

# THREE-DIMENSIONAL VEHICULAR STRUCTURE DESIGN COMBINING FINITE ELEMENT MODELING AND NUMERICAL OPTIMIZATION

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**Abstract.** This work is devoted to the design optimization of a three-dimensional vehicular structure (space frame vehicular structure), used as a chassis of a high performance roadster vehicle. In general, for this type of vehicle, a chassis must be as rigid and lightweight as possible in order to fulfill drivability (the degree of smoothness and steadiness of acceleration of an automotive vehicle) and maneuverability (the quality of being capable of maneuvering or changing position) requirements. As a result, this real world structure is characterized by a complex geometry, which entails a number of difficulties in obtaining the optimum design by using analytical formulation. Differently, the current state-of-the-art design of vehicles embraces the use of modern computer-based methodologies (Computer-Aided Design - CAD) that relies upon techniques such as the Finite Element Method and Numerical Optimization. In this work a chassis design methodology that integrates a set of nature-inspired optimization tools developed under MATLAB® and finite element analysis using the commercial software ANSYS® is presented. Numerical results are reported, illustrating the success of using the presented methodology, as applied to the design optimization of a space frame vehicular structure.

**Keywords:** Numerical Optimization, Computer-based Design, Vehicular Structure Design

## 1. INTRODUCTION

The use of three-dimensional vehicular structures became popular in the sixties last century due to the interest in designing high performance race cars. This type of car requires high structural stiffness that can be offered by this type of arrangement. Another important feature of three-dimensional structures is that they provide high security level for the occupants with respect to crash and rollover. Most of the structures are constituted by members arranged according to a planar configuration, as illustrated in Fig. 1.

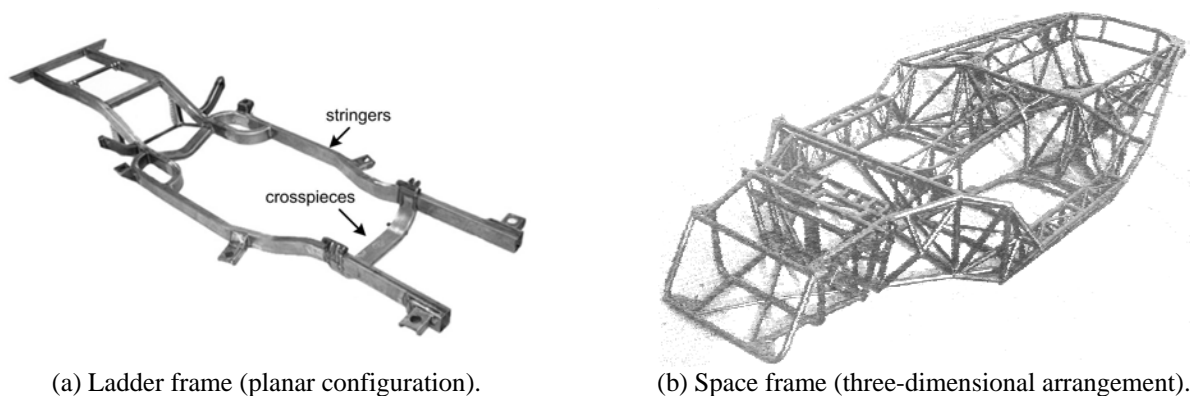


Figure 1. Two types of chassis.

In the design phase, the main concern is to obtain rigid and while lightweight structure. These characteristics fulfill drivability and maneuverability requirements (Souza, 1990; and Happian, 2002). According to the literature (Thompson et al., 1998; Aird, 1997; and Happian, 2002), for design purposes the most effective strategy should consider both the mass reduction and the increase of the torsional stiffness. Translating this to the design level, the engineer must choose the material (by defining the material density and the Young's modulus) and design the proper geometry of the structure (by defining the total mass and moment of inertia).

In terms of materials choice, Baker (2004) discusses that steel alloy and aluminum alloy are probably the ideal materials for the chassis construction. However, it must be pointed out that they may not be always economically interesting. In this case, the use of the 1020 carbon steel seems to be a recommended trade off solution.

On the other hand, in terms of the geometry, the design starts by choosing a basic form. Figure 2 illustrates some of the most common ones. The triangular form is the basis for the development of a rigid structure. In this case, shape and dimensions do not suffer extreme changes, unless one of its sides collapses. According to Adams (1993), diagonals bars (see Fig. 2c) represent a well-succeeded experience to increase the stiffness of square-shaped elements, since high strains along the diagonal direction appear in this type of element, even when the structure is subjected to small loading.

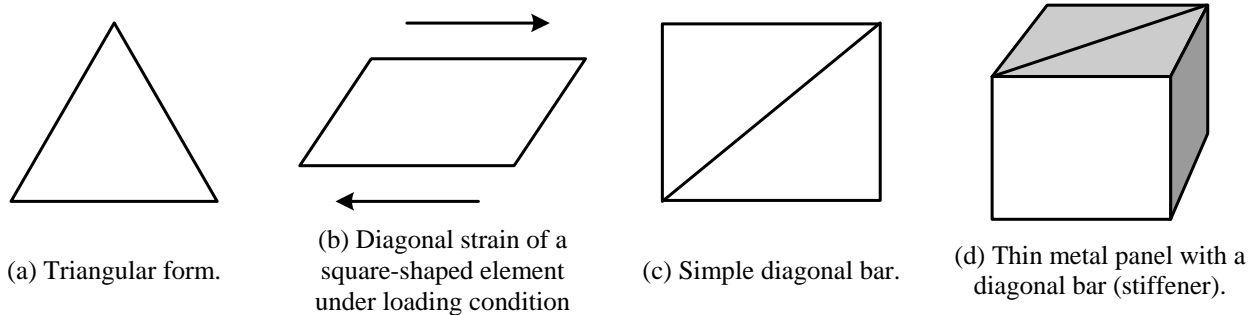


Figure 2. Different construction forms.

The design of a three-dimensional vehicular structure is a complex task. Differently from simple structures, where the analytical formulation for the physics may be available, the most common approach in this context is to make use of numerical models like those based on the Finite Element (FE) method. On the other hand, numerical optimization techniques have been widely used in design applications. In conjunction with computer automation capabilities, optimization is an efficient alternative to the “trial and error” development.

In summary, the design strategy adopted in this work embraces the use of nature-inspired optimization methods, as well as the finite element modeling of the vehicular structure. The choice of the optimization strategies has to do with two major aspects: first, authors aimed at testing heuristic methods in real world applications, and second it was desirable to take advantage of the robustness found in these techniques to handle the design case addressed. In the remainder, an overview regarding the modeling of the vehicular structure is presented and the optimization algorithms are discussed. Numerical results are reported, illustrating the success of the methodology presented, when applied in the design of a three-dimensional vehicular structure.

## 2. BASELINE DESIGN DEFINITION AND MODELING

The model was first obtained by consulting the literature about high performance race vehicles (Thompson et. al., 1998; and Aird, 1997). A structure for a high performance roadster vehicle with two passengers was used in this work. Figure 3 illustrates the initial configuration of the baseline design. Figure 3-(b) shows indications of the suspensions anchorage points. Lack of roof and the presence of side doors make this structure flexible. To overcome this drawback, left and right trusses were placed together with diagonal bars in the floor-plan (minimizing buckling tendencies). Before continuing, it is worth mentioning that the fact of being based on the literature does not mean that the baseline design corresponds to the optimal design.

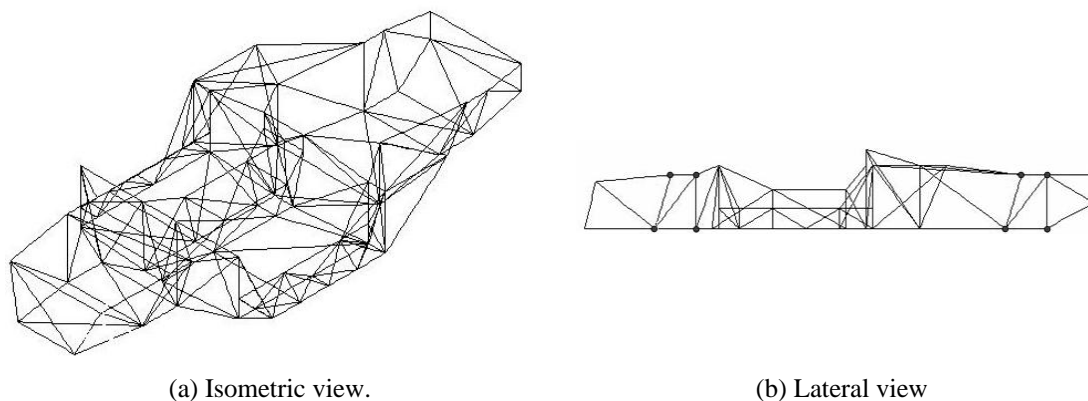


Figure 3. Baseline design of the space-frame chassis.

In terms of material, carbon steel circular tubes were chosen. The initial configuration presents 0.0508 m external diameter and 1mm of wall thickness. Table gives details about this initial design configuration

Table 1. Baseline details.

<b>Wheelbase [m]</b>	<b>Front and rear tracks [m]</b>
2.62	1.475
<b>Front suspension type</b>	<b>Rear suspension type</b>
Short long arm	MacPherson with aggregate

There are some options regarding the modeling of such a structure: one of them is to make use of shell elements. While accurate, this solution is expensive from the computational viewpoint, and thus, it is not convenient within the optimization framework. On the other hand, beam elements allow obtaining models at lower computational cost, without lacking the necessary accuracy in the design phase. The bar element (BEAM4) was chosen. This element can be used in the analysis of tension, compression, torsion and bending. Each element has twelve degrees of freedom (two nodes per element): translations along x, y and z nodal directions and rotations with respect to x, y and z nodal axes.

The formulated optimization problem deals with two responses obtained from the FE model, namely, the mass and the torsional stiffness. The baseline design has 19,167 degrees of freedom, the mass is 139.52 [Kg] and the torsional stiffness is 1728.1 [Kgf · m/deg]. An important point is that in a more realistic design scenario, it would be necessary to include other factors such as dynamic responses, manufacture constraints, etc.

### 3. NUMERICAL OPTIMIZATION AS A DESIGN TOOL

When incorporated to the design process, numerical optimization goes beyond the simple analysis of the structure. Fig. 4 illustrates a general scheme regarding the FE analysis. A possible way of incorporating numerical optimization in the cycle of development is given by Fig. 5. Modeling of the structure and analysis of design requirements are steps of the “problem definition and formulation”. After this first stage, a baseline design is proposed. After each “Optimization” step, the candidate solution is revised. If either the requirements were not satisfied or it is possible to achieve some extra improvement, the candidate solution is redefined as a baseline for a new iteration of the design cycle. This loop continues until the decision maker considers that the candidate solution has fulfilled the initial goals proposed. An extra refinement may be an intermediate step before obtaining the final design.

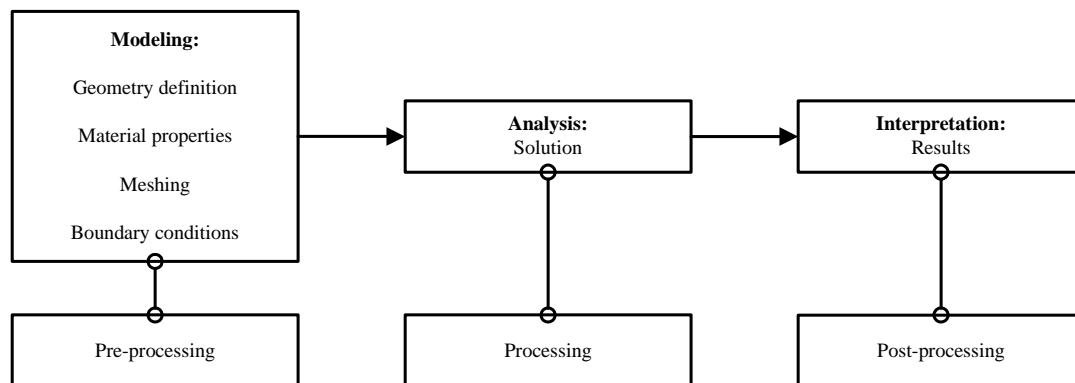


Figure 4 . FE methodology.

Looking deeply inside the “optimization” step shown in Fig. 5, it is worth mentioning that Venter and Sobieski (2002) claim that most general-purpose optimization software used in industrial applications makes use of gradient-based algorithms. However, in spite of the heavy computational effort as compared to gradient-based techniques, nature-inspired probabilistic methods have attracted much attention from the research community. These methods have several advantages, such as the easiness to code, the efficiency in using parallel computation architectures, the ability to overcome numerical convergence difficulties, and the capability of dealing with discrete and continuous variables simultaneously.

In this work, the “optimization” step follows a cascade-scheme that combines a global optimization method with a local optimization method. In the global optimization phase, a suite of heuristic optimization methods is applied to the optimization of a three-dimensional vehicular structure. Ant Colony Optimization (ACO), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) are the approaches used to perform this case study. These methods are briefly reviewed below. In the local optimization phase, a Nelder-Mead simplex direct search (MATLAB function *fminsearch*) is used. For this, the initial design is provided by the previous global optimization phase.

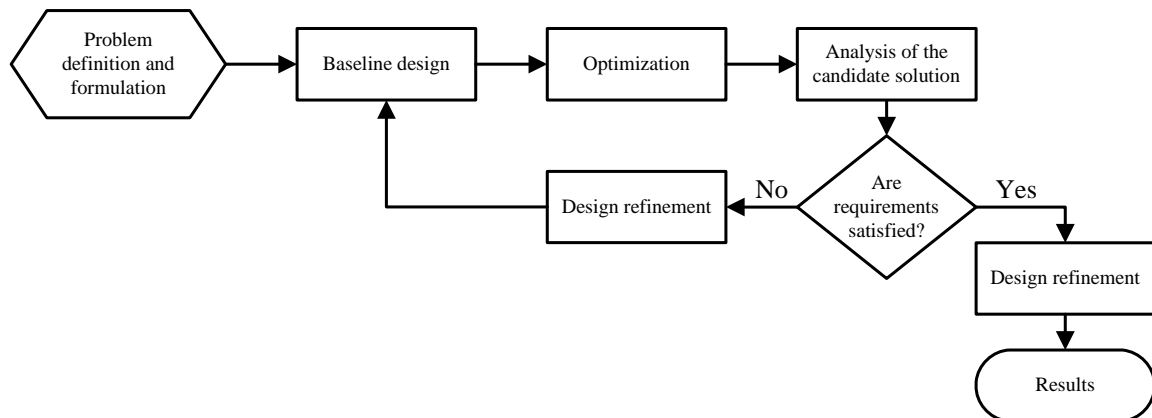


Figure 5. Optimization included in the design cycle.

### 3.1. Ant colony optimization

ACO was first introduced by Marco Dorigo in his doctoral thesis in 1992 (Dorigo, 1992) as a probabilistic technique for solving computational problems, which can be reduced to finding good paths through graphs. This population-based technique is inspired by the behavior of real ants and their communication scheme by using a pheromone trail. ACO has attracted much attention from the research community mainly due to its efficiency in solving combinatorial optimization problems, such as the traveling salesman problem (Dorigo et al., 1996) and the routing problem in a computer network (Di Caro and Dorigo, 1998). Nevertheless, the expansion to continuous variables is recent (Pourtakdoust and Nobahari, 2004) and it is seen as a new development in the history of ACO.

A moving ant lays some pheromone on the ground, thus marking the path. The collective behavior that emerges from the participating agents is a form of positive feedback where the more the ants follow a trail, the more attractive it becomes. ACO follows some basic concepts, as presented below (Pourtakdoust and Nobahari, 2004):

- A search performed by a population of ants, i.e., by simple independent agents.
- Incremental construction of solutions.
- Probabilistic choice of solution components based on stigmergic information of pheromone. A stigmergic process is the process through which the results of a worker insect's activity act as a stimulus for further activities.

Figure 6-(a) shows the outline of a basic ACO. More details about ACO are provided by Dorigo (1992), Dorigo et al. (1996), Di Caro and Dorigo (1998), and also by Pourtakdoust and Nobahari (2004).

### 3.2. Genetic algorithms

GA is an optimization algorithm used to find approximate solutions to difficult-to-solve problems through the application of the principles of evolutionary biology to computer science (Michalewicz and Fogel, 2000 and Haupt and Haupt, 2004). GA is based on Darwin's theory of survival and evolution of species, as explained in Michalewicz and Fogel (2000) and Haupt and Haupt (2004). GA uses biologically-derived concepts such as inheritance, mutation, natural selection, and recombination (or crossover).

The algorithm starts from a population of random individuals, viewed as candidate solutions to a problem. During the evolutionary process, each individual of the population is evaluated, reflecting its adaptation capability to the environment. Some of the individuals of the population are preserved while others are discarded; this process mimics the natural selection in Darwinism. The members of the remaining group of individuals are paired in order to generate new individuals to replace those which are discarded in the selection process. Finally, some of them can be submitted to mutation, and as a consequence, the chromosomes of these individuals are altered. The entire process is repeated until a satisfactory solution is found.

Figure 6-(b) shows the outline of a basic GA. Although the initially proposed GA algorithm was dedicated to discrete variables only, nowadays improvements are available to deal with discrete and continuous variables see Michalewicz and Fogel (2000) and Haupt and Haupt (2004) for more details.

### 3.3. Particle swarm optimization

Particle Swarm Optimization was introduced by Kennedy and Eberhart (1995). The method reflects the social behavior of some bird species. The main idea of the PSO is to reproduce the search procedure used by a swarm of birds when looking for food or nest. Consider the following situation: a swarm of birds is searching for food in the

neighborhood of a delimited area. Suppose there is just one place where food can be found and the birds do not know where it is, then if one bird is successful in its search, it can attract other birds, and as a result of this social behavior, the others will follow and also find the food. Following this principle, each individual learns (and contributes) primarily to the success of his fellows. This fact requires balance between exploration (the capacity of individual search) and exploitation (the capacity of learning from the neighbors).

Behind of the scenes, this is achieved by modeling the flight using a velocity vector, somewhat analogous to a search for direction. The velocity vector considers the contribution of the current velocity and other two portions referred to as the knowledge of the particle itself and that of the swarm, respectively, about the search space. In such a way, the velocity vector is used to update the position of each particle in the swarm. The outline of a basic PSO algorithm is illustrated in Figure 6-(c). PSO is comprehensively presented in Venter and Sobieski (2002) and Kennedy and Eberhart (1995).

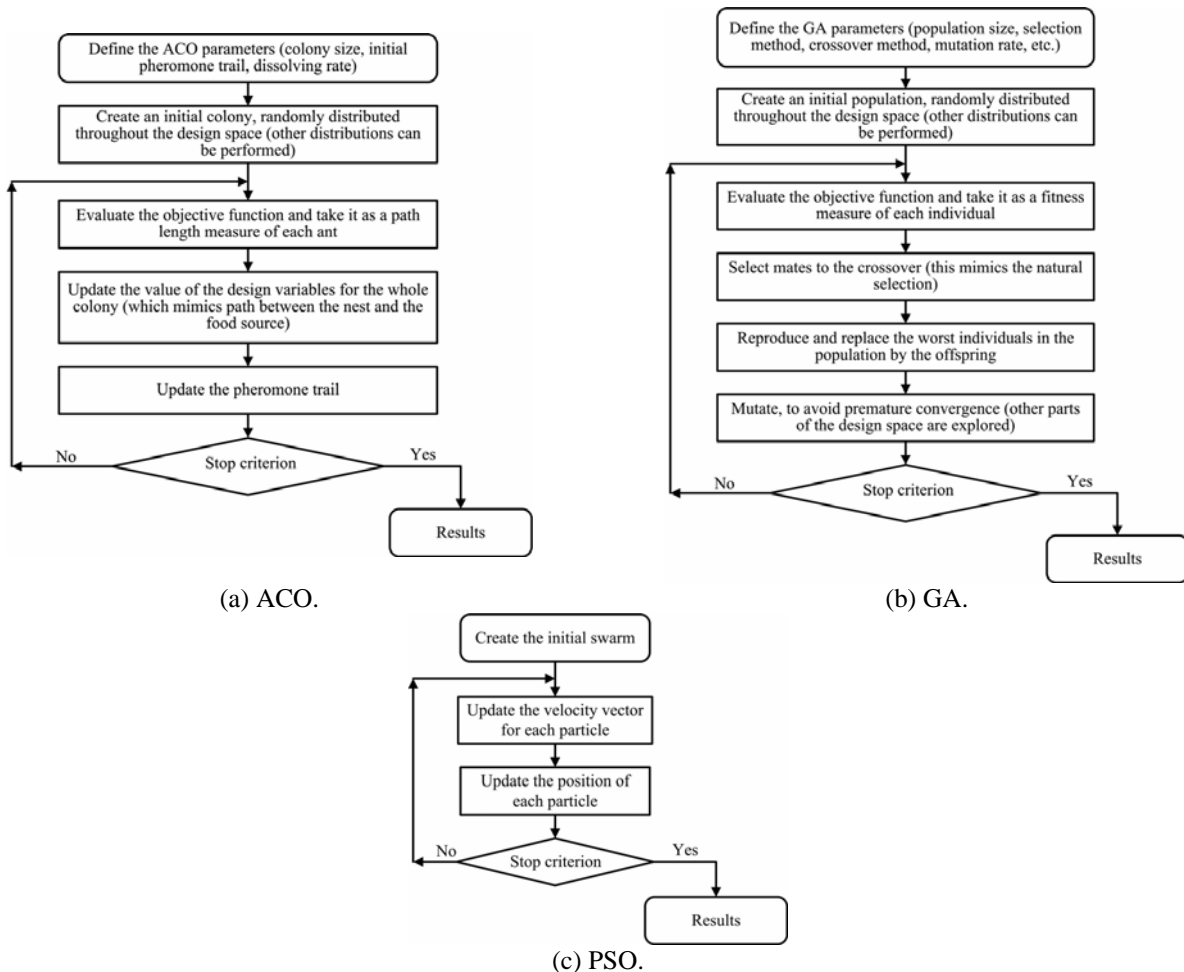


Figure 6. Basic schemes for some nature-inspired optimization methods.

### 3.4. Multi-objective and constrained optimization

The most general optimization problem is the multi-objective constrained one. In this scenario, numerical optimization is dedicated to the following nonlinear, constrained problem: find the point in the design space,  $\mathbf{x}^*$ , that will minimize the vector of objective functions, as presented by eqs. (1) and (2):

$$\mathbf{F}(\mathbf{x}) = \begin{Bmatrix} F_1(\mathbf{x}) \\ F_2(\mathbf{x}) \\ \vdots \\ F_p(\mathbf{x}) \end{Bmatrix}, \quad (1)$$

subject to:

$$\begin{aligned} x_i^l &\leq x_i \leq x_i^u, \quad i = 1, 2, \dots, N, \\ G_j(\mathbf{x}), \quad j &= 1, 2, \dots, M, \\ H_j(\mathbf{x}), \quad j &= M + 1, M + 2, \dots, L, \end{aligned} \quad (2)$$

where:

- $\mathbf{F}(\mathbf{x})$  is the vector of objective functions,
- $x_i^l \leq x_i \leq x_i^u$  imposes the side constraints to the design space, and
- $G_j(\mathbf{x})$  and  $H_j(\mathbf{x})$  are the inequality and equality constraint functions, respectively.

The basic nature-inspired algorithms are defined for unconstrained problems only. Since most engineering problems are multi-objective and/or constrained problems in one way or the other, it is important to add to the formulation the capability of dealing with this type of problem. For the sake of simplicity, it was decided to deal with multiple objectives by making use of the ‘‘Weighted Global Criterion Method’’ (Marler and Arora, 2004). This approach combines all objective functions to form a single scalar function, as given by eq. (3):

$$J(\mathbf{x}) = \left\{ \sum_{k=1}^P w_k \left( F_k(\mathbf{x}) - F_k^o(\mathbf{x}) \right)^p \right\}^{\frac{1}{p}}, \quad (3)$$

where,  $\mathbf{w}$  is a vector of weights ( $\sum_{k=1}^P w_k = 1$ ) and  $\mathbf{F}^o(\mathbf{x})$  is the ideal point (Marler and Arora, 2004), which is defined as  $F_k^o(\mathbf{x}) = \min_x \{ F_k(\mathbf{x}) \mid \mathbf{x} \in \text{Feasible space} \}$ ,  $k = 1, 2, \dots, P$ . Generally, the relative value of the weights reflects the relative importance of the objectives.

Following the same idea of keeping the formulation as simple as possible, constraints are handled by using the ‘‘Classical Exterior Penalty Function’’ (Michalewicz, 1995; and Coello, 2002). This technique penalizes unfeasible individuals by modifying the objective function in the unfeasible space. The idea is to increase the value of the objective function in this region. This means that during the optimization task, all individuals will tend to the feasible space. The formulation follows the scheme proposed by eq. (4).

$$J(\mathbf{x}) = F(\mathbf{x}) + \text{penalty}(\mathbf{x}), \quad (4)$$

where  $\text{penalty}(\mathbf{x})$  is zero, if no violation occurs, and positive otherwise.

In addition, this method puts all constraints together by using a set of functions  $f_j(\mathbf{x})$  given by eq. (5):

$$f_j(\mathbf{x}) = \begin{cases} \max \{ 0, G_j(\mathbf{x}) \}, & \text{if } 1 \leq j \leq M \\ |H_j(\mathbf{x})|, & \text{if } M + 1 \leq j \leq L. \end{cases} \quad (5)$$

In this method, the penalty function is written according to eq. (6):

$$\text{penalty}(\mathbf{x}) = r \sum_{j=1}^L f_j^\beta(\mathbf{x}), \quad (6)$$

where  $r$  and  $\beta$  are constants. The choice of  $r$  depends on the problem and must be defined by the user. On the other hand, a common choice for  $\beta$  is  $\beta = 2$ .

#### 4. OPTMIZATION RESULTS

Regarding the central part of the chassis, a total number of 31 nodal coordinates are assumed as continuous variables. The bounds for these variables are defined as an interval for which the center is taken from the baseline design. In the present work, the bounds range from 0.75 to 1.25 of the baseline values. It means that the baseline design is placed at the center of the design space and each node can be shifted to a position that has coordinates varying from

75% to 125% of the baseline counterparts. About the tube, the external diameter is a discrete variable that can assume one of the values shown in Tab. 2. For all these diameter values, the thickness ranges from  $1.06 \times 10^{-3} m$  to  $3.00 \times 10^{-3} m$ . It is worth mentioning that these values were obtained from commercial steel tubes found in the market. This way, the optimization is defined as a problem of 32 design variables (31 continuous and 1 discrete).

Table 1. External diameter.

Design variable values	1	2	3	4	5
Corresponding diameter $[\times 10^{-3} m]$	38.10	41.27	44.45	47.60	50.80

Figure 7 illustrates where the 31 nodal coordinates take place in the baseline design.

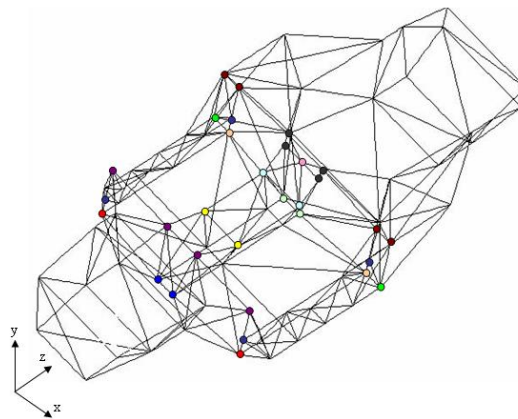


Figure 7. Nodal points for optimization.

Following the design framework suggested in Figure 1, four different formulations were tested in the first “optimization” step of the design cycle. Table 2 gives the description of each of the four formulations.

Table 2. Formulation of the optimization problem.

Scenario	Description	Formulation
# 1	The optimization problem is defined as the minimization of a dummy objective function, while both the mass and the stiffness are considered as design constraints.	Mass constraint: $G_1(\mathbf{x}) = \frac{M}{M_{limit}} - 1.0 \leq 0$ Stiffness constraint: $G_2(\mathbf{x}) = 1.0 - \frac{K}{K_{limit}} \leq 0$
# 2	Mass reduction is an objective function while stiffness increase is taken as a constraint.	Mass objective: $F(\mathbf{x}) = \frac{M}{M_{limit}}$ Stiffness constraint: $G(\mathbf{x}) = 1.0 - \frac{K}{K_{limit}} \leq 0$
# 3	Stiffness increase is an objective while mass reduction is a constraint.	Stiffness objective: $F(\mathbf{x}) = -\frac{K}{K_{limit}}$ Mass constraint: $G(\mathbf{x}) = \frac{M}{M_{limit}} - 1.0 \leq 0$
# 4	Multi-objective optimization containing two objective functions: mass reduction and stiffness increase.	Mass objective: $F_1(\mathbf{x}) = \frac{M}{M_{limit}}$ Stiffness objective: $F_2(\mathbf{x}) = -\frac{K}{K_{limit}}$

Table 4 contains the optimal results obtained in the first “optimization” step, in which all heuristic methods were set up with a population size of 50 and number of iterations of 50,  $M_{limit} = 100$  [Kg] and  $K_{limit} = 1900$  [Kgf · m/deg].

Table 3. Optimal results for the first step.

Method	Formulation	Mass		Torsional stiffness	
		Value [Kg]	% of reduction	Value [Kgf · m/deg]	% of increasing
ACO	# 1	107.24	23.1365	1897.7	9.8142
	# 2	115.93	16.9080	1937.8	12.1347
	# 3	100	28.3257	1765.08	2.1399
	# 4	105.31	24.5198	1937.8	12.1347
GA	# 1	107.96	22.6204	1774.54	2.6873
	# 2	126.34	9.4467	1937.8	12.1347
	# 3	100.03	28.3042	1809.56	4.7138
	# 4	100	28.3257	1937.8	12.1347
PSO	# 1	106.08	23.9679	2106.25	21.8824
	# 2	110.01	21.1511	1937.8	12.1347
	# 3	108.55	22.1975	1933.4	11.8801
	# 4	105.63	24.2904	1868	8.0956
<b>Baseline</b>		139.52		1728.1	

So far, given the values of both mass and torsional stiffness, PSO using formulation # 1 has shown to perform best in optimizing the original baseline structure. This way, this is the only configuration for the “optimization” step in a second iteration of the design cycle. Figure 8 illustrates the first candidate solution given by this configuration.

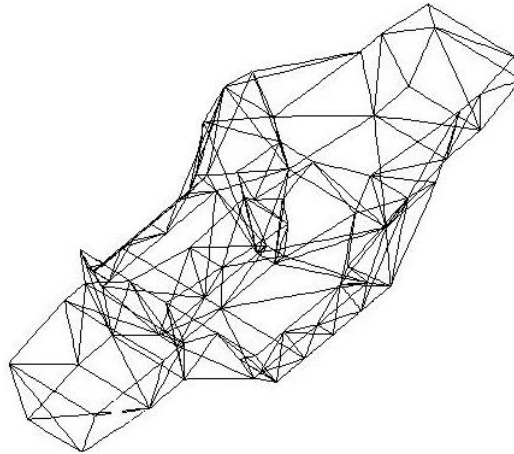


Figure 8. First candidate solution.

Table 4 summarizes all information about the only two iterations required to achieve an optimal design, following the framework given by Figure 5. A “design refinement” of the candidate solution in the first iteration was performed. After this, slight improvements can be observed both in the mass and torsional stiffness values. See the differences between the candidate solution of iteration # 1 and the baseline design of iteration # 2. In the second iteration, PSO was set up with a population size of 100 and number of iterations of 100,  $M_{limit} = 80$  [Kg] and  $K_{limit} = 2835$  [Kgf.m/deg].

Figure 9 illustrates the optimal design. As shown in Table 4, the final design presents an improvement of nearly 25.5% for the mass value and 62.6% for the torsional stiffness as compared with the initial baseline design.



Table 4. General data regarding the obtained results.

Design cycle iteration	Designs	Mass [Kg]	Torsional stiffness [Kgf · m/deg]	DOF of the model
# 1	Baseline	139.52	1728.1	19167
	Candidate solution	106.08	2106.25	18609
# 2	Baseline	105.7	2266	18675
	Candidate solution	109	2880	18333
Final design refinement	Optimal	104	2810	17643
<b>% Improvement (reduction for mass and increasing for stiffness)</b>		25.4587	62.6063	---

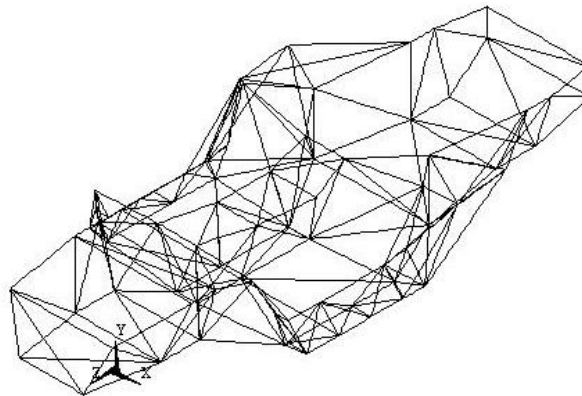


Figure 9. Improved Design (local optimum)

## 5. CONCLUSIONS

The present contribution demonstrated the application of numerical optimization, particularly nature-inspired optimization techniques to solve a realistic design optimization test problem represented by a three-dimensional vehicular structure. The investigation showed the possibility of using the present techniques in real world environment. The results are very encouraging in the sense that other system requirements, embracing for example the gravity center, dynamic and manufacture constraints, will be included in the optimization problem in further research work.

## 6. ACKNOWLEDGEMENTS

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## 7. REFERENCES

- Adams, H., 1993, "Chassis Engineering: Chassis Design, Building & Tuning for High Performance Handling", Hp Books, 133p.
- Aird, F., 1997, "Race Car Chassis Design and Construction", MBI Publishing Company, 128p.
- Baker, C.S., 2004, "FoES Formula SAE-A Space Frame Chassis Design", Dissertation of Bachelor, University of Southern Queensland, Faculty of Engineering & Surveying Southern Queensland, 101 p.
- Coello, C.A.C., 2002, "Theoretical and Numerical Constraint-Handling Techniques used in Evolutionary Algorithms: a Survey of the State of the Art", Computer Methods in Applied Mechanics and Engineering, Vol. 191, Issues 11-12, pp 1245-1287.
- Di Caro, G. and Dorigo, M., 1998, "AntNet: Distributed Stigmergic Control for Communication Networks", Journal of Artificial Intelligence Research, Vol. 9, pp. 317-365.
- Dorigo, M., 1992, "Optimization, Learning and Natural Algorithms", PhD thesis, Politecnico di Milano, Italy.
- Dorigo, M., Maniezzo, V. and Colorni, A., 1996, "The Ant System: Optimization by a Colony of Cooperating Agents", IEEE Transactions on Systems, Man and Cybernetics-Part B, 26(1):1-13.
- Happian, J.S., 2002, "An Introduction to Modern Vehicle Design", ISBN 0 7680 0596 5 ON -R-295, Society of Automotive Engineers, Inc., Reed Educational and Professional Publishing.
- Haupt, R. L. and Haupt, S. E., 2004, "Practical Genetic Algorithms", Wiley-Interscience Publication, 2nd edition New York, USA.

Kennedy, J. and Eberhart, R. C., 1995, "Particle Swarm Optimization", In Proceedings of the 1995 IEEE International Conference on Neural Networks, Perth, Australia, pages 1942-1948.

Marler, R. T. and Arora, J. S., 2004, "Survey of Multi-Objective Optimization Methods for Engineering", Structural and Multidisciplinary Optimization, 26:369-395.

Michalewicz, Z., 1995, "Genetic Algorithms, Numerical Optimization and Constraints", In Proceedings of the 6th International Conference on Genetic Algorithms, Pittsburgh, pages 151-158.

Michalewicz, Z. and Fogel, D. B., 2000, "How to Solve it: Modern Heuristics", Springer-Verlag, 1st edition, Inc. York, New York, USA.

Pourtakdoust, S. H. and Nobahari, H., 2004, "An Extension of Ant Colony System to Continuous Optimization Problems", In Proceedings in ANTS 2004, Fourth International Workshop on Ant Colony Optimization and Swarm Intelligence, Brussels, Belgium.

Souza, Ten.Cel.M.A., 1990, "Chassis – Estudo dos Pneus e Rodas", Apostila de aula, Instituto Militar de Engenharia, 96 p.

Thompson, L.L., Raju, S. and Law, E.H., 1998, "Design of a Winston Cup Chassis for Torsional Stiffness", SAE Technical Paper Series No. 983053, Motorsports Engineering Conference Proceedings, Vol. 1: Vehicle Design and Safety; Dearborn, Michigan, USA.

Venter, G. and Sobieski, J. S., 2002, "Particle Swarm Optimization", In Proceedings of the 43rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference, Denver, CO, USA, AIAA-2002-1235.

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