a model based on heuristic approaches was created.

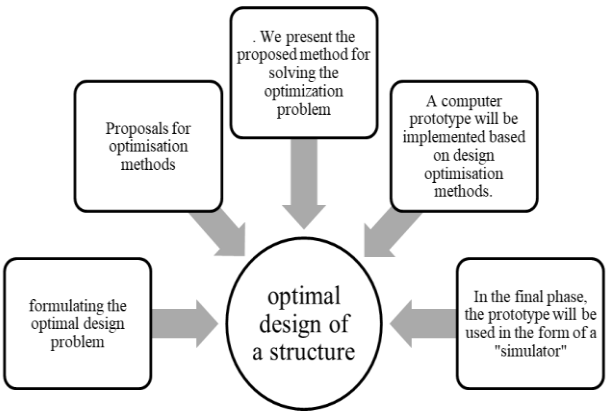

Fig. 1. Methodological approach.

2. MATHEMATICAL REPRESENTATION OF THE GLOBAL OPTIMIZATION PROBLEM

Optimization is a common and widely used term to define and implement design techniques for product development [7].

Optimization usually means enhancing or perfecting a project in various performance areas. However, from a mathematical standpoint, optimization has a specific definition. According to reference [8] It operates under the premise that the design process is a selection procedure where the most effective functional form is chosen from numerous possible alternatives.

The functional configuration is then expressed by selecting the appropriate quantity values and design features that correctly represent the current configuration. This is how the problem is mathematically represented as:

$$\begin{cases} \text{minimize } f(x) \\ gi(x) \leq 0 \\ hj(x) = 0 \\ (x) = (x1\ , x2, \ldots \ldots \ldots \ldots xn) \end{cases} \qquad (1)$$

f is the objective function to be minimized, g and h are respectively the inequality and equality limiting functions that define the admissible domain of solutions, and (x) is the vector of design variables that describe the optimization formulation of the optimization problem suitable for the metal structure.

3. PROPOSED SOLUTION METHODS

A. Metaheuristics

An optimization technique known as meta-heuristics," Meta" meaning supernatural, and heuristics are two Greek terms that have been combined, In reality, these algorithms are designed as general methods for solving a wide variety of complex problems without substantially modifying the strategy adopted. They are often used in the fields of operations research, engineering or artificial intelligence [9].

By sampling an objective function, metaheuristics are often stochastic iterative algorithms that approximate a global optimum or the global extremum of a function. Like search algorithms, they attempt to learn the characteristics of a problem in order to approach the optimal solution [10,11].

Meta-heuristics are very varied, ranging from simple local search to complex global search algorithms. However, these techniques employ a high degree of abstraction, which allows them to be adapted to a wide variety of problems [12].

B. Metaheuristic Classification

Meta-heuristics are often nondeterministic; they might not even figure out the best answer until they confirm it's the best[13]. A distinction can be made between meta-heuristics that produce a population of solutions in the search space during each cycle and those that produce a unique solution. You cannot be sure of finding an optimal solution using single-solution metaheuristics, as these often require more search space.

C. Genetic Algorithms

Genetic algorithms GA were developed by Charles Darwin and inspired by biological mechanisms. From the 1990s onwards, a number of publications mentioned the use of GAs to solve optimization problems in the field of civil engineering. A GA is an iterative algorithm that evolves a set of solutions, randomly initialized, and called a population [14]. Our algorithm uses coding to encode all the sections of the search space. This step associates a data structure, called a chromosome, with each point in the state space, the aim being to optimize the weight and cost of a metal structure. In the understanding that each person is unique, GAs aim to simulate the evolutionary process of species in their natural habitat, a similarity with Darwin's theory of evolution and Mendel's modern genetic [15].

Fig. 2 represent an overview of a life cycle of GA works [16]:

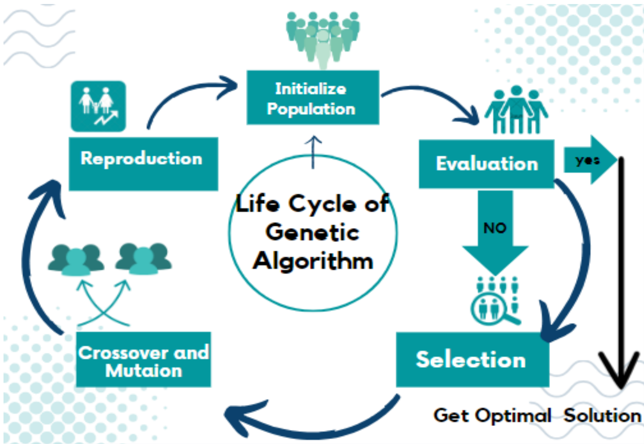

Fig. 2. Life Cycle of Genetic Algorithm

The steps are as follows:

- Initialization: To begin, the algorithm generates a population of potential solutions (individuals), which are commonly represented as strings of binary or real-valued variables.

- Fitness Evaluation: Individuals in the population are assessed using a fitness function that assesses how successfully they tackle the challenge at hand. The fitness function directs the algorithm to produce better results.

- Selection: Individuals from the existing population are chosen to be parents for the following generation. The likelihood of selection is generally related to an individual's fitness, favoring superior answers.

- Crossover: The chosen individuals go through crossover, which entails merging pieces of their genetic information to produce new offspring. This procedure is analogous to biological reproduction.

- Mutation: To increase population variety, some individuals endure random alterations known as mutations. This stops the algorithm from reaching a poor result too fast.

- Replacement: A new generation of individuals replaces the previous generation, and the process is repeated from step 2 for a specified number of generations or until a termination, condition is fulfilled.

4. GENETIC ALGORITHM APPLICATION AND OPTIMIZATION

The first application in this article is a classic issue of optimizing the weight of a ten-bar lattice, which has already been covered in other sources, in order to compare our conclusions. The second application is a theoretical example involving the weight and production cost optimization of a 2D to 5-bar gantry in accordance with Eurocode3. This is to recognize and acknowledge GAs' interest.

D. Example 1: 10-bar lattice

This example was picked from the literature [17] and involves the optimization of the weight of a 10-bar planar lattice using evolutionary algorithms to create a comparison in order to establish the validity of the findings achieved. As a result, the geometry and properties of the materials utilized were assumed identical.

- Density of steel= 2770 kg/m^3, Young's modulus E=6.89 104 MPa

1) Example Demonstration :

- The aim is to reduce the overall weight of a 10-bar planar lattice.

- Two forces of F= 444.822 kN are applied to the structure at nodes 2 and 4. The allowed stress in the bars in this case is 172.37MPa and the vertical displacement at node 2 is limited to: U_{ymax} =-5.08 cm.

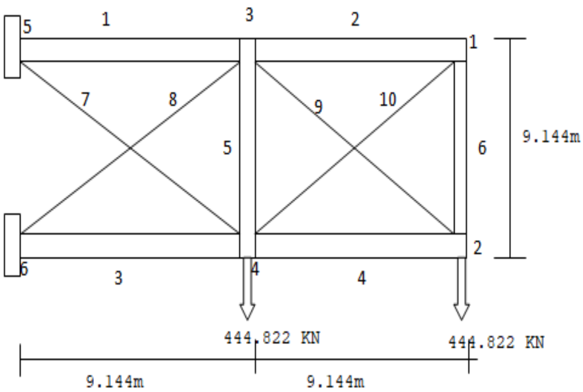

Fig. 3. 10-bar flat latticework

TABLE I. THE BEST STRUCTURE WITH NPOP = 60 AND NGENER=100

Paramètres de l'algorithme	
Cc = 4	Coefficient of penalties on constraint verification
Pc=0.85	Crossover probability
Pm=0.005	Probability of mutation
npop = 60	population size
nGener=100	iterations
RESULTS	
Weight	2359,6KG

Bar numbers	21	2	11	12	3
Bar cross-sections cm²)	2.8e-3	1.1e-3	2.0e-3	2.1e-3	1.2e-3
Bar numbers	3	12	11	12	2
Bar cross-sections (cm²)	1.2e-3	2.1e-3	2.0e-3	2.1e-3	1.1e-3

```
Iteration 95: Best Cost = 2372.2128
Iteration 96: Best Cost = 2372.2128
Iteration 97: Best Cost = 2372.2128
Iteration 98: Best Cost = 2372.2128
Iteration 99: Best Cost = 2364.9742
Iteration 100: Best Cost = 2359.6362
>> out.bestsol

ans =

  Position: [0.0028 0.0011 0.0020 0.0021 0.0012 0.0012 0.0021 0.0020 0.0021 0.0011]
      Cost: 2.3596e+03
```

Fig. 4. 10-bar element iterations results

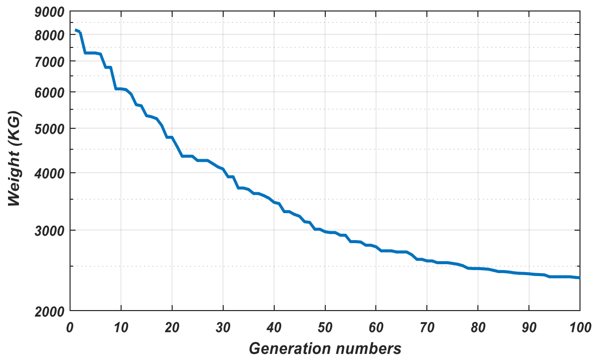

Fig. 5. 10-bar element optimization results

E. Comparison of outcomes with others

Comparison of Our application's results with earlier Table 1, findings discovered in other publications about the same example with the same variables, sections, and limitations.

TABLE II. COMPARISON OF THE OUTCOMES OF 10-BAR LATTICE OPTIMIZATION

	AG 2023	Z. El Maskaoui 2017
Optimum Weight (kg)	2359,6	2519, 56
Section of optimum	21-2-11-12-3-3-12-11-12-2	42-17-38-30-1-11-35-34-38- 26

We notice that the results we achieved are similar to, if not slightly better than, those found in other references, and consequently, we will have verified or supported our process for expressing the various aspects of an optimization issue as well as those of genetic algorithms.

Moreover, we anticipate that this will assist us in optimizing the weight and manufacturing cost of any construction, which is what we'll be doing in the second case.

F. Optimal Weight and Cost of Manufacturing for 2d Gantry Design

The optimization approach given here is utilized to discover the best design for the gantry depicted in Figure. The five bars represent the optimization variables.

1) Example Demonstration:

- The bars have a density of =7800 kg/m^3, Young's modulus E=2.10* 10^4 MPa and the steel used is of the grade: S235
- The aim is to identify the optimal arrangement for the bar cross-sections.
- Two forces of F = 50 KN are applied to the structure at nodes 4, and the allowed stress in the bars in this case is 235 MPa.
- The horizontal displacement at node 4 is limited to: U_x max =1,8cm

In Fig. 6, we show the results of optimization findings for the weight and cost of a planar gantry.

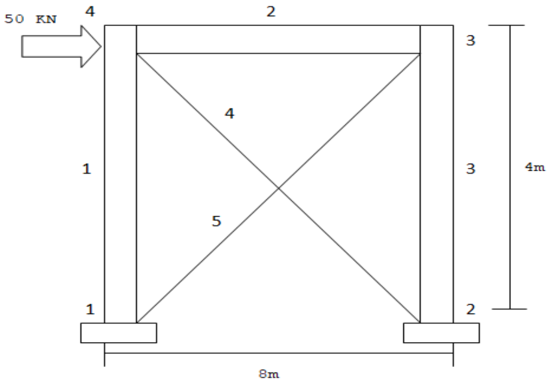

Fig. 6. 1-floor gantry crane.

The column cross-sections are of type HEB, whereas the beam cross-sections are of type IPE. The beams with the same cross-section belong to the same group, which will be a design variable later on.

2) The optimization problem can be suitably formulated as follows:

$$\text{Min } CG\ (I, Xa, Xn) \qquad (2)$$

- Under the constraints Ci where :

CG: the overall production cost of the structure ;

I: vector of the dimensional characteristics of the bars;

Xa: support nature vector; Xn: node nature vector.

Ci: stress, with i = 1,..., N where N is the number of stresses associated with the structure.

a) Objective function:

$$(CG) = (Cpu)(W) \qquad (3)$$

(Cpu) : unit cost for a KG of steel

(W): weight of the structure

$$(W) = \rho \sum_{j=1}^{ne} AjLj \qquad (4)$$

b) Optimization Variables:

The dimensional properties of elements, the type of connections (beam to beam, column to column, etc.) between elements, and the type of connections between columns and foundations are the three types of design variables that can be used to create different design solutions for a structure[18].

c) The Element's Dimensional Properties:

- IPE sections for beams: 18 components ranging in height from 80 mm to 600 mm.
- HEA and HEB sections for columns: 49 elements ranging in height from 100 mm to 1000 mm.

TABLE III. DIMENSIONAL PROPERTIES

Design variable	Eléments	Section type
Bars	2	IPE
	1 , 3, 4, 5	HEB, HEA

3) Constraints:

The various regulatory requirements for the dimensioning of steel structures (The dimensioning constraints are those defined by EC3 regulations) [19,20], as well as the requirements linked to the client's financial restrictions and the limits of the architectural sketch, constitute the constraints of the optimization issue. Consequently, these constraints are linked to the: Strength of cross-sections

- resistance of elements to buckling(EC3, 5.36):

$$\frac{NEdi}{NRdi} + \frac{MyEdi}{MyRdi} + \frac{MzEdi}{MzRdi} \leq 1 \,; i = 1 \ldots\ldots n \qquad (5)$$

NEd: normal design load; NRd: resistant normal force;

MEd: design yielding moment; MRd: resistant yielding moment;

- Column buckling resistance (EC3, 5.51)

$$\frac{NEdi}{xyi * NRdi} + kyi\frac{MyEdi}{MyRdi} + kzy\,\frac{MzEdi}{MzRdi} \leq 1; i = 1..p \; (6)$$

x: buckling coefficient ; k : moment coefficient ;

- limitation of the deformations of the bent elements:

$\nu i \le \nu lim, i = 1,..,p$ (7)

- limitation of horizontal frame deflections:

$$\mu i\ (I, Xa, Xn) \le \mu limi\ , i = 1,..,p \qquad (8)$$

- limitation of the overall cost of building the structure:

If the client sets the budget for the structural work package, however, this is a limit that must not be exceeded. In this case, the best solution will be compared with CGlim on the basis of its overall cost CG. It is said that :

$$CG \le CGlim \qquad (9)$$

4) Summary of the algorithm steps:

Fig 7 gives a summary of the different steps of the algorithm.

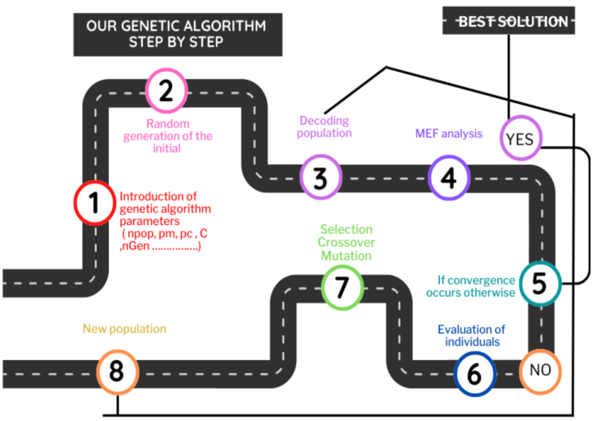

Fig. 7. Summary of the algorithm steps.

TABLE IV. TABLE 4 THE BEST STRUCTURE WITH NPOP = 50 AND NGENER=100

Algorithm parameters					
C = 3	Coefficient of penalties on constraint verification				
Pc=0.80	Crossover probability				
Pm=0.002	Probability of mutation				
npop = 50	population size				
NGener100	Iterations				
RESULTS					
Weight	2766,9 Kg				
Bar cross-sections (cm²)	3,88E-03	2,01E-03	3,88E-03	2,60E-03	2,60E-03

Bar numbers	22	5	22	43	43

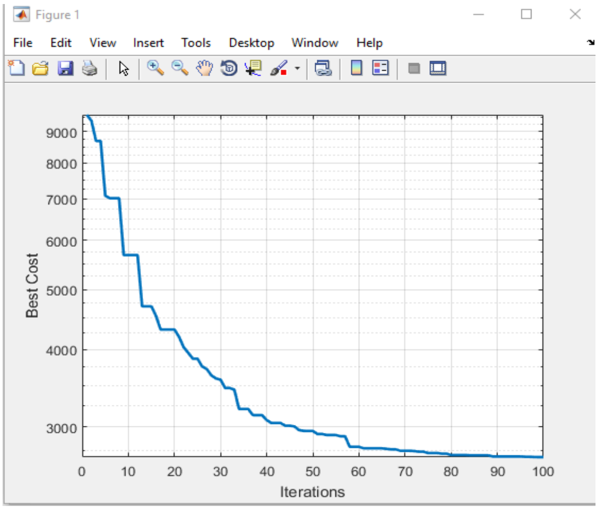

Fig. 8. Evolution of the structure's mass

TABLE V. THE BEST STRUCTURE WITH NPOP = 80 AND NGENER=100

Paramètres de l'algorithme					
C = 3	Coefficient of penalties on constraint verification				
Pc=0.80	Crossover probability				
Pm=0.002	Probability of mutation				
npop = 80	population size				
nGener=100	Iterations				
RESULTS					
Weight	2231,623 Kg				
Bar cross-sections (cm^2)	3,4E-03	1,64E-03	3,4E-03	2,53E-03	2,53 E-03
Bar numbers	44	4	44	20	20

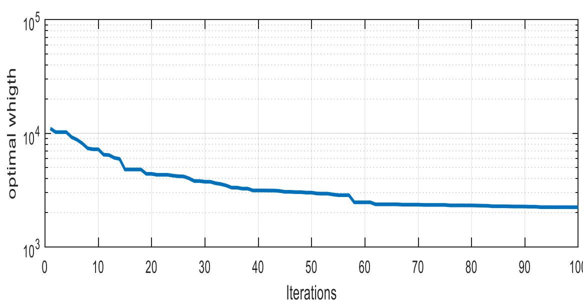

Fig. 9. Evolution of the structure's mass through generations and population numbers

We can observe that the weight of the top person are extremely near or even close for various collections, depending on the size of the population. This is because the algorithm converges on the individual with the lowest penalty:

phii=W*(1+Cc*(p1+p2+…….pn)); with n number of penalty;

So, if p1 and p2 are zero since the individual meets the constraints on the acceptable constraint and arrow, which yields phii=W, it will eventually offer the best weight of the least penalized individual, or one that is not punished at all.

Using the objective function (3) we get:

$(C_{profiles}) = (C_{pA}) * (W)$

Then the average prices for materials of the structural steel is: 450 DZD/kg.

TABLE VI. RESULTS COST COMPARISON

GAs Approach	Weight	Cost (DA)
50 npop	2766,9 Kg	1.245.105
80 npop	2231,623 Kg	1.004.230

The results of the genetic algorithm optimization show that the optimal solution is the one that corresponds to the minimum weight (2231.623 kg) after 80 populations. However, this solution corresponds to the minimum cost (here equal to 1,004,230 DZD).

5. CONCLUSION

We have attempted to demonstrate in this paper that the use of meta-heuristics, particularly "genetic algorithms," as a design aid tool to guide engineering decision-makers toward optimal solutions offers an innovative and powerful approach to solving complex design problems. These algorithms optimize structural performance while considering a wide range of constraints and variables.

The main advantage of genetic algorithms lies in their ability to explore a very broad set of alternatives and uncover optimal or near-optimal solutions. Moreover, the accuracy with which the problems are modeled, the appropriate selection of optimization parameters, and the rigorous validation of the obtained results significantly affect the quality of the outcomes.

Finally, we can assert that this dimensioning tool is endowed with artificial intelligence, moreover, is an optimizer that helps save on raw materials. This method has also allowed us to explore other types of structures in our future research projects.

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