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# Optimization of Bolted Joints for Aircraft Engine Using Genetic Algorithms

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***Abstract:*** *Genetic Algorithms mimic the evolving technique of nature to better fit populations to a certain environment. Despite this technique has proved its adequacy in several fields, its application in Aerospace is still limited, mostly because of the high quantity of acceptability criteria that the design must pass and the amount of design parameters. The presented paper explores required GA architecture's adaptations to be applied in highly restricted systems such as those commonly found in Aerospace applications. The proposed GA was applied to the design of an Aircraft Engine's Axial Casing bolted joint following static strength restrictions as per FAR 33 regulations. The set of Elitism, interdependent geometric restrictions, Crossing, and Reproduction modules proved the applicability of the presented multi-objective GA architecture under 14 restrictions for normal, limit and ultimate loads. As it is described, the conversion is quickly achieved due to the shortage of the search space; therefore a modified Variable Crossing per Scheme is proposed to expand the diversity of the genome to compensate the relatively low impact of the Mutation module. Finally, the process and solutions found were compared against the traditional design process, showing the feasibility of this technique in complex applications in terms of quality of the solution and developing time.*
***Keyword:*** *Aircraft Engine, Bolted Joints, Genetic Algorithms, Optimization.*

## I. Introduction

The requirements for the design of components in the aerospace industry are considerably larger and more restrictive compared to other industries because their failure could result in accidents with a high fatality's ratio. Examples of these components are the axial bolted joints whose failure could result in the complete separation of sections for an aircraft engine.

To guarantee the airworthiness of these components, the regulation agencies such as the Federal Aviation Administration (FAA) or the European Aviation Safety Agency (EASA), require series of requirements to demonstrate the security of the elements [Ref. 1]. Among others, the parts must demonstrate structural positive margins of safety for:

- No deformation under limit loads (maximum load in service)
- No rupture under ultimate loads (loads covering an unexpected event, such as landing with failed landing gear)
- Damage tolerant parts
- Cyclic Fatigue

In order to accomplish all the requirements and get the airworthiness certification, the aircraft usually follows the design process described below:

**Phase 1 Conceptual Design:** Definition of basic functions of the product based in customer requirements.

**Phase 2: Preliminary Design:** Models and analyses are performed for the chosen conceptual design. Through analysis and experience on previous similar products, the first structural calculations are carried out and compared to requirements.

**Phase 3: Detailed Design:** Based in results from the Preliminary Design, the design is refined and optimized. The final design is tested and certified.

Due to the complexity of the system and the multiples interactions between design's groups working on the simultaneous design of different components of the turbine, the optimization is only carried out at the latest part of the detailed design phase, thus most of the optimization range is narrowed due to its impact to adjacent systems and lack of time. Proof of that are the several cost and weight reduction projects and redesigns throughout the life of the product.

Despite the proved capability of evolving computational techniques, such as the genetic algorithms, there are just few applications reported for the aerospace industry [Ref. 2]. It can be highlighted the works of Xie et all [Ref. 3] for the optimization of an aircraft wing and Ali et all and Marta [Ref. 4 and Ref. 5] for the conceptual design of an aircraft.

The objective of this research was to evaluate the application of evolving computational techniques in the design and optimization of a structural element for the aerospace industry that could be applied to early phases of the design, and to evaluate in quality and time the results compared to the traditional method. Based on its complexity, the design of an axial bolted joint for an aircraft engine provides a good case of study for a real application.

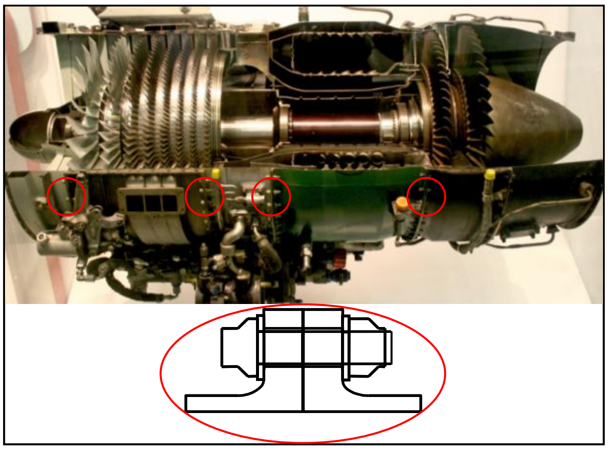

Figure 1. GE J85 Jet Engine External Bolted Joints

In this research, the following contributions are made:

- A novel architecture of an evolving computational technique using Genetic Algorithms (GA) is presented focused to solve the problem of a high restricted system of solutions using populations of tailor made genome performing under several restrictions and highly constrained acceptance criteria. The structure is composed of elitism functions, variable cross reproduction and selective functions for the reproductions.
- The structure of the GA was evaluated for designing a part where there is extensive work performed in order to optimize it with traditional methods: an axial bolted joint for an aircraft engine, being this a novel application of the GA's in a specific Aerospace design problem.

## II. Bolted Joint Calculation

As previously stated, a bolted joint in general, and particularly those joining the multiple casings along the aircraft engine, has several design restrictions. Some of these restrictions are the ones guaranteeing the design strength under different load events such as Normal Loads (loads expected to happen every flight), Limit Loads (maximum loads to be expected in service) or Ultimate Load (limit loads multiplied by a prescribed factor of safety, used for non-expected in service events). From the Federal Aviation Regulation, paragraph 33.24 [Ref. 1], the following set of requirements is imposed in order to have a valid design:

<u>Requirements under Normal Operation Loads</u>

1. More than 20% Margin of Safety (MoS) for net tension stress on the bolt against average yield strength with average preload.
2. Positive MoS for concentrated stresses on threads and on head's fillet against minimum yield strength with average preload.
3. Positive MoS for crush stress against minimum yield strength with average preload.
4. Positive MoS for flange bending stress against minimum yield strength.

5. More than 20% Separation Margin with minimum preload.
6. More than 20% Anti-rotational Margin with minimum preload.

Requirements under Limit Loads

7. Positive MoS for net tension stress on the bolt against average yield strength with average preload.
8. Positive MoS for concentrated stress less than average yield strength with average preload
9. Positive MoS for crush stress against average yield strength with average preload.
10. Positive MoS for flange bending stress against average yield strength.
11. Positive Separation Margin with average preload.
12. Positive Antirotational Margin with average preload.

Requirements under Ultimate Loads

13. Positive MoS for net tension stress on the bolt against minimum ultimate strength with average preload.
14. Positive MoS for flange bending stress against minimum ultimate strength.

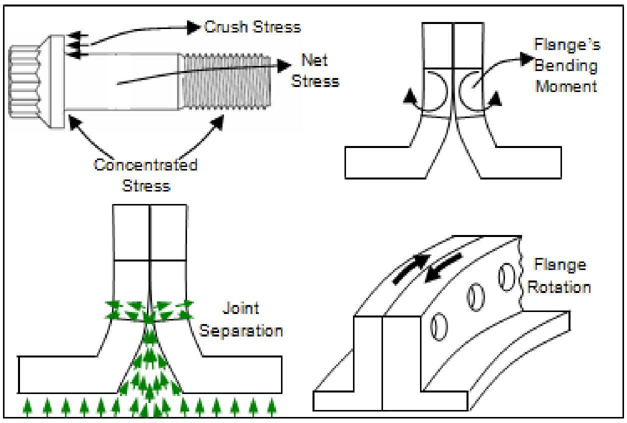


Figure 2. Summary of Bolted Joint Requirements

In order to calculate the margin of safety associated to each requirement, it is required to evaluate the load components acting on each casing's flange. The loads on a flanged cylindrical bolted joint such as those used in an aircraft engine come from several sources. Internal pressure, thrust, vibration, temperature gradients, and torque are only examples of these load excitations. The loads considered for the study case can be divided in Axisymmetric and Asymmetric loads as described in Fig. 3.

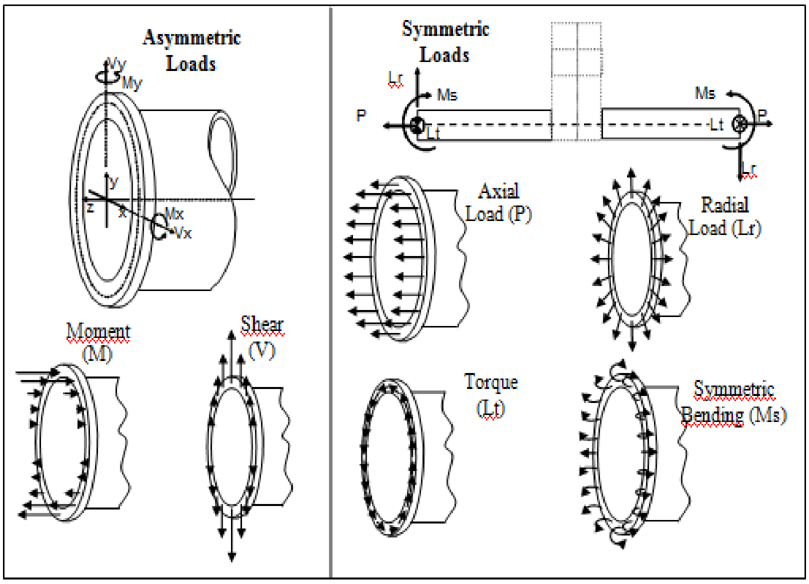


Figure 3. Bolted Joint Loads

The analysis described in this paper corresponds to a bolted joint with Normal, Limit and Ultimate loads of an aircraft engine in the order of ~30,000 lbs of thrust; however the methodology can be extrapolated to other thrust levels.

Once that the asymmetric and symmetric loads are translated into an axial, radial force and a bending moment for each segment defined by the pitch of the bolt (Fig. 4), each of them were analyzed as an eccentric prying joint following the procedure defined by Bickford (Ref. 6). This process has to be repeated for each set of loads (normal, limit, ultimate), for each bolted joint segment (number of bolts in the design) and each design proposal. Due to the nature of the iterative process, it is proposed the use of a Genetic Algorithm to find an optimal solution that minimizes the weight under the several design restrictions.

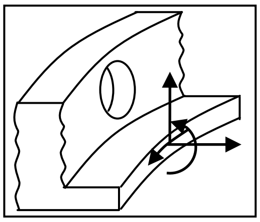

Figure 4. Segment of a Bolted Joint

## III. GENETIC ALGORITHM

**Background:**

The GA's were developed by John Holland in the 1960s as an abstraction of biological evolution and gave a theoretical framework for adaptation under the GA. But it was not until the development of computers where this field showed its potential [Ref. 7].

The basic architecture of a GA (Fig. 5) consists in a population of individuals whom genetic information consists in chromosomes mathematically modeled as bits (0, 1). A group of chromosomes create a scheme which represents a design characteristic in the model (such as a variable design's dimension). Once that an initial population is created, each individual is evaluated using a fitness function and according to its performance, a score is assigned related to the optimization goal. The best suited individuals are picked for crossover and generate children individuals forming the next generation. Since only the best individuals were selected for defining the next generation, as evolution in nature, the population would improve generation by generation.

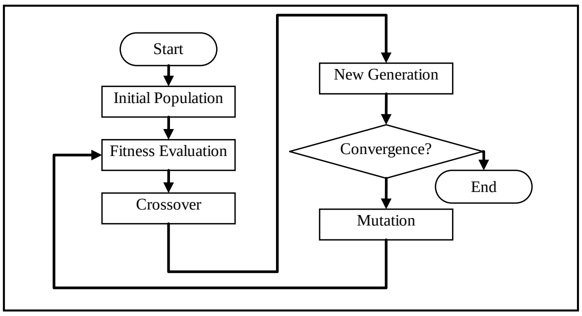


Figure 5. Basic GA Architecture

**GA Modeling:**

For the presented case of study, it was assumed that the diameters and thicknesses of the casings to join were already defined by the designer and those are considered inputs for the GA (Fig. 6). The flanges and bolted joint elements, such as bolts, nuts, washers, and the required torque to join them are modeled in the GA through 9 schemas:

1. Bolt & Nut type
2. Bolt & Nut Quantity equally spaced.
3. Bolt & Nut Material
4. Left Flange Thickness
5. Right Flange Thickness

6. Washer Quantity &Thickness
7. Torque applied to the bolt
8. External diameter of flanges and Radius of action of the Bolted Joint
9. Radii of flange and case union

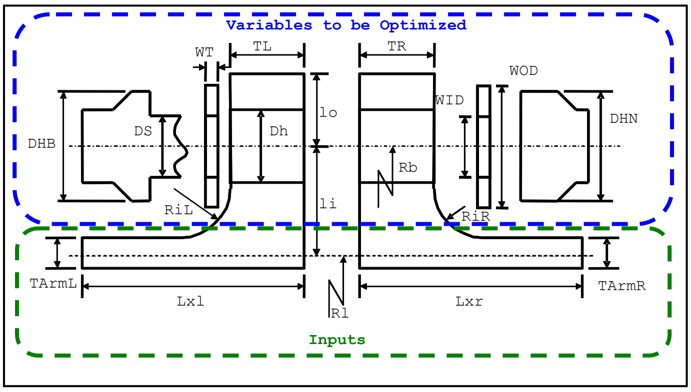


Figure 6. Inputs and Elements Optimized in a Bolted Joint

In order to guarantee a wide range of potential solutions, the system was modeled with 22 genes that create a search space of $4.2x10^6$ combinations:

Table 1. Genome of Each Individual Representing a Design

| Genes | Combinations | Characteristic |
|---|---|---|
| 2 | 4 | Bolt Type |
| 1 | 2 | Bolt Material |
| 4 | 16 | Bolt Quantity |
| 3 | 8 | External Flange Diameter |
| 2 | 4 | Radii |
| 3 | 8 | Left Flange Thickness |
| 3 | 8 | Right Flange Thickness |
| 2 | 4 | Washers |
| 2 | 4 | Torque |

To avoid having individuals with non-functional designs, such as a design having a diameter of the flange's bolt hole larger than the bolthead diameter, some features are defined as a function of the Individual's gens. For example, the search space for the external flange diameter consisted in 8 combination between 1 to 3 times the bolthole radius, and this last was defined as the diameter of the bolt plus a fixed clearance. This guarantees that the $4.2x10^6$ combinations represent in fact valid designs from the geometrical point of view.

**Elitist Function:**

The GA uses an elitist function that forces the algorithm to work with only valid individuals; this means that any geometrically valid design have to pass the 14 design requirements previously to be part of the population.

This rule was followed not only for the creation of the first generation's population, but also after a new individual was created after the crossing and reproduction. While this created a highly restricted system, it helped to work exclusively with valid designs, speeding up the process and emulating what should have been done in the Preliminary and Detailed Design Phases of the traditional design methodology.

**Crossing:**

As a first option, it was considered the most frequent crossing method, which consists in the wheel roulette for defining a crossing point in the genome of the parents, and mixing the gametes to create two descendents as shown in Fig. 7. [Ref. 8, Ref. 9].

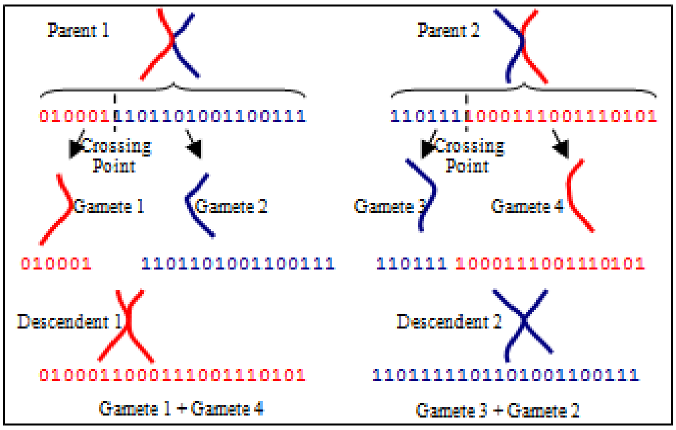


Figure 7. Random Unique Crossing

As specified before, the design was modeled using 9 schemes or groups of genes defining the physical characteristics of the bolted joint (Fig. 8). Since this method has a unique cross point, 10 of the 23 (43%) potential cross points are actually boundary of the schemes, thus there are 43% that the individuals created with this technique would have the same scheme as one of their parents. As it will be shown later, this has an impact on the converging time and the possibility of getting stuck on local optima.

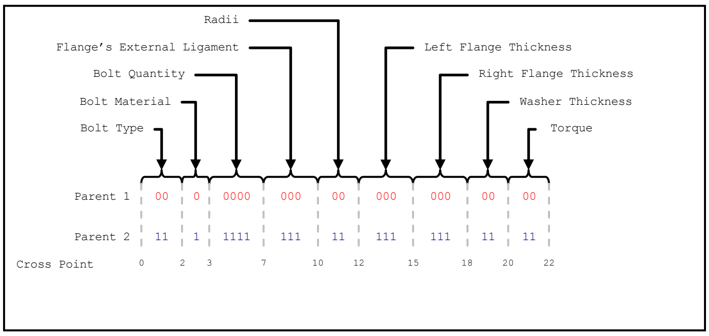


Figure 8. Random Unique Crossing Points

Opposite than the single point genetic algorithm and other methods (Ref. 10), a second option of a variable crossing per each scheme was developed. This consists in randomly picking a crossing point for each scheme that represents a physical characteristic, such as the bolt quantity (Fig. 9). This crossing generates non-continuous gametes from the parents, then having creating a larger genome pool for the population.

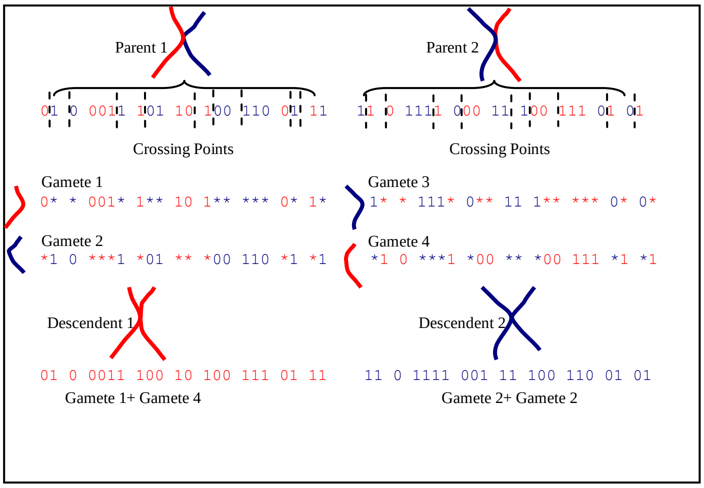


Figure 9. Variable Crossing per Scheme

Since there are 9 crossing points for each individual, the descendents would preserve parents´ characteristics defined characteristic and searching faster for improving combinations of those characteristics. This option maximizes the diversity of the population in highly restricted systems. The difference between these two methods can be easier visualized through an example. If the scheme defining the genome of bolt quantity of one parent represents 50 bolts and the for the other parent 30 bolts, the unique crossing point will most likely generate individuals with either 50 or 30 bolts, since the probability of having the unique crossing in the bolt quantity scheme is only 3/23. The Variable Crossing per Scheme will break the gene's sequence in order to find intermediate values as well.

**Reproduction:**

Most of the existing GA methods present a system of reproduction where a couple of parents create a couple of descendents as shown in Fig. 7 and Fig. 9. This process guarantees to have continuity in the population size throughout the generation. For the presented case of study, this method did not perform very well. Since the system is over-restricted due to the high quantity of design requirements, the possibility of finding two valid parents that could create two valid descendents was very low, and when this happened, it was because the parents' genomes were so similar, that the created descendents had a very small improvement in performance, moreover they were almost identical. In order to guarantee that a couple of parents, not sharing a similar genome, could generate valid descendents, it was decided to select only one individual from those generated for the crossover, using the child with better performance. It was also decided that if after 20 attempts a valid individual was not generated, to replace the child with the best performing parent for the next population through a tournament selection. To guarantee the dimension of the population, this process was repeated until the new generation had the same dimension as its precedent.

**Mutation:**

Different rates of Mutation were imposed to the algorithm between 1% to 3%, however no significant impact was recorded in the results. Most likely, the null effect of mutation comes from the fact that, due to the high constrained system, the probability of creating a valid individual was too low and the elitism criteria rejected the potential mutation.

**Convergence:**

The convergence criteria used in the algorithm was through the number of generations without a change of added volume (as all the materials in the design where Inconel 718) for the best evaluated individual of the population. This number was increased from 3 to 10, however after 5 no significant changes were recorded.

## IV. Results

Although the elitism helped to converge in terms of number of generations, it took a great amount of iterations just to have a valid initial population. As shown in the Fig 10-a, only in less than 10% of the cases it was required one iteration to create a valid individual. In average it took ~17 iterations to get a valid design. Additionally, the elitism had an impact in the computational time for the GA. From several experiments, it was measured that approximately 20% of the GA computational time was consumed by producing valid individuals for the initial population.

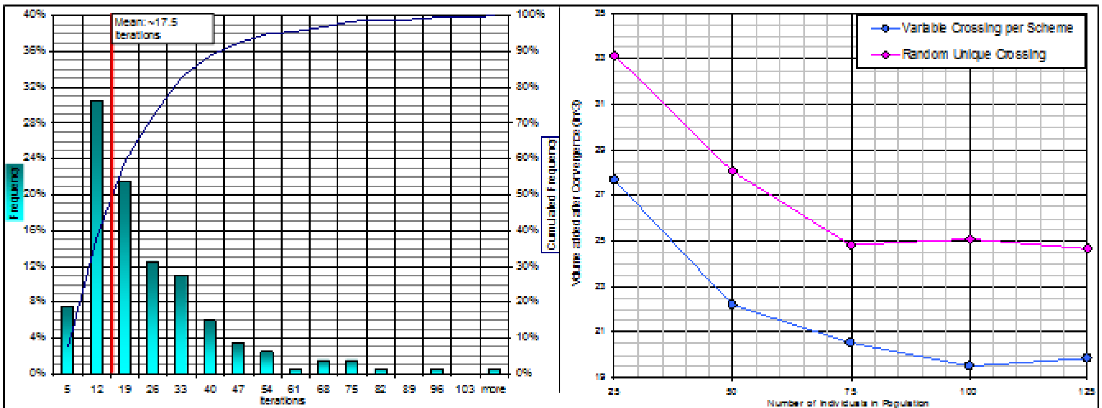


Figure 10-a. Iterations for First Generation

Figure 10-b. Evaluation of Crossing Techniques

Figure 10. Evaluation of GA Parameters

Since the convergence is achieved very fast (usually in less than 20 iterations), it is very important to have a relatively large population to guarantee that a wide spectrum of design characteristics are represented. In order to evaluate the quantity of individual required in the population to have reliable results, the GA was run 200 times with populations of 25 to 125 individuals. The analysis was repeated for the two crossing techniques explained above. Comparing the results of Figure 10.b, it can be noted that after 100 individuals in the population, there is no a substantial improvement in the results, thus 100 individuals can be considered as appropriate for the analyzed problem. Additionally, it can be seen a clear positive offset of the variable crossing per scheme technique over the random unique crossing. This can be explained by the fact that the variable crossing per scheme technique adds diversity to the population by expanding the search area to new proposals and in this over-constrained system, the diversity avoids being stuck in local optima.

Fig 11 show the general behavior of results of the volume added in average per generation and the volume added by the best individual in the generation. Fig 12 shows graphically the evolution of the design characteristics.

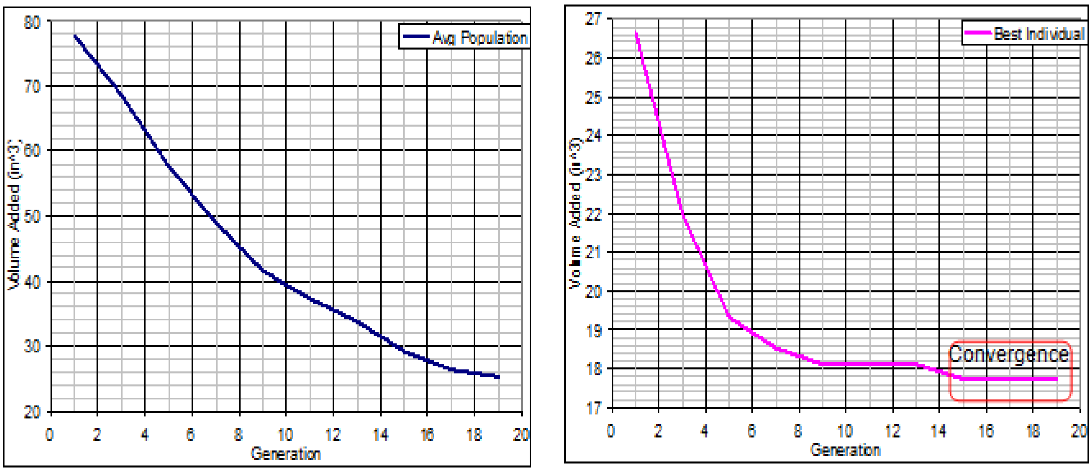


Figure 11. Average Added Volume and Volume for Best Individual per Generation

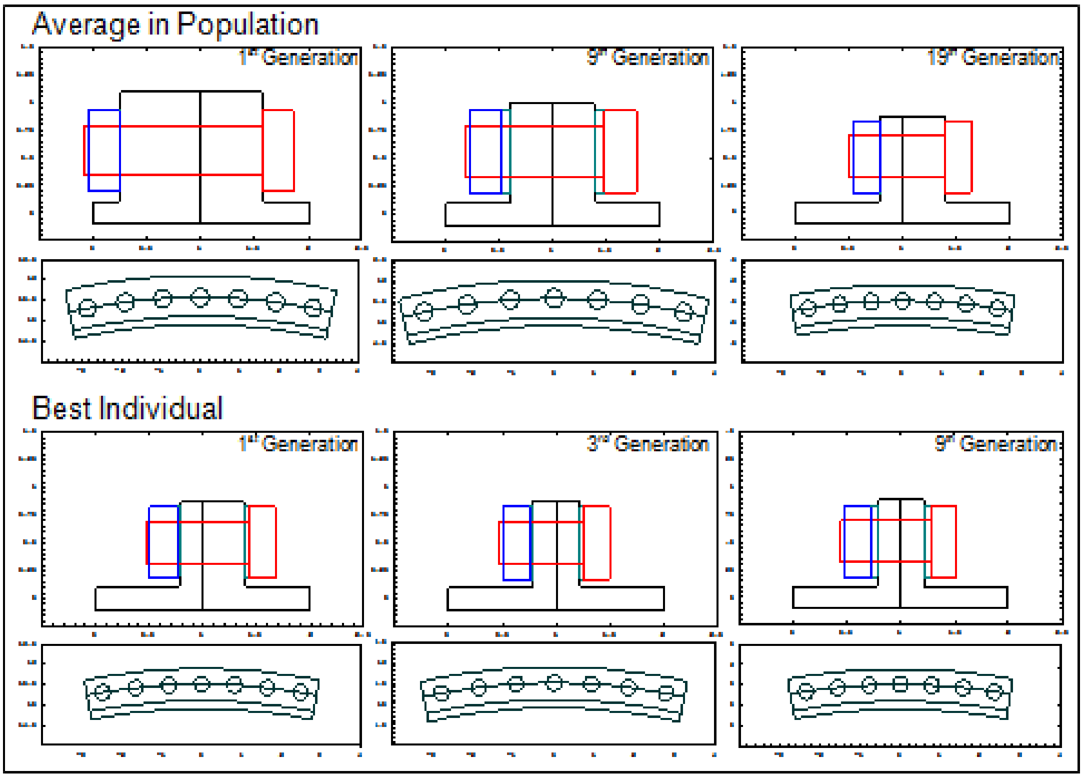


Figure 12. Evolution per Generation for Average Population and Best Individual

Before analyzing the study case with the GA tool, it was traditionally analyzed by a designer using a spreadsheet containing the evaluation function (Margins of Safety to the 14 design requirements). After approximately 5 hours it was possible to find the first acceptable design. It was needed approximately 3 more hours to find an optimal solution that added $58in^3$ of volume. Despite the fact that the comparison was performed with only one case, the result is contrasting. In average, the solution using the GA takes 15 minutes for a population of 100 individuals and the volume added is approximately $19.4in^3$.

## V. CONCLUSION

The current situation of the aerospace industry, with fuel economy as prime criteria for improving aircraft and engines, combined with higher costs of production and more exotic and costly materials, requires novel optimization techniques that could be applied in the early design phases. Although there had been several evolutionary computing techniques evolving computational techniques reported in the literature, the application of these tools are still limited to experimental systems, despite their potential for improving designs faster than traditional design methods. As shown in this research, the single point crossover GA technique does not work very well, because the highly constrained nature of the problem. On the other hand, once the populate generation was solved, the alternative crossover proposed in the research led to fast results and with positive potential, both in time and technical parameters, compared with traditional design processes.

However, the GA based proposed system, requires a lot of knowledge from the designer in order to define the initial constraints for the problem to be solved. Whereas the engineering judgment is very important, the research showed promising results with better technical parameters, weight reduction and shorter developing time. Despite the promising results of this research showing the potential of using evolutionary optimization techniques for the aerospace industry, still a lot of work is required in order to meet the regulations for such specialized industry. It is also important to note that the GA's do not work completely independently since the engineering judgment is critical to define the boundaries of each explored design parameter, and if the range does not include the global optima, simply the GA will not find it.

This roadblock can be avoided by using the GA's in steps, starting with an obviously large range for each design parameter, and then narrowing the range in the following runs.It is intended to explore further applications of these techniques increasing the number of design requirements that were ignored in this first approach such as thermal loads, damage tolerance, buckling, low cycle and high fatigue. Additionally, other systems and design problems will be explored such as the design of flanges, stringers, panels or the shape of an aircraft window.

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