Journal of Computational Applied Mechanics 2023, 54 (2): 268-284

DOI: 10.22059/jcamech.2023.355499.809

RESEARCH PAPER

Effect of different aero-structural optimization in the commercial airplane

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Abstract

Aircraft wing design using Multidisciplinary Design Optimization (MDO) techniques is a complex task that involves different disciplines, mainly aerodynamic and structure. This study develops and explores a coupled aero-structural multidisciplinary model that optimizes the performance of CRJ-700 aircraft, taking into account its path-dependent behavior. Two approaches, namely distributed and monolithic architectures, are available to achieve this aim. The decomposition strategies employed in these architectures differ and can significantly impact the design process. Therefore, comparing these methods can assist designers in understanding the design cost and accuracy of the results obtained. Eventually, optimizing the aircraft problem involved leveraging two methods: Multidisciplinary feasible (MDF) and Collaborative optimization (CO). Finally, the results obtained by two approaches; CO gives a high range value; MDF will be converged after 6013 times of the call function; but the number of call functions in the system-level of CO is around 4000 and the average of it for aerodynamic and structure optimizers are around 500 and 20, respectively. The range of the optimum wing of MDF approach raise about 41% and for CO approach raise about 66% compared to the baseline wing ranges.

Keywords: Multidisciplinary design optimization (MDO), Multidisciplinary design feasible (MDF), Collaborative Optimization (CO), Aerodynamic forces, Shape optimization, Commercial airplane

1. Introduction

Aerospace engineering is a dynamic field that encompasses a wide range of disciplines, including aerodynamics, fluid dynamics, fluid mechanic, CFD, and spacecraft design. This field involves the study of how objects move through the air, as well as how fluids interact with solid objects. The principles of aerospace engineering are used in the design and construction of aircraft, spacecraft, satellites, and missiles. This field is constantly evolving, with ongoing research and development aimed at improving efficiency, safety, and performance. By combining engineering principles with scientific knowledge of aerodynamics and fluid dynamics, aerospace engineers work to create innovative solutions to the challenges of flight in both the Earth's atmosphere and beyond[1–6].

With the steady rise in air traffic, there is a pressing need to improve the performance and efficiency of aircraft. To encounter these requirements, various constraints have been placed on the development of future aircraft concepts, the refinement of design tools, and the augmentation of design process quality. Design optimization is an

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approach that uses mathematical optimization algorithms in conjunction with simulation tools in order to rapidly identify the optimal solution within a design space. As opposed to traditional trial-and-error methods which are time-consuming and do not guarantee the best possible performance, this approach eliminates such drawbacks while ensuring that all criteria are met and constraints respected [7].

The aeronautic industry is presented with a considerable challenge to lessen the environmental effects of air travel, such as exhaust and noise. For example, the Flightpath 2050 vision for European aviation [8] has set forth ambitious goals that are influencing the development of future aircraft. As other important aspects such as life-cycle cost including operations and maintenance must also be taken into account, the requirements for greening must be integrated at the initial stages of design [9].

In order to achieve the balance between environmental impact and speed and capacity, aircraft multidisciplinary optimization should be employed in the design process. This would enable aircraft to be adapted to different situations, allowing for the best performance with minimal environmental and economic consequences. Recent developments in material sciences and computer sciences have resulted in a new field of research, which focuses on adaptation. This has been enabled by the comprehensive theoretical framework for incorporating multifunctionality into materials and high-speed digital computers for transforming this framework into practical design and production methodologies. Adaptive structures represent a novel approach that integrates sensors, actuators, and control circuit elements into one system that can adaptively respond to changes in the environment [10]. In order to sustain laminar flow, aircraft components with high Reynolds numbers or sweep require a laminar flow control (LFC) system. However, the performance penalties associated with added weight and complexity have limited the application of LFC systems in aircraft. Natural laminar flow (NLF) technology is being considered an attractive option for reducing drag on future aircraft, and is currently available on components with low sweep and/or Reynolds numbers, such as the Honda Jet wing, Boeing 787 nacelle and Boeing 737 Max winglet [11, 12]. Applying NLF technology to the main wing of a typical transonic transport aircraft has the potential to substantially decrease drag, leading to improved aerodynamic performance and lower operating costs. A new computationally based NLF design method is being developed which can predict significant regions of laminar flow on configurations with high leading-edge sweep and high Reynolds numbers[13].

Since the dawn of aviation, engineers have sought to create an aircraft that produces maximum lift while minimizing drag. This ambition has resulted in the development of the flying wing (FW) aircraft, which lacks an empennage and fuselage, with the entire payload being located within the wing. These aircraft are deemed ideal for unmanned aerial vehicles (UAV) and micro aerial vehicles (MAV) due to their structural efficiency, aerodynamic performance, and stealth capacity. Despite these advantages, flying wings remain less prevalent than their conventional counterparts in recent years [14–23], as evidenced by their comparatively low number of successful developments.

Numerous studies have been conducted to optimize the design of the wing alone, as well as a few others on optimizing the wing within a more elaborate arrangement such as a wing-body or a wing-body-tail configuration. However, there has not been an in-depth exploration of the impact of horizontal-tail shape and trimming using RANS CFD. This paper presents the optimization results from lift-constrained drag minimization of the CRM wing-body-tail configuration [24] utilizing RANS CFD, with both wings and tail shape optimization simultaneously [25]. Numerous analyses such as vibrations or fluctuations helped to understand the better performance of wings or their structures of them to identify the objective to optimize or solve the problem [26–35]. To become more accurate, Farajpour et al. have done many investigations to analyze these issues and check both structural and fluidic and even a combination of them [34–43].

Aircraft wing design using Multidisciplinary Design Optimization (MDO) techniques is a complex task that involves different disciplines, mainly aerodynamic and structure. Different levels of analysis are used for wing design and optimization. Typically simple empirical methods are used in the earliest stages of the concept design. The design task proceeds toward the final design by increasing the complexity of the analysis methods. For instance, a variety of methods are available for aerodynamic analysis of a wing; from a simple lifting line theory or a vortex lattice method up to complex Euler and Reynolds-Average Navier-Stokes methods. Similarly for structural weight estimation, various methods with different levels of fidelity are available. The difficulty lies in the quest or development of analysis methods that are sufficiently simple to be used thousands of times during the optimization. At the same time, these methods should be sophisticated enough to capture changes in the local geometry. Multidisciplinary Design Optimization or MDO, is a methodology for the design of systems in which strong interaction between disciplines motivates designers to simultaneously manipulate variables in several disciplines [44].

The multidisciplinary feasible (MDF) method is examined by Cramer et al [45]. Also, it is the traditional MDO approach and it involves solving a single optimization problem that calls a multidisciplinary analysis (MDA) when objective or constraint values are required. The MDA explains the governing equations for all disciplines. The MDA module takes the design variables and solves all governing equations until the coupling variables have converged. The values of the objective and constraints can then be computed. By requiring the solution of the MDA at each design point, MDF confirms that each optimization iteration is multidisciplinary feasible. This is a very desirable property since if the optimization is terminated impulsively, a physically realizable design point is at hand. The effort required to implement MDF for a given problem is directly related to the effort required to build an appropriate MDA module. Antoine and Kroo [46] explored the incorporation of environmental performance into a Multi-Disciplinary Optimization (MDO) framework for preliminary aircraft design with the aim of reducing significant environmental impact. The results demonstrated that flying slower and at lower altitudes can effectively reduce environmental impact. Noise drop has also been comprised of multidisciplinary optimization [47–49].

To better understand the contribution of flying wings' multidisciplinary design optimization, Nikkhoo et.al[50] performed the optimization for flying GIS UAVs. Hence the results conclude that by approaching MDO the range of the UAV increases sharply, also the lift goes high too.

To counterbalance such issues, multi-level optimization techniques have been developed. This research concentrates on one of these techniques, namely collaborative optimization (CO). This optimization tool is applicable to large-scale multidisciplinary design optimization and has clear advantages in both computational and organizational aspects. Nevertheless, issues with convergence and computation time have been reported [51, 52].

Collaborative optimization (*CO*) is a multi-level decomposed methodology for a large-scale multidisciplinary design optimization. The collaborative optimization is known to have computational and organizational advantages. Its decomposed architecture along disciplines removes the necessity of direct communication between disciplines and guarantees the autonomy of disciplines. However, collaborative optimization has several problems at convergence characteristics and computation time [53, 54].

Designing aircraft poses a challenge due to the complexity of interactions between various subsystems, making it a multidisciplinary system. The design process of such aircraft requires the consideration of multiple relevant disciplines, including aerodynamics and structural systems, in a cohesive range formulation to ensure accurate assessment of its performance. The primary objective of this research is to develop and explore a coupled aero-structural multidisciplinary model that optimizes the performance of CRJ-700 aircraft, taking into account its path-dependent behavior. Two approaches, namely distributed and monolithic architectures, are available to achieve this aim. The decomposition strategies employed in these architectures differ and can significantly impact the design process. Therefore, comparing these methods can assist designers in understanding the design cost and accuracy of the results obtained. These methods devide to two approach: Multidisciplinary Feasible (MDF) and collaborative optimization (CO). The Breguet range is considered an objective function and to maximize it, both wing structure weights should be minimized and simultaneously maximized the lift-to-drag ratio of the wing. To do this type of optimization, the Multidisciplinary Feasible (MDF) method and Collaborative Optimization (CO) are selected which could couple both structure and aerodynamic equations to enrich the optimum range and values.

2. Physical definition

Bombardier Aerospace has created several regional and business aircraft in the last 10 years, including the CRJ-700, which is a 70-seat version of the successful Canadair Regional Jet CRJ-200. The CRJ-700's wing design was completely new and included leading-edge devices. Safety, simplicity, and performance were the main priorities during the development of the CRJ-700's aerodynamic configuration, especially in regards to low-speed characteristics. To ensure safety, it was important to have clear stall characteristics with a downward pitch and minimal rolling. Double-slotted hinged flaps, similar to those used on the CRJ-200, were chosen for simplicity. Lastly, performance was maximized by achieving as much lift as possible and excellent second-segment-climb capability.

The wing of Bombardier CRJ-700 aircraft is preferred and its specification expressions are in Table 1 and Fig 1.
Alloy Al 7075-T6 is considered the material used in the manufacturing of the wing. Young modulus of Aluminum 7075-T6 is 72 GPa and Density of Aluminum 7075-T6 is 2.81 g/cm3.

The CRJ-700 was built to transport a group of 70 passengers and three crew members on trips spanning up to 1685 nautical miles (or 1985 nautical miles in the extended-range model), with a cruising speed of Mach 0.78. It can operate at a maximum speed of Mach 0.83 and reach a maximum cruising altitude of 35,000 feet. The aircraft is designed to lift off at a maximum weight of 73,000 pounds. More over, the wingspan of bombardier CRJ-700 is 76.25 ft.

Also, the wing’s sweep, taper ratio, and aspect ratio are aforementioned as $\Lambda = 30^0$, $\lambda = 0.3$ and AR=8, respectively. Hence the combination of jig twists and spar thicknesses that maximizes the range of this wing, while ensuring that the wing structure will not fail at a maneuver condition with a load factor n 2.5.

Table 1: Bombardier CRJ700 specifications.

Specification	Value
Range	R = 1685 n.mi
Cruise Mach number	M = 0.78
Cruise altitude	H=3500 ft
Wing span	B=23.24 m
Thickness/chord ratio	t/c=0.12
Max section lift coefficient	CLmax=0.6
Engine SFC (GE CF34)	SFC=0.38
Take of weight	TOW=323608N
Operating empty weight	OEW=193498N
Range	R = 1685 n.mi
Cruise Mach number	M = 0.78
Cruise altitude	H=3500 ft

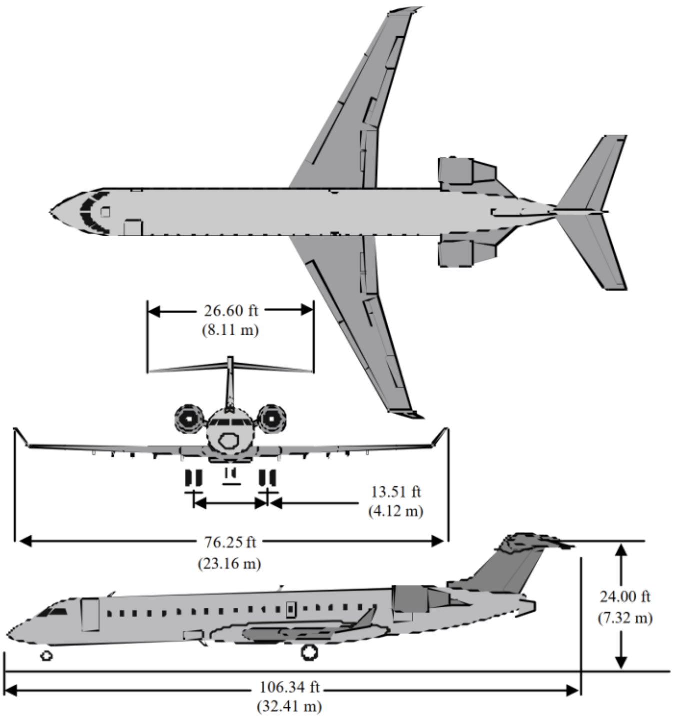


Fig 1: CRJ-700 aircraft general arrangement [55]

3. Definition of applied techniques

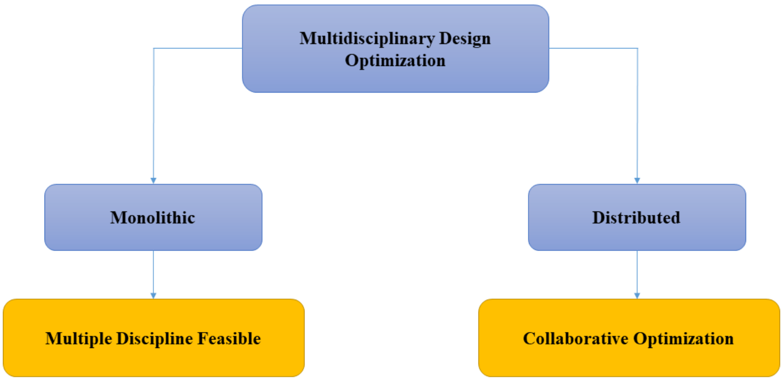


Fig 2: Multidisciplinary design optimization flowchart division

Multidisciplinary design is divided to two approach (Monolithic and Distributed) that reveals in Fig 1 [56, 57]. One approach to MDO is to consider the different disciplines as a single monolithic analysis. This is conceptually very simple, and once all disciplines are coupled to form one single multidisciplinary analysis module, one can use the same techniques that are used in single discipline optimization.

The disadvantages of monolithic architectures become apparent as problem sizes increase. Because only a single optimization problem is formed, that one problem must handle the thousands of variables and constraints present in the original MDO problem. This can be costly if the coupling between the disciplines is weak.

The only opportunity for parallelizing the optimization procedure would be the use of different processes for each member of the population when using a genetic algorithm or running the analyses for different design points when calculating gradients by finite differencing or when evaluating the points for a response surface.

Another disadvantage of monolithic architectures is organizational. The autonomy of each discipline is necessarily restricted so that the optimizer can access variable and constraint information from each discipline at the same time. This can present problems if the disciplinary groups are widely distributed in an organization or if some disciplines have many more constraints and variables or much more computationally-intensive analyses than others.

Engineers have long recognized the value of decomposing large design problems into smaller ones. The tendency to divide and conquer seems to be part of the human nature. Consider for example the design of an aircraft: it is typically divided among disciplinary teams including the structures team, the aerodynamics team, the propulsion team, and the controls team.

There are two major reasons for decoupling large problems into smaller ones:

1. The first reason is to increase efficiency. Several engineers working in parallel should be able to solve the problem faster than a few engineers solving the problem in a serial fashion;
2. The second reason is to exploit design expertise. Different engineers have different talents, training, and experience. Their contribution is maximized by allowing each of them to work in their own specialty area with as much autonomy as possible.

However, some control must be maintained over the different groups of engineers because coupling usually exists between the groups, and the overall objectives for the system must be achieved.

These approaches of decomposing the original large MDO problem into smaller subproblems that are specifically designed to converge to the solution of the original problem are referred as distributed architectures.

These architectures formulate smaller subproblems based around giving each discipline control of local design variables and local constraints. The smaller subproblems can then be solved independently using parallel computation. A coordination problem is then solved to update problem information and 'push' these subproblem solutions toward convergence at the optimal solution. Conceptually, this approach is most effective when the problem has a sparse structure. That is, the number of global variables, global design constraints, and consistency constraints is small relative to the problem size. This structure reduces the amount of computational work imposed on the coordination problem. Distributed architectures are still being actively researched, as they have tended to perform poorly on some test problems compared to the monolithic architectures. However, it can be argued that many of the test problems are too small to show the potential of the distributed architectures.

3.1. Multidisciplinary Feasible(MDF)

To clarify in this investigation, Multidisciplinary Feasible (MDF) is chosen in this section and all results are obtained from this approach[58]. In this investigation, the Breguet range calculates fuel consumption used as a function of structural weight and aerodynamic performance reveals in Eq.1 [59, 60].

The aim of present work is to modify the wing of Bombardier CRJ700 that is reached to the maximum range. The standard form of the problem can be mathematically stated as,

$$\text{Maximize} \quad R\,,\ \left\{R=\frac{V}{SFC}\frac{L}{D}\ln\left(\frac{W_{\text{initial}}}{W_{\text{final}}}\right)\right\} \tag{1}$$

With respect to x

Subject to $L-W=0$

$$n\sigma_j - \sigma_{yield} \leq 0$$

Where x is the design variable and contains spar thickness as t and jigtwists as γ. L and W are the lift force and weight of the wing, individually [52, 61]. The load factor is called (n), too. Also, In the above equation, R represents the Breguet ranges, and V is considered as velocity. Although, L, D, and SFC are revealed as lift, drag, and Specific Fuel Consumption, respectively.

Where the aero-structural analysis is as,

Aerodynamic governing equation: $A\Gamma = v(u)$ (2)

Structural governing equation: $Ku = f(\Gamma)$ (3)

Where K is the stiffness matrix, f is the vector of external forces, A is the aerodynamic influence coefficient matrix, and v is a vector of panel boundary conditions. The state variables that must be solved for by the aero structural analysis are the finite-element displacements, u, and the panel circulations, Γ. The angle of attack at which the wing flies is returned to the wing to see the resulting lift (= weight of the spar + fixed non-spar weight). In addition, the program will return the lift and elastic twist distributions, and the stress distribution on the spar. The stress distributions can be used to specify material failure constraints. Moreover, the objective function, design variables, and constraints are clearly identified in Table 2.

Table 2: Classification of the objective function, design variables, and constraints

Objective function	$-R = -\frac{V}{SFC}\frac{L}{D}\ln\left(\frac{W_{initial}}{W_{final}}\right)$
Design variable	Spar thickness= t Twist= γ
Constraints	$n\sigma_j(u) - \sigma_{yield} \leq 0$ $L(\Gamma) - W(t) = 0$

Furthermore, Fig 3 and Fig 4 reveal the flow chart of the problem with the MDF approach and data flow. As shown in the figure, the initial values of design variables are given and then the coupled governing equations of structure and aerodynamic parts are solved. Subsequently, the objective function would be calculated based on the results of MDA. The optimization algorithm will try to find the best output and finally, the algorithm will check the answer of the optimization process. If the optimized output is matched with the solution of governing equations, the simulation would be stopped otherwise the optimized output will be mentioned new design variables, and run the procedure again.

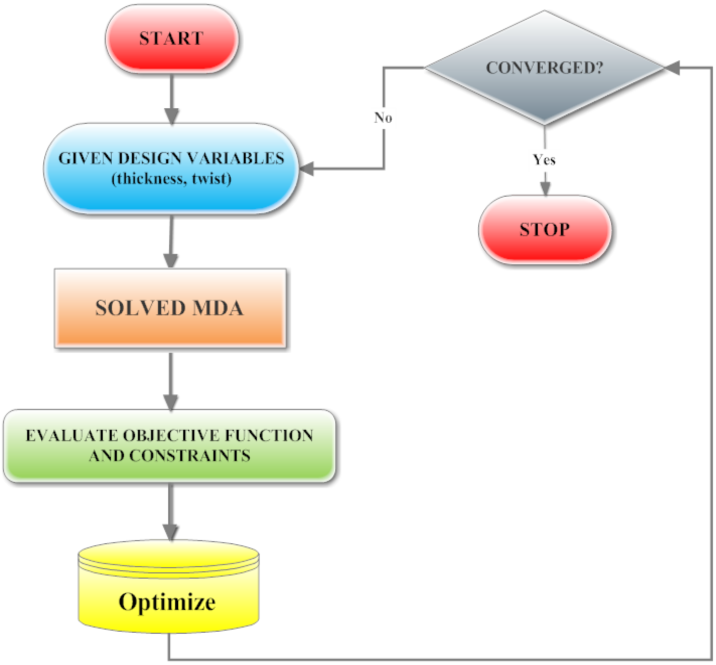


Fig 3: MDF flowchart

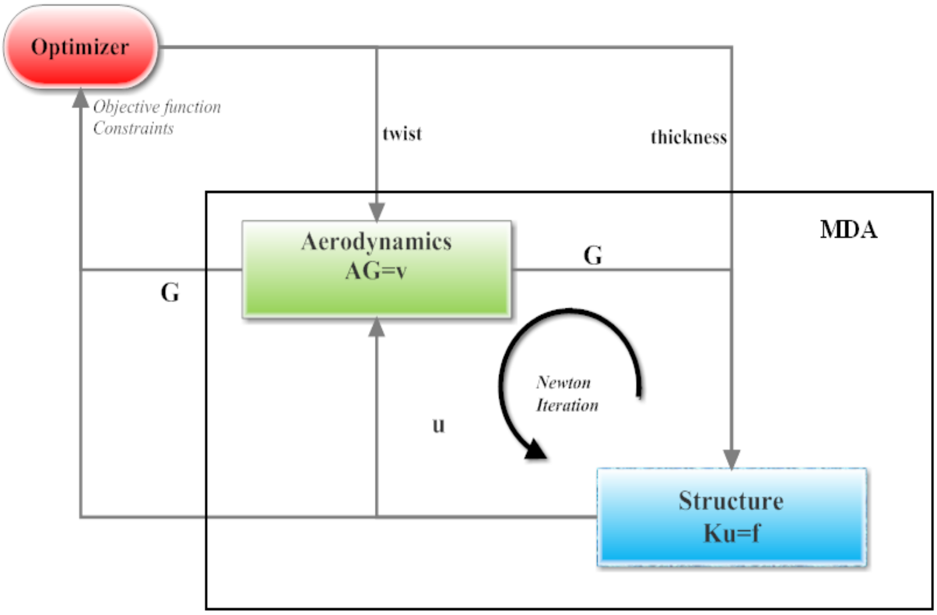


Fig 4: MDF data flow and MDA

3.2. Collaborative Optimization (CO)

In this section, Collaborative Optimization (CO) is chosen and all results are obtained by this approach also the problem will be explained in standard form [62, 63]. The main goal is to maximize the Breguet range of the Bombardier CRJ700 wing. The range equation was obtained as shown in Eq1.

In this work, velocity (V), and engine SFC are fixed. Moreover, wing span, chord, sweep, taper ratio, aspect ratio, Mach number, and cruise altitude are also constant. Only two parameters are considered as a design variable, thickness, and jigtwist.

An important point in this problem is that lift force and weight should be equal. Lift force will be achieved by the aerodynamic governing equation and the weight is computed by the structural equation. The weight doesn't equal the take-off weight (TOW), exactly and is given as:

$$\mathrm{W=ZFW+}W_{reserves}+\frac{1}{2}W_{maneuver} \tag{4}$$

ZWF represents zero fuel weight. The standard form of the problem can be mathematically stated as,

$$\text{Maximize}\quad \mathrm{R},\ \left\{\mathrm{R}=\frac{\mathrm{V}}{\mathrm{SFC}}\frac{\mathrm{L}}{\mathrm{D}}\ln\left(\frac{\mathrm{W_{initial}}}{\mathrm{W_{final}}}\right)\right\} \tag{5}$$

With respect to x
Subject to L-W=0

$$\mathrm{n\sigma_j}-\mathrm{\sigma_{yield}}\le 0$$

Where x is the design variable and contains spar thickness as t and jig twists as γ. L and W are the lift force and weight of the wing, respectively. The load factor is called (n), too. The problem statement in the form of CO has divided into two parts; the first one is related to the system-level problem and it can be expressed as;

$$\text{Minimize}\ -\mathrm{R},\ \left\{\mathrm{R}=\frac{\mathrm{V}}{\mathrm{SFC}}\frac{\mathrm{L}}{\mathrm{D}}\ln\left(\frac{\mathrm{W_{initial}}}{\mathrm{W_{final}}}\right)\right\} \tag{6}$$

With respect to t^t, Γ^t, u^t
Subject to $j_1 \le \varepsilon$
$j_2 \le \varepsilon$

$$\mathrm{L}(\Gamma^t)-\mathrm{W}(t^t)=0$$

Where superscript t represents system-level target values whereas t^t is named as thickness target, two others are the target of coupling variables (Γ^t, u^t). j_i is a measure of the interdisciplinary $j_i$compatibility of each discipline and they are calculated by solving every discipline sub-problem. In the current work, two disciplines are chosen; aerodynamic and structure. The aerodynamic sub-problem is given as,

$$\text{Minimize}\quad j_1, \{j_1=\sum(\Gamma-\Gamma^t)^2 \tag{7}$$

With respect to jig twist
Subject to $CL(\Gamma)/\,maxcl - 1 \le 0$

Where max cl has a constant value (maxcl=0.6) and Γ can be found by solving the aerodynamic governing equation according to jigtwist and u^t. Alpha is also fixed and its value is zero.

$$A\Gamma=\mathrm{v}(\mathrm{jigtwist}, u^t) \tag{8}$$

The next discipline is the structural one and this sub-problem is defined below;

$$\text{Minimize}\quad j_2, \{j_2=\sum(\mathrm{t}-\mathrm{t}^t)^2+\sum(\mathrm{u}-\mathrm{u}^t)^2 \tag{9}$$

With respect to t
Subject to $\mathrm{n\sigma_j(t,u)}-\mathrm{\sigma_{yield}}-1\le 0$

Where n is the load factor (n=2.5) and σ_{yield} is yield stress ($\sigma_{yield}=505*10^6\,pa$). The design variable (t) is spar thickness, too. Furthermore, to compute the displacement (u), the structural governing equation is needed to solve and the equation provides the displacement by using Γ^t and t.

$$ku=f(\Gamma^t) \tag{10}$$

Moreover, the objective function, design variables, and constraints are clearly identified in Table 3.

Table 3: Classification of the objective function, design variables, and constraints

System -Level	Objective Function	R
	Design variable	t^t, Γ^t, u^t
	Constraints	$j_1 \leq \varepsilon$, $j_2 \leq \varepsilon$ $L(\Gamma^t) - W(t^t) = 0$
Sub-Problem (Aerodynamic)	Objective Function	j_1
	Design variable	jigtwists (γ).
	Constraints	$CL(\Gamma)/\, maxcl - 1 \leq 0$
Sub-Problem	Objective Function	j_2
	Design variable	spar thickness (t)
	Constraints	$n\sigma_j(t,u) - \sigma_{yield} - 1 \leq 0$

In this section, three figures are applied to show how the collaborative optimization algorithm works. Fig 5 illustrates the CO flow chart and it is clearly demonstrated several processes in this algorithm. The data flow is also depicted in Fig 6 and finally, the design task is decomposed as shown in Fig 7. Each of the disciplinary units becomes an independent sub-problem. Each sub-problem consists of two parts: a subspace optimizer and an analysis routine. The optimizer modifies the input values for the sub-problem analysis and uses the analysis output values to form the constraints and objective. In addition, the optimizer accepts a set of target values for these variables. The goal of the subspace optimization is to adjust the local design variables to minimize the difference between local design variables and state variables and the target values passed to the subspace optimizer.

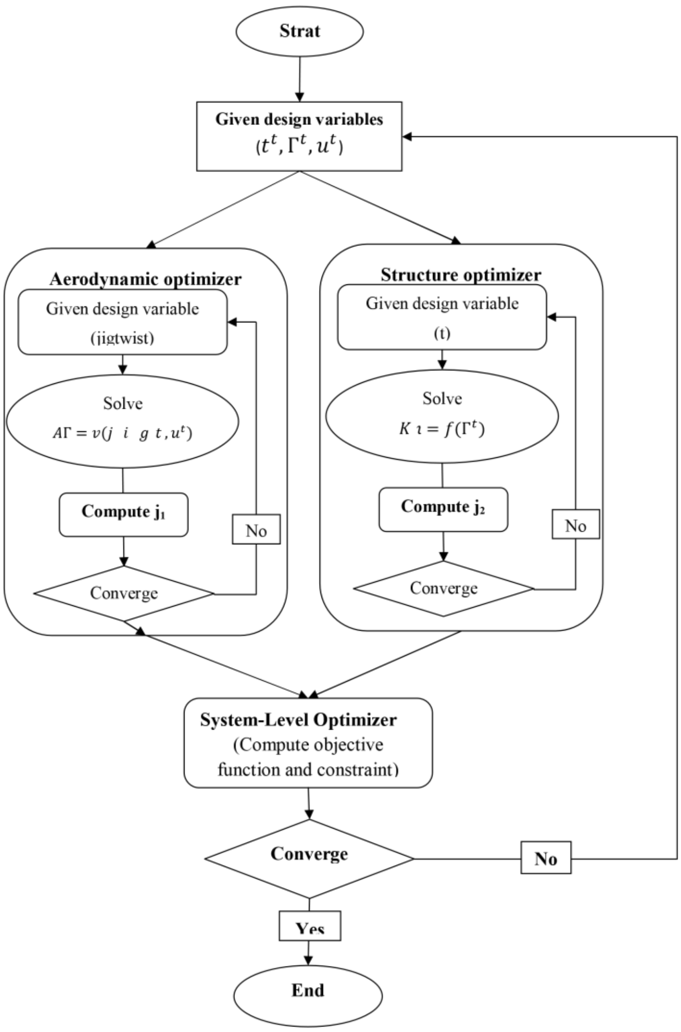


Fig 5: CO algorithm

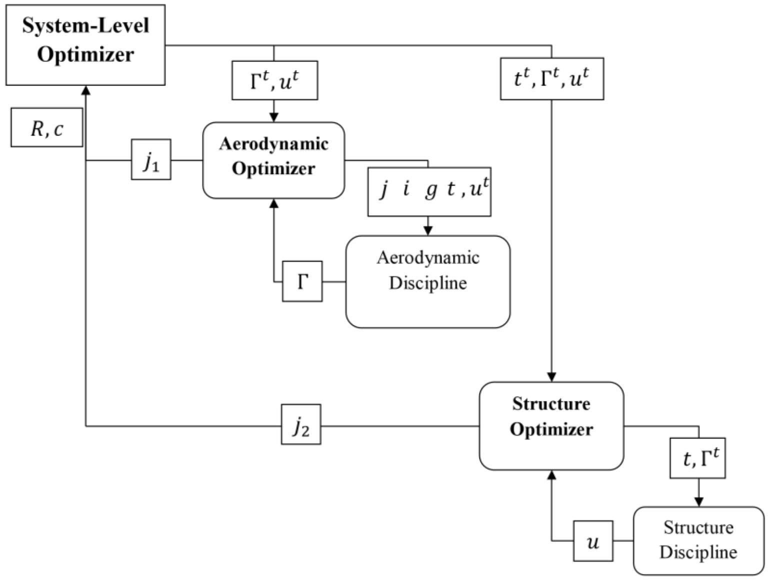


Fig 6: CO data flow

To designate these target values, CO methodology adds a system-level optimizer. This optimizer specifies the target values of the design parameters and state variables and passes them to each sub-problems. The system-level optimizer's goal is to adjust the parameter values so that the range is maximized while the system-level constraints are satisfied.

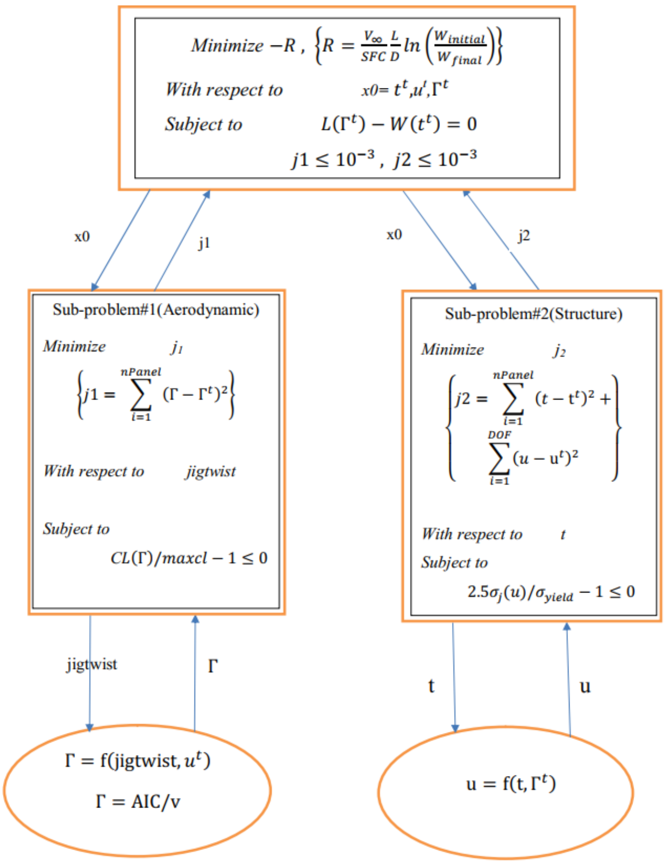


Fig 7: Collaborative form of aircraft design problem

To prove the accuracy of the MDF and CO method of this investigation, all visualizations are based on the Sellar problem [64]. According to the validation, the method has good agreement to prove the efficiency of this work.

4. Results

To do this type of optimization, the Multidisciplinary Feasible (MDF) method and Collaborative Optimization (CO) are selected which could couple both structure and aerodynamic equations. This investigation is also solved by using Vortex Lattice Method (VLM) for the aerodynamic governing equation and coupling it to the structure equation thus the MATLAB function, Fmincon is the final step of converging of this program. Therefore, the maximum range of the mentioned aircraft for the MDF optimization approach will be **2378.65** (n.mi). Moreover, lift, drag forces, and weight of the wing, which is obtained in maximum range, are represented in Table 4. According to MATLAB's results, the maximum range increased from 1685 to 2378.65 (n.mi).

This problem is also solved by collaborative optimization and the maximum range of the mentioned aircraft will be 2810.59 (n.mi). Moreover, lift and drag forces are equal to 2.7797×105 and 1.56×104, respectively.

4.1. Comparison of CO and MDF

Now, a comparison of two architectures (CO and MDF) is carried out. The results of them can be contrasted in Table 4. According to these results, the range of the MDF approach raises about 41%, and for CO approach raises about 66% compared to the baseline wing ranges. Based on the aforementioned table, the value of the lift force along spanwise direction of the multidisciplinary design feasible is higher than collaborative optimization. Although, the Drag force of the mentioned wing is bigger in MDF too. Hence, the breguet range of the CO is bigger than MDF as a result.

Table 4: Comparison of various approaches

	CO	MDF
Iteration Number	32	189
Fun count	4025	6013
Lift	2.78×10^5	2.83×10^5
Drag	1.56×10^4	1.62×10^4
Max Range (n.mi)	2810.59	2378.65

To examine the finding objects and result and to reveal the aero-structural behaviour of the wing the following section is performed. For the optimum aerodynamic performance of a wing, the desired lift distribution would be as an ellipse; because this distribution generates the lowest induced drag, ensuring the optimum aerodynamic performance of the wing. In this problem, the aerodynamic phenomena are not just considered; the structure of the wing should be regarded, too. Therefore, the lift distribution will not be similar to an ellipse. Actually, the lift is higher in the root and has a lower value near the tip wing. This lift distribution along the spanwise of the baseline wing and two optimized wing demonstrates in Fig 8. According to the mentioned figure, the MDF optimization has a higher lift by about 6%, but gradually the behaviour of both optimization lift distributions has become the same.

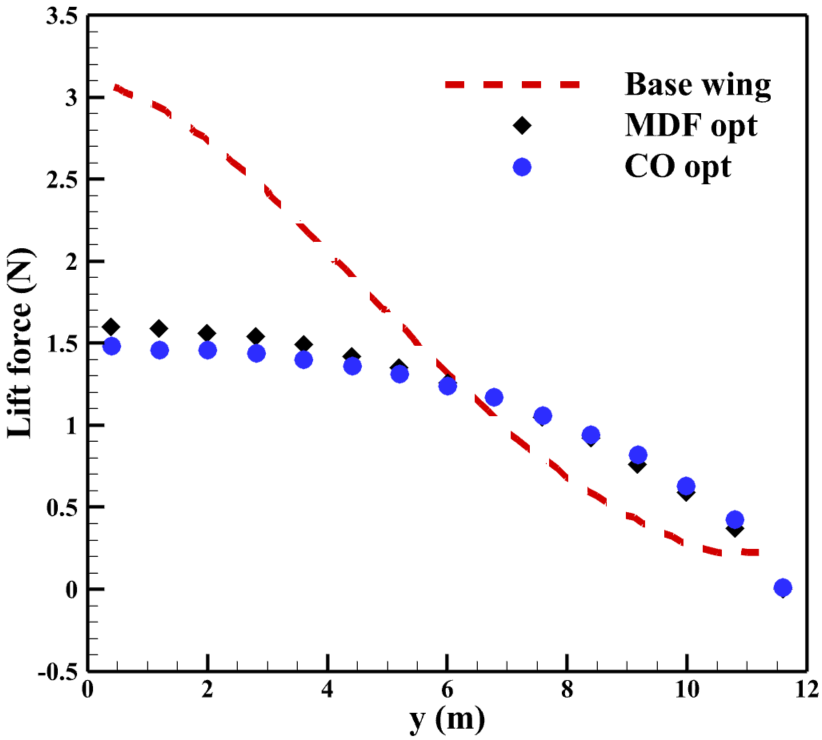


Fig 8: Lift distribution according to wing span

Wing weight reduction and stress play an important role in this problem. Stress is high in the wing root and a thicker spar is sufficient. Therefore, the weight of the wing in the root rises. On the other hand, any increase in drag would bring a large penalty in weight, especially in a long-range aircraft. Therefore, the lift curve shifts towards and becomes triangular and induced drag declines.

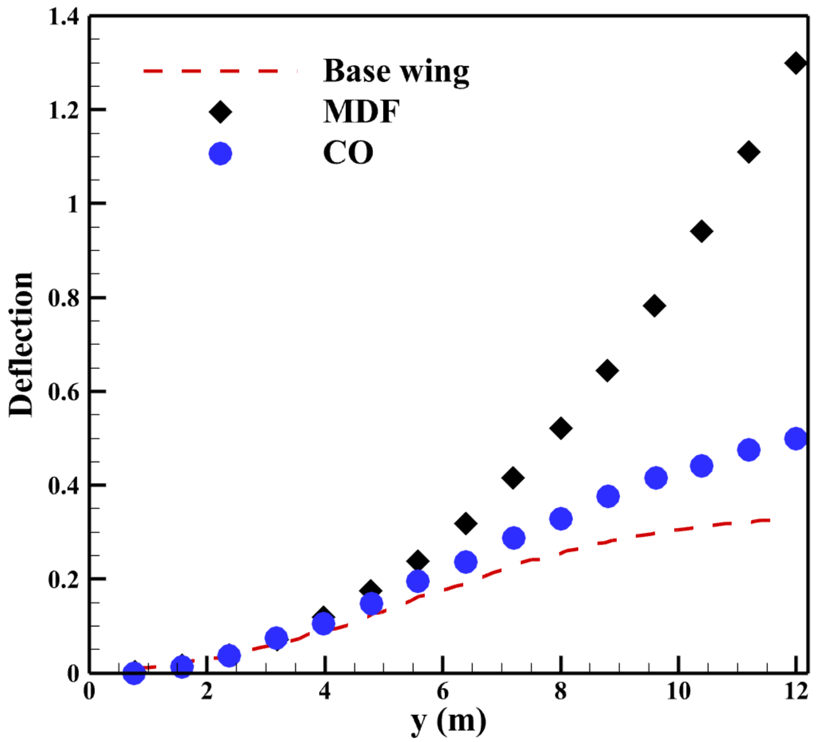
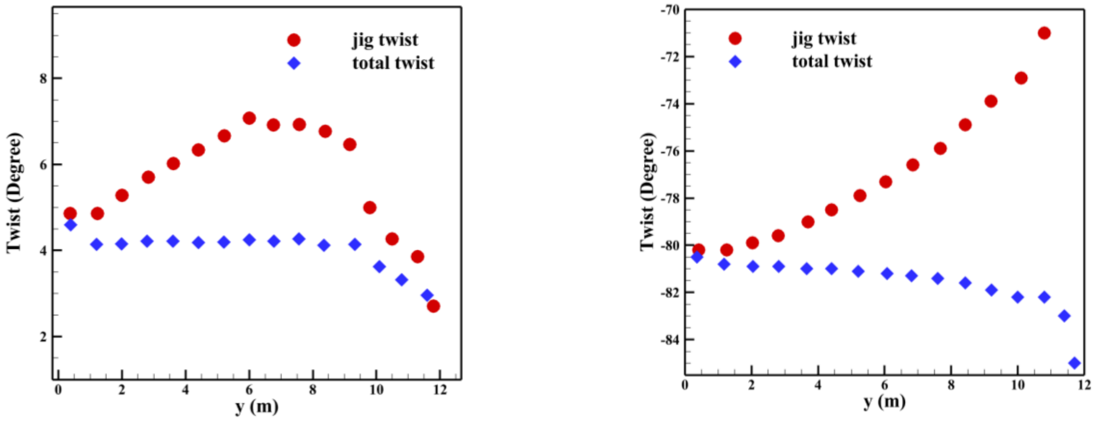


Fig 9: deflection distribution across the wing span

According to Fig 9, the investigation has higher deflection after optimizing. the tip of the wing (the end of the wing) is so light because of this the wing has so much deflection. In CO optimization the deflection is less than in MDF optimization step by step.



(a) CO (B) MDF

Fig 10: Twist distribution along the wingspan (a) collaborative optimization (b) multidisciplinary decipline feasible

Moreover, the twist disturbution of these two methods are revealed in Fig 10. According to the above figure, in the collabrative approach the jigtwist disturbution increases initially and then dectreses sharply. Eventhough, the jig twist in multydisciplinary design increases sharply about 12.5%. the total twist of Co reduces 40% and the total twist of MDF decreses about 6.25% and this is the results of twist of both methods.

The majority of the two optimization approaches are performed before, hence to understand the comparison of each section between these two approaches this investigation reveals the difference between them:

4.2. Complexity of implementation

Collaborative optimization is more complex than MDF. Because it has three optimizers and they should be converged separately. In the mentioned problem, MDF was easy to handle and it needed an iteration loop between two disciplines; whereas, target design and state variables should be defined in the CO method; therefore, many problems may have existed here.

4.3. Number of optimization variables (total, per level)

In MDF, each discipline has a design variable (jigtwist for aerodynamic and spar thickness for structure); displacement and (horseshoe) vortex are also considered state variables. Consequently, there are two design variables and two state variables in MDF. Nevertheless, collaborative optimization includes a system level and two sub-levels. At the system level, three optimization variables are defined; spar thickness (t^t), displacement (u^t), and horseshoe vortex (Γ^t). The variables, denoted by t, are named target variables. Moreover, jigtwist is a local design variable in the aerodynamic discipline, and thickness (t) is a local variable in the structure that explicitly affects the objective function and global constraint. Vortex (horseshoe vortex Γ) and displacement (u) are state variables in aerodynamic and structure sub-problems, respectively.

4.4. Computational cost (run time)

MDF's run is very faster than CO's run simulation time. The system level and two sub-levels give more time. Actually, three optimizers exist and convergence criteria, local and global constraints for all of them should be satisfied. CPU running time in MDF is around 2 minutes; whereas, this period for CO is much more. For example, 16 minutes are needed for simplified criteria. As shown in Table 4, MDF will be converged after 6013 times of the call function; but the number of call functions in the system-level of CO is around 4000 and the average of it for aerodynamic and structure optimizers are around 500 and 20, respectively. Therefore, the running time of CO is much more than MDF.

4.5. Convergence history

In Fig 11, the convergence history of both methods is shown. A significant point is that CO quickly converged in a small iteration number when it is compared with MDF.

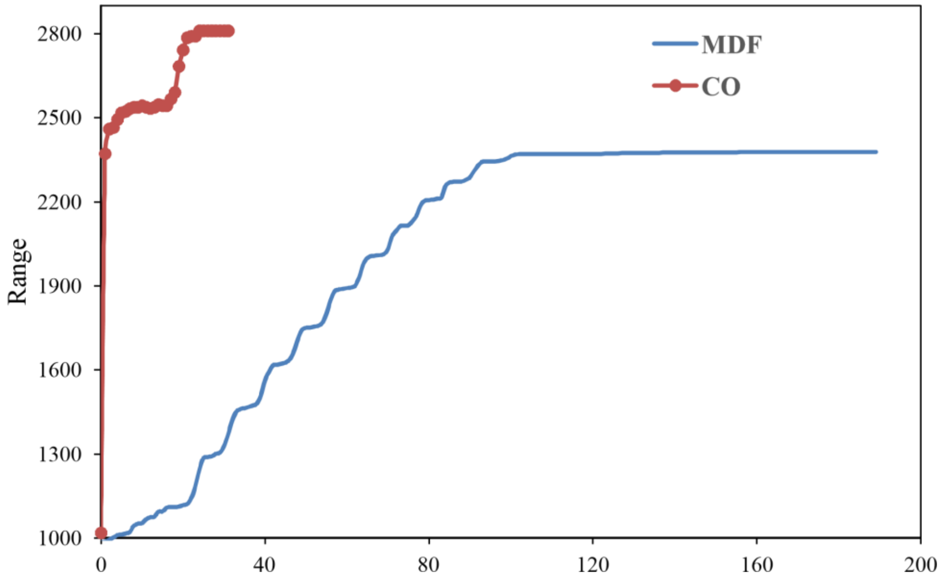


Fig 11: Convergence history of Function value obtained from CO and MDF

5. Conclusion

The intricate interplay among aircraft subsystems presents a formidable challenge to aircraft design, thereby making it a multidisciplinary undertaking. To effectively engineer aircraft, a comprehensive design process must account for a multitude of disciplines such as aerodynamics and structural systems within a coherent range formulation to ensure precise performance evaluation. The principal aim of this investigation centers on developing and investigating a coupled aero-structural multidisciplinary model to optimize the performance of the CRJ-700 aircraft while considering its path-dependent behavior. Two strategies, distributed and monolithic architectures, are viable means to this end. However, their decomposition schemes vary and may significantly impact the design process. Thus, comparing such methods can aid designers in assessing the design cost and the accuracy of the results obtained. Ultimately, optimizing the aircraft problem involved leveraging two methods: Multidisciplinary feasible (MDF) and Collaborative optimization (CO). The important thing that may strike readers, is the different results obtained by the two approaches. CO gives a high range value; consequently, the optimum point may be a local minimum in this problem and the global minimum may be achieved by changing the initial conditions or scaler parameters. Another view is that the exact optimum point will be obtained if the new convergence criteria are defined instead of default values. After performing these two kinds of optimization methods, the results are as follow:

- ✓ The breguet range of the MDF approach raise from 1685 to 2810.59 (N.m). Hence, the MDF appraoch increses about 41% in brequet range.
- ✓ The breguet range of the CO approach raise from 1685 to 2378.65 (N.m). Therefore, the CO appraoch increases about 66% in brequet range.
- ✓ MDF will be converged after 6013 times of the call function; but the number of call functions in the system-level of CO is around 4000 and the average of it for aerodynamic and structure optimizers are around 500 and 20, respectively.
- ✓ Collaborative optimization is more complex than MDF. As it has three optimizers and they should be converged separately.

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