

PEDRO DAVIM BASTOS

**WING STRUCTURAL DESIGN: AN APPROACH WITH
TRUSS-BASED MODULAR STRUCTURES AND
METAMODEL-BASED OPTIMIZATION**



UNIVERSIDADE FEDERAL DE UBERLÂNDIA
FACULDADE DE ENGENHARIA MECÂNICA

2024

PEDRO DAVIM BASTOS

**WING STRUCTURAL DESIGN: AN APPROACH WITH
TRUSS-BASED MODULAR STRUCTURES AND
METAMODEL-BASED OPTIMIZATION**

Final Paper submitted to the Faculty of Mechanical Engineering from Federal University of Uberlândia in partial fulfillment of the requirements for the degree of Aeronautical Engineer. *FINAL VERSION*

Advisor: Prof. Dr. Higor Luis Silva

Uberlândia - MG

2024

PEDRO DAVIM BASTOS

**DIMENSIONAMENTO ESTRUTURAL DE ASAS: UMA
ABORDAGEM COM ESTRUTURAS TRELIÇADAS
MODULARES E OTIMIZAÇÃO BASEADA EM UM
METAMODELO**

Trabalho de Conclusão de Curso apresentado à
Faculdade de Engenharia Mecânica da Universidade
Federal de Uberlândia como parte dos requisitos
para obtenção do título de Bacharel em Engenharia
Aeronáutica. *VERSÃO REVISADA*

Orientador: Prof. Dr. Higor Luis Silva

Uberlândia - MG

2024

*This work is dedicated to my parents, Sérgio Jr. and Adriana,
and to my grandfather, Sérgio,
who gave me all the tools and unconditional support necessary,
which were integral in order to reach this moment.*

ACKNOWLEDGEMENTS

I would like to firstly thank my parents, Sérgio Jr. and Adriana, for always being there and supporting me, all I have accomplished and will accomplish is due to your teachings and love. Also my younger brother, Rafael, who I couldn't be more proud and happy to be a bigger brother to. Especially my partner, Ananda, who is not only my best friend but also my safe haven.

I would like to strongly thank the full support and advices given by Prof. Dr. Higor Luis Silva, my great advisor and personal friend. From being the tutor in my Aircraft Design classes and Tucano Aerodesign to being my advisor in this work, you were not only thoroughly present, but a gift in my graduation. Thanks to you I was motivated enough to publish and present this work in conferences and journals abroad, giving it my all while developing it, and for all of that I am very grateful. Thank you for the guidance and the knowledge you passed onto me, but on top of all of that, being a true friend.

I sincerely want to express my gratitude to Aline Isabel, Gabriel Guimarães, Luca Morla, Mateus Furtado, Murilo Passos, Pedro Guerreiro and all my other friends who were also members of Tucano Aerodesign. From the many nights studying and working on our aircraft together to just enjoying ourselves, I will never forget how important you all were.

I would like to acknowledge the Federal University of Uberlândia, which became my first home away from home, the Faculty of Mechanical Engineering and all the professors who guided me to my bachelor, inspiring me and making a difference throughout this journey. I would also like to thank the Minas Gerais State Agency for Research and Development (FAPEMIG) for the financial support.

I would especially like to acknowledge the examination board for their patience reading this work and for their feedback, which strongly improved this work.

“ Keep your eyes to the skies never glued to your shoes.”
(Malcolm James McCormick)

RESUMO

BASTOS, P.D. Dimensionamento Estrutural de Asas: Uma Abordagem com Estruturas Treliçadas Modulares e Otimização Baseada em um Metamodelo. 2024. 84 p. Trabalho de Conclusão de Curso (Graduação em Engenharia Aeronáutica) – Faculdade de Engenharia Mecânica, Universidade Federal de Uberlândia, Uberlândia - MG, 2024.

Classicamente, diversos projetos e tecnologias disruptivas visando otimizar e reduzir o peso estrutural durante o dimensionamento estrutural de uma aeronave já foram investigados. Com a substituição de combustíveis fósseis por sistemas propulsivos elétricos e, consequentemente, com a remoção de tanques de combustível da estrutura interna da asa, é possível repensar e desenvolver novas alternativas de como otimizar e reduzir o seu peso. Com isso, baseado na *wingbox* do *Common Research Model*, esse estudo visa demonstrar a efetividade de uma estrutura interna treliçada em cumprir esse objetivo no caso de aeronaves comerciais, introduzindo uma nova abordagem de dimensionamento estrutural, na qual as estruturas internas tradicionais, como nervuras e longarinas, são completamente substituídas por uma estrutura treliçada, com suas juntas representadas por elementos de massa. A análise estática da estrutura é executada utilizando o NASTRAN como solver e é integrada com uma otimização por enxame de partículas em MATLAB, que otimiza as variáveis do problema de otimização. Essas variáveis são o raio externo e espessura de cada elemento de treliça da malha estrutural, que tem seus limites máximos e mínimos determinados através de um metamodelo Kriging simplificado do modelo de otimização da aeronave. As condições de contorno são baseadas nas do *Common Research Model* original e em um modelo aerodinâmico que pode determinar as cargas atuantes na estrutura em diferentes condições. A possibilidade de remover elementos desnecessários para manter o perfil aerodinâmico da asa também é avaliada. Sendo assim, a estrutura interna da asa é otimizada com a função objetivo de minimizar o peso com base em restrições estruturais. Os resultados, verificados por pós-análises de flambagem e de aeroelasticidade, demonstram que as estruturas treliçadas modulares podem ser uma boa estratégia em dimensionamentos de asas, em termos de modularidade e de redução de peso.

Palavras-chave: Dimensionamento de Asas, Estruturas Aeronáuticas, Otimização.

ABSTRACT

BASTOS, P.D. Wing Structural Design: An Approach with Truss-Based Modular Structures and Metamodel-Based Optimization. 2024. 84 p. Trabalho de Conclusão de Curso (Graduação em Engenharia Aeronáutica) – Faculdade de Engenharia Mecânica, Universidade Federal de Uberlândia, Uberlândia - MG, 2024.

Disruptive projects and technologies have been presented with the aim of improving and reducing structural weight during aircraft design. With the replacement of fossil fuel by electric propulsive systems and, consequently, with the removal of fuel tanks from the wing's inner structure, it is possible to rethink and develop new ways to optimize and reduce its weight. Therefore, based on the Common Research Model's wingbox, this work aims to showcase the effectiveness of a truss-based inner structure in fulfilling this objective in commercial aircraft, bringing a new structural design approach, in which the conventional inner structures, such as ribs, spars, and stringers, are replaced solely by a truss-based one, and its joints are represented by mass elements. The linear static analysis of the structure is performed using NASTRAN as its solver, which in turn is integrated into a particle swarm optimization in MATLAB that optimizes the design variables of the optimization problem. Those include the outer radius and thickness of each truss of the structural mesh, which have their maximum and minimum bounds determined using a Kriging metamodel of the simplified wing structure. Boundary conditions are based on the original Common Research Model and an aerodynamic model that is able to determine the acting loads in different conditions. The possibility of removing unnecessary elements is also evaluated, while still ensuring the minimum aerodynamic profile necessary to form the wing. The wingbox structure is then optimized in search of the lowest structural weight considering stress constraints. The results, verified by a buckling and an aerodynamic flutter post-analyses, show that truss-based modular structures can be a good strategy in structural wing designs, in terms of modularity and reduction of weight.

Keywords: Wing Design, Aircraft Structures, Optimization.

LIST OF FIGURES

Figure 1 – Energia Family.	21
Figure 2 – B17’s truss-based internal structure.	21
Figure 3 – SUGAR.	22
Figure 4 – HERA.	22
Figure 5 – Innovative joint designs.	23
Figure 6 – Pareto front for 8 nodes per rib and 10 truss-based ribs.	24
Figure 7 – Final structural mesh for lowest wing mass.	25
Figure 8 – Outer radius and thickness distribution for lowest wing mass.	25
Figure 9 – Truss-based structural mesh.	26
Figure 10 – ANN architecture.	30
Figure 11 – Wind tunnel experiment using the CRM.	33
Figure 12 – CRM views.	34
Figure 13 – Original FEM.	34
Figure 14 – Coordinate system for a bar element.	35
Figure 15 – Truss patterns parallel to.	36
Figure 16 – Joints represented by mass elements.	36
Figure 17 – Truss-based FEM.	37
Figure 18 – Constraint boundary condition.	38
Figure 19 – CRM.65 BTE airfoil.	39
Figure 20 – Aerodynamic model.	40
Figure 21 – RBE3 element for load application at 25% wing chord.	40
Figure 22 – C_L vs α for the CRM 65.BTE airfoil.	41
Figure 23 – V-n diagram.	42
Figure 24 – V-n diagram with gust lines.	43
Figure 25 – Aeroelastic model.	45
Figure 26 – 5 modes CRM flutter analysis comparison.	45
Figure 27 – Comparing optimization methods.	46
Figure 28 – Structural sections.	47
Figure 29 – Removable (red) and necessary (grey) elements considering minimum aerodynamic profile.	47
Figure 30 – Flowchart of the optimization process.	48
Figure 31 – Global metamodel.	49
Figure 32 – Exemplifying the advantages of LHS.	50

Figure 33 – Correlation functions for $-2 \leq d_j \leq 2$ and $\theta = 0.5, 1$ and 5	51
Figure 34 – Normalized MSE for all 15 combinations.	52
Figure 35 – Computational time for the chosen combination.	53
Figure 36 – Light Tune.	53
Figure 37 – Lightning Tune.	54
Figure 38 – Extra Lightning Tune.	55
Figure 39 – Loads obtained for the maneuver condition.	57
Figure 40 – Loads and constraints applied to the FEM in maneuver condition.	57
Figure 41 – Hyperparameter optimization of separate metamodel 4 - Lightning Tune. . .	58
Figure 42 – MSE for each separate metamodel.	59
Figure 43 – Hyperparameter optimization of the global metamodel - Extra Lightning Tune. .	62
Figure 44 – Each structural section's maximum σ_{max} prediction contrasted with the real value (Sections 1-6).	64
Figure 44 – Each structural section's maximum σ_{max} prediction contrasted with the real value (Sections 7-10).	65
Figure 45 – Each structural section's maximum σ_{max} MSE.	65
Figure 46 – Global metamodel verification by conditions 1 and 2.	66
Figure 47 – Global metamodel wing weight prediction contrasted with the real value. . .	66
Figure 48 – Wing weight for the 5 best maximum options evaluations.	68
Figure 49 – Removable elements.	68
Figure 50 – Skin thickness fit to the best possible.	69
Figure 51 – Optimization process convergence.	71
Figure 52 – Detailed optimization process with a population size of 500.	72
Figure 53 – Optimized wingbox's displacement.	72
Figure 54 – Optimized wingbox's maximum combined stress.	73
Figure 55 – Optimized wingbox's removed elements.	73
Figure 56 – Buckling analysis (eigenvector #1).	75
Figure 57 – First five modes of vibration for the optimized wingbox.	76
Figure 58 – V-g-f diagram for the optimized wingbox.	76

LIST OF TABLES

Table 1 – CRM wing and flight properties.	33
Table 2 – Original FEM properties.	35
Table 3 – Truss-based FEM properties.	36
Table 4 – Carbon fiber laminate plate properties.	37
Table 5 – Carbon fiber tube properties.	37
Table 6 – Performance properties of the NASA CRM.	39
Table 7 – Geometric properties of the CRM.	39
Table 8 – Inputs for the aeroelastic model.	44
Table 9 – Discretized frequency function.	44
Table 10 – Optimization process proportional penalization.	46
Table 11 – Metamodel proportional penalization.	55
Table 12 – Outer radius hyperparameters for each separate metamodel (K_n) - Lightning Tune.	59
Table 13 – Thickness hyperparameters for each separate metamodel (K_n) - Lightning Tune.	59
Table 14 – Outer radius hyperparameters lower bounds for the global metamodel per metamodel (K_n) - Extra Lightning Tune.	60
Table 15 – Thickness hyperparameters lower bounds for the global metamodel per metamodel (K_n) - Extra Lightning Tune.	61
Table 16 – Outer radius hyperparameters upper bounds for the global metamodel per metamodel (K_n) - Extra Lightning Tune.	61
Table 17 – Thickness hyperparameters upper bounds for the global metamodel per metamodel (K_n) - Extra Lightning Tune.	61
Table 18 – Outer radius hyperparameters for the global metamodel per metamodel (K_n) - Extra Lightning Tune.	62
Table 19 – Thickness hyperparameters for the global metamodel per metamodel (K_n) - Extra Lightning Tune.	63
Table 20 – Global metamodel requirements (Req) verification.	67
Table 21 – Optimization parameters.	70
Table 22 – Optimization results.	70
Table 23 – Number of elements removed per structural section (S_n).	73
Table 24 – Wingbox's mass distribution.	74
Table 25 – Weight per structural section (S_n).	74
Table 26 – First five buckling eigenvalues for the optimized wingbox.	75

LIST OF ABBREVIATIONS AND ACRONYMS

ANN	Artificial Neural Network
AoI	Area of Interest
CFD	Computational Fluid Dynamics
CRM	Common Research Model
DHC	Dynamic Hill Climbing
FAA	Federal Aviation Administration
FEM	Finite Element Model
FLEXOP	Flutter Free FLight Envelope eXpansion for ecOnomical Performance improvement
FS	Factor of Safety
GA	Genetic Algorithm
HERA	Hybrid-Electric Regional Aircraft
LHS	Latin Hypercube Sampling
MAC	Mean Aerodynamic Chord
MSE	Mean Square Error
MTOW	Maximum Takeoff Weight
NASA	National Aeronautics and Space Administration
PKNL	No Looping p-k
PSO	Particle Swarm Optimization
RSM	Response Surface Methodology
SUGAR	Supersonic Ultra Green Aircraft Research
TBW	Truss-Braced Wing
VLM1	Fixed-Speed Horseshoe Vortice Lattice Method

LIST OF SYMBOLS

AR — Aspect Ratio

b — Wingspan

B_{best} — Best fitness value for all particles in all iterations

c — Chord

c_1 — Particle learning rate

c_2 — Swarm learning rate

C_1 — Limit compression stress in the longitudinal direction

C_2 — Limit compression stress in the transverse direction

C_L — Lift coefficient

$C_{L_{cr}}$ — Lift coefficient at cruise speed

$C_{L_{max}}$ — Maximum lift coefficient

$C_{L_{\alpha}}$ — Lift coefficient derivative per angle of attack

C_M — Moment coefficient of the respective rib

c_{ref} — Reference chord

d — Difference between sample input and a vector inside the project space

E — Young's Modulus

E_1 — Young's Modulus in the longitudinal direction

E_2 — Young's Modulus in the transverse direction

F — Scaling factor

$f(x)$ — Objective function

g — Gravity speed

G_{12} — Shear modulus in the longitudinal/transverse plane

h_{cr} — Altitude at cruise speed

i — Current individual

I — Iteration

j — Individual in a population
 K_g — Gust alleviation factor
 K_n — Kriging metamodel of structural section n
 L — Lift force
 M_{cr} — Mach number at cruise speed
 M_t — Torsion moment
 n — Load factor
 n_{psl} — Positive stall line load factor
 n_{gust} — Gust load factor
 n_{nsl} — Negative stall line load factor
 n_z — Maneuver load factor
 NP — Number of population size
 p — Probability of individual surviving
 P — Position of particle
 P_{best} — Best fitness value for the particle j in all iterations
 r — Randomly selected scaling factor
 R — Objective function fitness value
 $r_{i_{ext,tube}}$ — Truss outer radius
 $r(x)$ — Regression function
 Re_{cr} — Reynolds number at cruise speed
 S — Total wing area
 S_{12} — Limit shear stress in the longitudinal/transverse plane
 S_{exp} — Exposed wing area
 S_{ref} — Reference area
 T_1 — Limit traction stress in the longitudinal direction
 T_2 — Limit traction stress in the transverse direction
 $t_{i_{ext,tube}}$ — Truss thickness
 U_1 — Gust design speed in stall condition
 U_2 — Gust design speed in cruise condition
 U_3 — Gust design speed in dive condition

V_{cr} — True airspeed in cruise condition

V_d — True airspeed in dive condition

V_{max} — Maximum true airspeed

V_p — Velocity of particle

x — Design variable

x_r — Randomly selected design variable

y_i — Rib position regarding wingspan

$y(x)$ — Predicted output value

$Z(x)$ — Correlation function

α — Angle of attack

Γ — Dihedral angle

λ — Taper ratio

μ_g — Airplane mass ratio in pitch

ν — Poisson's ratio

ν_{12} — Poisson's ratio in the longitudinal/transverse plane

ρ — Density

$\rho_{air_{FL}}$ — Air density at corresponding flight level

ρ_{cr} — Air density in cruise condition

σ_{adm} — Limit traction/compression stress

σ_{max} — Maximum combined stress of each truss

θ — Hyperparameter

CONTENTS

1	INTRODUCTION	17
1.1	Main Objectives	18
1.2	Document Structure	18
2	LITERATURE SURVEY	20
2.1	Recent Work	20
2.1.1	<i>Industry</i>	20
2.1.2	<i>Academia</i>	23
2.2	Optimization	24
2.2.1	<i>Key Concepts</i>	24
2.2.2	<i>Differential Evolution</i>	26
2.2.3	<i>Genetic Algorithm</i>	27
2.2.4	<i>Particle Swarm Optimization</i>	28
2.3	Metamodels	28
2.3.1	<i>Key Concepts</i>	28
2.3.2	<i>Response Surface Methodology</i>	29
2.3.3	<i>Artificial Neural Network</i>	29
2.3.4	<i>Kriging</i>	30
3	METHODOLOGY	32
3.1	Structural Model	32
3.2	Aerodynamic Model	39
3.3	V-n Diagram	40
3.4	Aeroelastic Model	43
3.5	Optimization Model	45
3.6	Metamodel	48
4	RESULTS AND RESULTS' ANALYSIS	56
4.1	Loads	56
4.2	Metamodel	58
4.3	Optimization	68
4.4	Post-analyses	74
4.4.1	<i>Buckling</i>	74
4.4.2	<i>Aeroelasticity</i>	75

5	CONCLUDING REMARKS	77
5.1	General Remarks	77
5.2	Future Perspectives	78
	BIBLIOGRAPHY	79

INTRODUCTION

“Airplanes are not tools for war. They are not for making money. Airplanes are beautiful dreams. Engineers turn dreams into reality.”

— Hayao Miyazaki

The concept of minimizing an aircraft’s empty weight, although essential, is not entirely novel in the aerospace industry. Since the beginning of its relatively short but intense history, reducing the aircraft’s empty weight has always been a priority, due to the fact that reducing weight directly correlates with lowering fuel consumption and, consequently, decreasing operational costs.

However, in recent times, the aerospace industry has also started addressing new concerns with great urgency, such as environmental impacts. The industry aims to emit fewer pollutants and reduce noise emissions (MASIOL; HARRISON, 2014; GRAHAM; HALL; MORALES, 2014). As a result, research focus has shifted towards alternative propulsion systems, replacing conventional fossil fuel-based engines with hydrogen cells and hybrid-electric systems (FRIEDRICH; ROBERTSON, 2015; PETRESCU *et al.*, 2020; PORNET; ISIKVEREN, 2015). This follows a parallel shift in industry focus, with the development of projects such as Embraer’s *Energia Family* and the European Union’s HERA. Nonetheless, optimizing an aircraft’s empty weight remains central to these works (SILVA *et al.*, 2021; SGUEGLIA *et al.*, 2020).

The wing design plays a critical role in the structural weight of an aircraft. Given that, optimizing wing performance and weight are key concepts in minimizing an aircraft’s empty weight. Throughout the history of the aeronautical industry, several attempts have been made in order to achieve these goals, such as aeroelastic tailoring of wings using curvilinear stiffeners (STANFORD; JUTTE, 2017; JUTTE *et al.*, 2014) and composites (STANFORD; JUTTE; WU, 2014; GUIMARÃES *et al.*, 2017), or the structural design of wings accounting for buckling constraints (GUIMARÃES *et al.*, 2019; JR; HAFTKA, 1979).

Additionally, as the industry shifts towards replacing fossil fuel-based engines and removing fuel tanks, there is an opportunity to redesign the inner volume of the wingbox and explore alternative optimized structural arrangements to minimize weight, given the removal of fuel tanks from its inner structure. Recent studies have combined these concepts with an innovative approach: a wingbox with truss-based modular structures (SILVA; GUIMARÃES; CASTRO, 2023; STRAGIOTTI; IRISARRI; JULIEN, 2024). Even though modular wing structures may be associated with morphing wings (FINISTAURI; XI; WALSH, 2012; TANG *et al.*, 2016), in this case, conceptually, it involves the replacement of the internal structure of a traditional wingbox, embodied of ribs, spars and stringers, by a truss-based one. Then, the trusses are responsible for providing all the needed structure integrity of the wingbox and, consequently, most of its empty weight.

1.1 Main Objectives

This work aims to implement the concept of a truss-based modular internal wingbox structure into a large-scale model suitable for research purposes. The prototype chosen for this implementation is NASA's Common Research Model (CRM) wingbox, a large scale model ideal for research compatibility. The first step involves replacing the internal structure of the wingbox with a truss-based structure, composed of bar elements. Mass elements will represent the joints between trusses, while plate elements will represent the skin panels. Boundary conditions will be established based on the original CRM's wing-fuselage connection constraints, and the loads will be determined using an aerodynamic model.

Once the structure and boundary conditions are defined, the integration of a single-objective particle swarm optimization in MATLAB and NASTRAN's SOL101 will be employed envisaging to optimize the wingbox mass. This optimization process will consider the discrete outer radius and thickness of each individual truss, focusing on key structural responses such as total displacement and stress of the truss-based structures. The minimum and maximum bounds of the design variables will be determined through a Kriging metamodel of the simplified wing structure, in order to minimize the computational cost. Additionally, unnecessary bar elements that do not contribute to maintaining the minimum aerodynamic profile can be removed. Finally, post-analyses on both buckling and aeroelasticity will be conducted using NASTRAN's SOL105 and SOL145, respectively, to ensure the structural and aeroelastic integrity of the optimized wingbox.

1.2 Document Structure

The document's structure is as follows:

- Chapter 2: presentation of a literature survey, covering the recent work and theoretical

basis used for the models developed in this work, such as key concepts and different approaches to single-objective optimization and metamodeling.

- Chapter 3: overview of the methodology, displaying the models used in the course of this work, including structural, aerodynamic, optimization and aeroelastic models, with the inclusion of a metamodel.
- Chapter 4: presentation of the results and their analyses, including the determined loads, the maximum and minimum bounds for the optimization model, its local minimum and the aforementioned buckling and aeroelastic post-analyses.
- Chapter 5: overview of the concluding remarks, reflecting on the choices made along the development of this work and their consequent results, including some remarks on potential future improvements.

LITERATURE SURVEY

“The story of civilization is, in a sense, the story of engineering - that long and arduous struggle to make the forces of nature work for man’s good.”

— Lyon Sprague DeCamp

THIS chapter dives into the recent work developed by the industry and academia relating to structural innovations and truss-based structures. The basics and the theory behind the optimization and metamodeling techniques used in this work is described in detail.

2.1 Recent Work

2.1.1 Industry

Ever since NASA’s N+3 topics, which cover the objective to reduce the emission of noise and pollutants, industry focus has shifted into developing sustainable aircraft. One of the highlights in lowering aircraft impact in the environment is EMBRAER’s Energia Family (Figure 1) which is exploring alternative propulsive systems in order to meet its goals. The innovative aircraft include hybrid-electric, hydrogen fuel cell, all-electric and hydrogen gas turbine as options, aiming to nullify carbon emissions and minimize noise emission in 60-80% (EMBRAER, 2021). The alternative powered engines allow for the removal of fossil fuel tanks from the wing’s internal structure, opening up all new kinds of possibilities to further optimize its wingbox, such as the one discussed in this study.

Historically, the B-17 Flying Fortress’ structural project followed the truss-based internal structure approach, with an “N” truss pattern present its wing’s spars and ribs (Figure 2). Its glaring issue was put in the spotlight in April 2021 by Airworthiness Directive (AD) 2034-10-04, with the temporary grounding of all remaining B-17s, whereupon the wing-fuselage attach structure’s joint separated and allowed the wing to shift two inches at the attach point. Even

Figure 1 – Energia Family.



Source: Embraer (2021).

though the AD allowed the ungrounding of the B-17s, given the completion of its procedure, the significance of this problem, dating all the way back to AD 77-17-11 (January 1979), results in conservative thoughts concerning to truss-based cantilever wing aircrafts.

Figure 2 – B17's truss-based internal structure.



(a) Ribs.



(b) Spar.

Source: Aerovintage (2022).

However, new manufacturing technologies, such as Truss-Braced Wings (TBWs), which are alternatives cantilever ones, may allow to bypass this problem, while even enhancing aircraft performance, specially with recent advancements in academia, which display the effectiveness of the TBW in comparison to the cantilever (GERN *et al.*, 2001; BHATIA *et al.*, 2009; BHATIA; KAPANIA; HAFTKA, 2012; MALLIK; KAPANIA; SCHETZ, 2013). The industry is also taking part in the development of TBWs, regarding projects such as Boeing's Supersonic Ultra Green Aircraft Research (SUGAR) and European Union's Hybrid-Electric Regional Aircraft (HERA), which are displayed in Figures 3 and 4, respectively. This is mainly due to its role in

increasing aerodynamic efficiency, while maintaining structural stiffness, which contributes in the aforementioned reduction of pollutants due to reduced burning of fossil fuels.

Figure 3 – SUGAR.



Source: Boeing (2023).

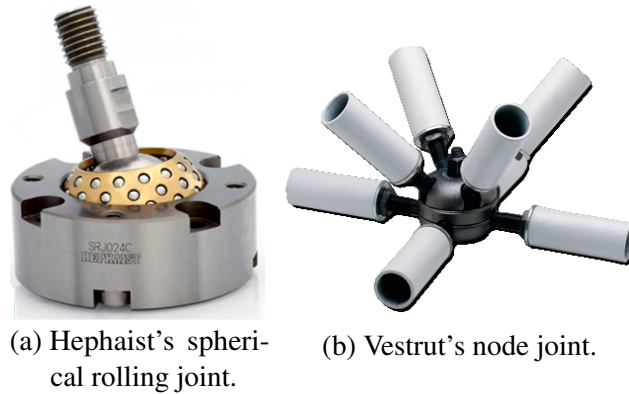
Figure 4 – HERA.



Source: HERA (2023).

Other significant advancements (YE *et al.*, 2021; BAI; YANG, 2013) include using additive manufacturing and fiber reinforced polymers in order to optimize the manufacturing of the trusses' joints, which can be challenging considering the complex geometries and necessary structural integrity. Prime examples of industry advancements that cover these requirements would include Hephaist's spherical rolling joint and Vestrut's node joint (Figure 5), which allow for high rigidity and precision while covering different angles.

Figure 5 – Innovative joint designs.



Source: Hephaist (2022).

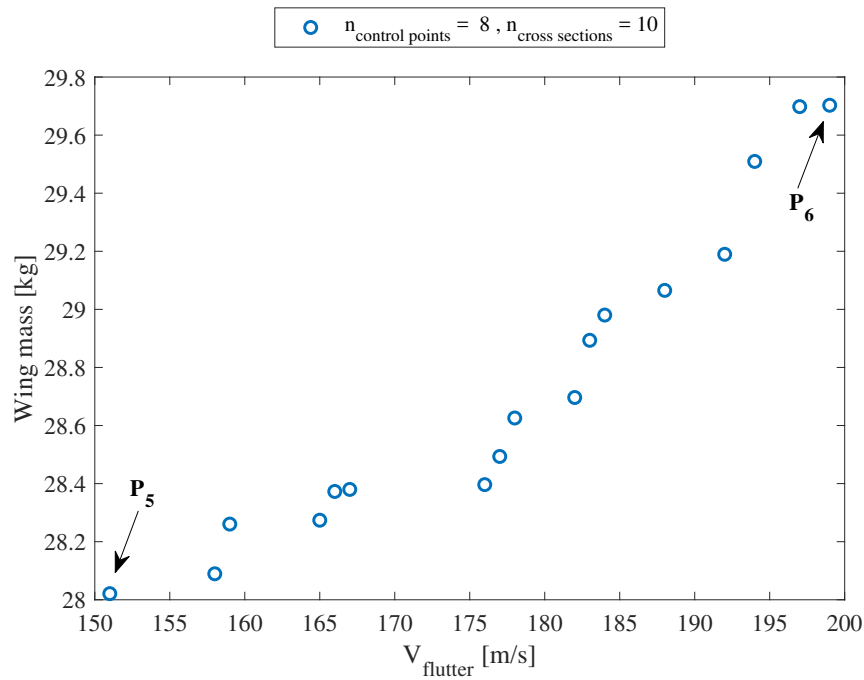
2.1.2 Academia

Outside of TBWs (BHATIA; KAPANIA; HAFTKA, 2012; MALLIK; KAPANIA; SCHETZ, 2013) and morphing wings (FINISTAURI; XI; WALSH, 2012; TANG *et al.*, 2016), recent works in academia have not yet considered the truss-based topology a popular choice. However, as seen in the new industry direction, groundbreaking topologies are intensively taking place. Given that, some new studies have assessed the truss-based structure concept.

Silva (2022) developed a structural and aeroelastic optimization of a Flutter Free FLight Envelope eXpansion for ecOnomical Performance (FLEXOP) inspired wing using truss-based modular structures, aiming towards minimizing the structural weight of the wing and maximizing the flutter speed. Two optimizations took place, initially referring to the structural mesh, with the number and position of truss-based ribs and nodes assessed, followed by an optimization of each trusses' outer radius and thickness, with the possibility of removing elements. The pareto front of the second optimization's result for the best fit for the first optimization can be seen in Figure 6. Then, the final structural mesh for the lowest mass wingbox is displayed in Figure 7, with the outer radius and thickness distributions available in Figure 8. Even though it was not the work's focus, it also estimated a reasonable mass of 150 g for each joint in the structure for the correct representation of the total wing weight in an aeroelastic analysis.

More recently, Stragiotti, Irisarri and Julien (2024) highlighted ultralight truss structures as emerging candidates for designing innovative thin high AR wings. This is even more important considering the involvement of TBWs in the advancements towards aircraft sustainability and, since the brace aids with resisting the bending moment by adding one more fixation point, the wing is considerably thinner and has a higher AR when compared to a cantilever one (GERN *et al.*, 2001; BHATIA *et al.*, 2009). The research tackles a similar challenge as this one, that being how to optimize these structures for maximum efficiency, considering the number of design variables. It proposes a novel two-step optimization strategy, in which a first optimization solving

Figure 6 – Pareto front for 8 nodes per rib and 10 truss-based ribs.



Source: Silva (2022).

a relaxed formulation is used to find a good starting point for the second optimization, which is imposed with additional mechanical constraints to the first step. Using this technique, two CRM-based wingboxes are designed for a +2.5 g maneuver load case, a first one containing 315 elements (257 optimizable) and a second one containing 2370 elements (1127 optimizable), resulting in 21.34 ton and 20.09 ton wing weights, respectively. A more comprehensive view of the structural mesh developed for both can be seen in Figure 9.

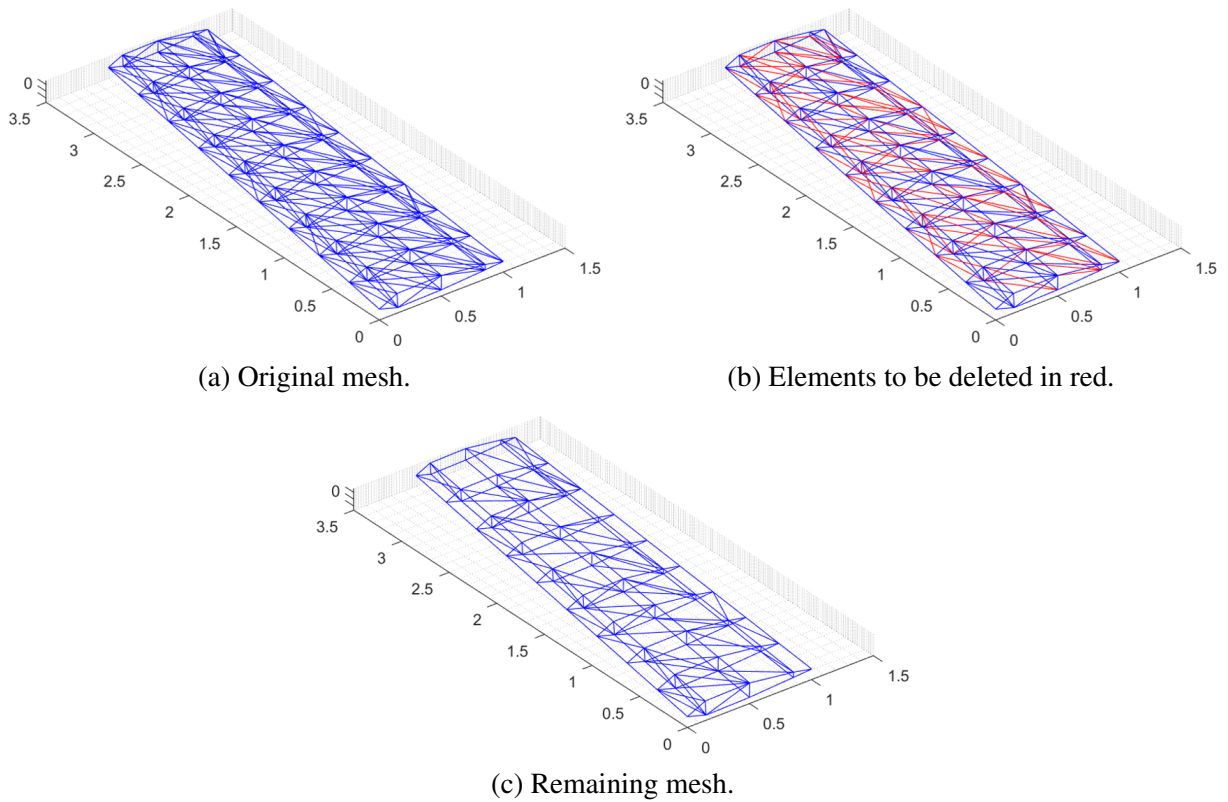
2.2 Optimization

2.2.1 Key Concepts

There is an ever-growing demand on engineers to increase performance while decreasing operational costs. It has led them into developing revolutionary tools in order to enable decision-makers to efficiently allocate limited resources, design complex systems, and solve challenging problems. One of the more modern and mathematical-based techniques is optimization, which is of essential use in any industry. In the aerospace industry it is no different, with a clear necessity to optimize the aircraft down to the absolute details. From parameters such as minimizing drag, maximizing performance, minimizing weight, maximizing range, it is a never ending cycle of design improvement.

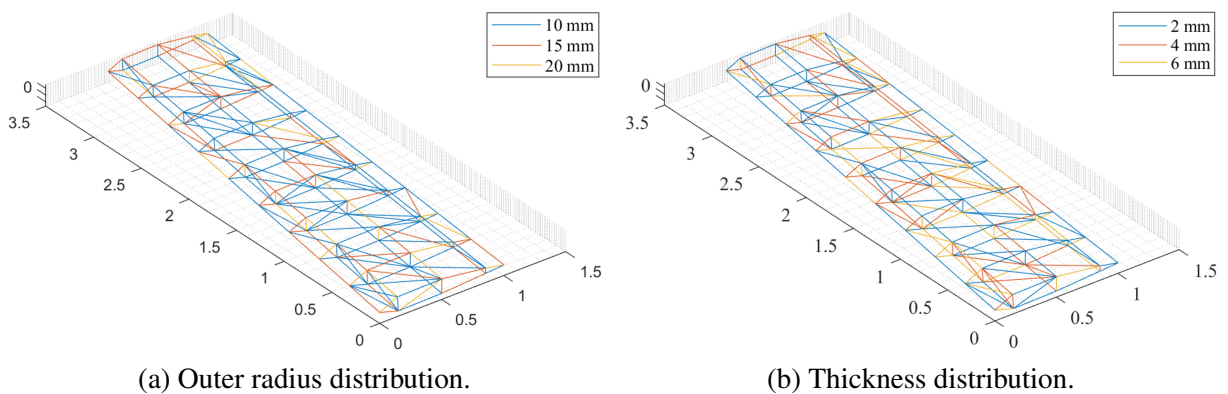
According to Rao (2019), optimization is the act of obtaining the best result under given

Figure 7 – Final structural mesh for lowest wing mass.



Source: Silva (2022).

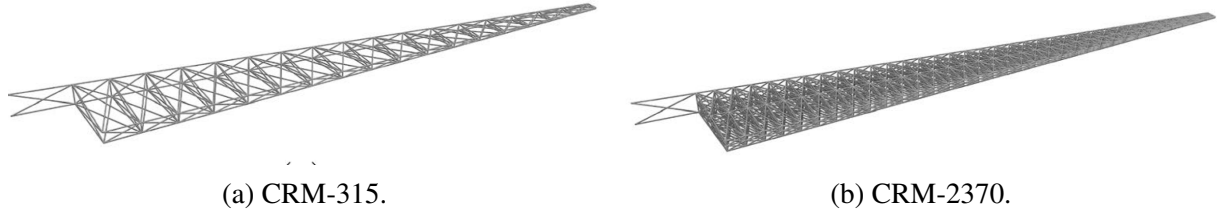
Figure 8 – Outer radius and thickness distribution for lowest wing mass.



Source: Silva (2022).

circumstances, being it maximizing or minimizing an effort or benefit, which can always be described by a function. The function is commonly denominated objective function “ $f(x)$ ”, which is a criteria for comparing the different alternative acceptable designs and for selecting the best one, i.e, the global maximum or minimum. The variables that affect the objective function are the design variables, which are collectively represented by a vector (Equation (2.1)). More

Figure 9 – Truss-based structural mesh.



Source: Stragiotti, Irisarri and Julien (2024).

often than not, the design variables may not be chosen arbitrarily, albeit due to manufacturing or performance limitations, and have to be restricted by design constraints in order to find the correct global minimum, or at least a local minimum, in the case of heuristic models. The constraints may be described by a discretization of the design variables, a function that limits them, or even a penalization that drives the optimization problem away from them.

$$x = \{x_1, x_2, \dots, x_n\} \quad (2.1)$$

There is no single method available for solving all optimization problems efficiently. Hence, a number of optimization methods have been developed for solving different types of optimization problems, and have to be tested for each specific situation. This work dives into three stochastic modern methods of optimization: differential evolution, genetic algorithm and particle swarm optimization, which are based on certain characteristics and behavior of biological, molecular, swarm of insects, and neurobiological systems. Due to their heuristic nature, the methods explore a diverse range of solutions and have the potential to escape local optima. All three are population-based techniques, meaning that a number of individuals are evaluated before attending the next iteration. When the differences of best individuals between iterations is lower than a pre-determined convergence, the global optimum has been found.

2.2.2 Differential Evolution

Differential Evolution (DE) is an optimization technique based on evolutionary computation, ideal in non-linear applications with many local optima, such as the one presented. An initial population of design variables is randomly generated. Then, for each individual of the population, a mutation vector is created by adding the weighted difference, represented by a scaling factor “ F ”, between two randomly selected individuals to another randomly selected individual. Through a discrete crossover and greedy selection, the mutation vector is combined with the current individual in order to generate a trial vector, which is compared to the current individual. Whichever has the best fit to the objective function survives as the next individual.

The DE formulation described in this work is based on the work of Jr *et al.* (2016), which determines an ideal population size of 5 to 10 times the size of the design variables vector and a $F = 0.5$. It also uses an upgraded mutation scheme, described in Equation (2.2), whereupon “ x_{r_1} ” to “ x_{r_5} ” are candidate solutions randomly chosen, and “ x_{best} ” is the candidate solution associated with the best fitness value to the objective function.

$$\begin{aligned}
 rand/1 &\rightarrow x = x_{r_1} + F(x_{r_2} - x_{r_3}) \\
 rand/2 &\rightarrow x = x_{r_1} + F(x_{r_2} - x_{r_3} + x_{r_4} - x_{r_5}) \\
 best/1 &\rightarrow x = x_{best} + F(x_{r_2} - x_{r_3}) \\
 best/2 &\rightarrow x = x_{best} + F(x_{r_2} - x_{r_3} + x_{r_4} - x_{r_5}) \\
 rand/best/1 &\rightarrow x = x_{r_1} + F(x_{best} - x_{r_1} + x_{r_1} - x_{r_2}) \\
 rand/best/2 &\rightarrow x = x_{r_1} + F(x_{best} - x_{r_1}) + F(x_{r_1} - x_{r_2} + x_{r_3} - x_{r_4})
 \end{aligned} \tag{2.2}$$

2.2.3 Genetic Algorithm

The Genetic Algorithm (GA) is based on the principles of natural selection, i.e., Darwin’s theory of survival of the fittest, with basic elements of natural genetics, such as reproduction, crossover, and mutation used in the genetic search procedure. This technique is ideal for nonlinear problems, being it with discrete, mixed or continuous design variables, and it can find the global optimum solution with a high probability.

An initial population of individuals is randomly generated and each individual’s fit to the objective function is assessed. The individuals may be discrete due to the variables representation as binary. In the next iteration, the selection of new individuals is not entirely random, with a bias towards previous individuals with a valuable fitness value, through a process called reproduction. The bias is described in Equation (2.3), whereupon “ R ” describes the fitness value and “ p ” the probability for selecting the individual “ i ” for the next generation’s mating pool, considering all individuals “ j ” in a population of size “ NP ”. The reproduction stage ensures that highly fit individuals live and reproduce, and less fit individuals die.

$$p_i = \frac{R_i}{\sum_{j=1}^{NP} R_j} \tag{2.3}$$

Then, individuals for the next generation are created through a mutation applied to the crossover of weighted probability selected individuals in the mating pool. The process goes on until the number of assigned iterations is reached or the global minimum is found.

2.2.4 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an optimization technique based on the behavior of a swarm of animals, such as birds, in which a bird in a flock would be a particle in the swarm. In this method, when one bird locates a target or food (or maximum/minimum of the objective function), it instantaneously transmits the information to all other birds, so they stick together in a cohesive way. Nevertheless, even though other birds gravitate towards the food, they stay separated, not to prematurely converge into it. Finally, there is a component of each bird's own independent thinking as well as its past memory, but aligned as to follow the general heading of the flock, i. e., since each particle has a position and a velocity, it wanders around in the sample space by itself, while remembering the best position the swarm has discovered.

The velocity " V_p " in the iteration " i " of a particle " j " is as displayed in Equation (2.4). There, " c_1 " is the particle and " c_2 " the swarm learning rate, usually assumed to be 2 (RAO, 2019). Meanwhile, " r_1 " and " r_2 " are uniformly distributed random numbers in the range 0 and 1. Finally, " $P_{best,j}$ " is the best fitness value for the particle " j " and " G_{best} " in all particles of the optimization process.

$$V_{pj}(i) = V_{pj}(i-1) + c_1 r_1 [P_{best,j} - X_j(i-1)] + c_2 r_2 [G_{best} - X_j(i-1)], \quad j = 1, 2, \dots, N \quad (2.4)$$

The position of particle " j " is described in Equation (2.5). If the positions of all particles converge to the same set of values, the method is assumed to have converged. If not, the iterations are continued until a maximum value is reached.

$$X_j(i) = X_j(i-1) + V_j(i), \quad j = 1, 2, \dots, N \quad (2.5)$$

2.3 Metamodels

2.3.1 Key Concepts

Hand in hand with the ever-growing demand on engineers to increase performance while decreasing operations costs, it is the necessity to reduce the cost for a project to be developed. Hence, another modern technique commonly used in engineering problems nowadays is metamodeling, which refers to the method to develop a representative model of another model that is expensive to run. That is ideal in stochastic analyses, which require several evaluations to be completed before one design can be assessed, featuring high-fidelity numerical analyses, which have to be detailed in order to have representative results, which are both time consuming characteristics. Therefore, metamodeling is a key if you have a model which is computationally expensive to be executed and has to be executed repeatedly to achieve a global minimum.

According to Jurecka (2007), the fundamental idea of the metamodeling concept is to find an empirical approximation model, which can be used to describe the typically unknown relation between input variables and response values of a process or product. For example, given the structure, as a design variable, and boundary conditions, as a pre-assigned variable, of a beam, a well-trained metamodel could predict a specific output, such as maximum stress or displacement. In order to develop the metamodel, sampling points describing the relationship between the inputs and outputs, which represent the complete sampling space described by the inputs, have to be created for both training and validation. Then, given an analytical formulation to describe that relationship, the approximation models can then be used to predict the behavior of the original system at any point in the sampling space. This work dives into three specific formulations, Response Surface Methodology (RSM), Artificial Neural Network (ANN) and Kriging.

2.3.2 Response Surface Methodology

The RSM is a simple and straightforward metamodel method, which led to it being one of the more commonly used formulations. It consists of a polynomial regression to the dataset, which demands that a large training sample set is available given the number of coefficients in the polynomial and, therefore, its applications usually consist of second order regressions. The model is represented by a surface, which is of easy conception and, generally, are computationally cheap to be developed. However, its benefits also lead to its limitations, not being indicated to model non-linear unpredictable systems (LIN; SIMPSON; CHEN, 2001).

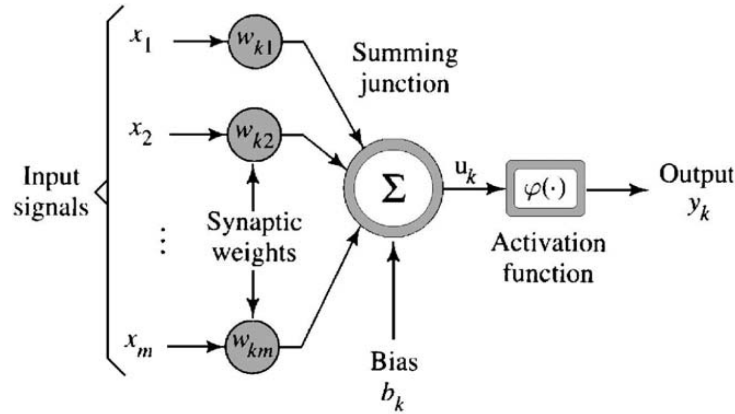
2.3.3 Artificial Neural Network

As presented by Fonseca, Navarrese and Moynihan (2003), ANN is an information processing system derived from the mathematical models of biological neural networks, thoroughly utilized in the aerospace industry (NAPOLITANO; CHEN; NAYLOR, 1993; CHEN *et al.*, 2014). The use of ANNs as a simulation metamodel is particularly indicated where computing costs are important and, given their architecture, they allow for complex relationships between a large number of inputs and an output.

The architecture, which is displayed in Figure 10, consists initially with an input layer, whereupon each neuron in the input layer represents a feature of the input dataset, namely a design variable. Also of a hidden layer, where the analytical formulation is more robust and consists of three basic elements. A set of connecting links or synapses, each given a weight to an input, turning it into a weighted neuron. An adder, which is a summing junction of the weighted neurons. Finally, an activation function, that defines the output of the neuron in terms of the induced local field, basically deciding whether a neuron should be activated or not, based on the weighted sum of its inputs and a bias, which is an adjustable constant applied to the activation

function that helps the neuron's output to be shifted to achieve the desired activation. Ultimately, the output layer is reached, referring to the predicted result by the ANN given the input layer.

Figure 10 – ANN architecture.



Source: Fonseca, Navarrese and Moynihan (2003).

Even though ANN's complex architecture allows it to overcome many of the disadvantages of more simple approaches to metamodeling, such as RSM's limitation to approximate a subset of a nonlinear multi-input simulation domain, selecting the architecture of an ANN model is not straightforward, given the different possibilities for the hidden layer elements and the necessity of training the synapses. The former is represented by the different options, such as the more traditional feedforward (SVOZIL; KVASNICKA; POSPICHAL, 1997) or more modern convolutional (LI *et al.*, 2021) and recurrent (SALEHINEJAD *et al.*, 2017) ANNs. The latter is displayed commonly in determining the optimal number of hidden layers and neurons, and more generally in cases like overfitting, when the ANN developed by the training samples underperforms in previously unseen data. Both reasons are intensified by lack of reliable techniques for selecting architecture and training ANNs in the literature, demanding experience in order to obtain a successful ANN (KECHAGIAS *et al.*, 2022).

2.3.4 Kriging

Originated as a geostatistical method used for interpolating the value of a random field at an unmeasured location from observations of its value at nearby locations, Kriging is now popular for approximating the mapping process of a deterministic computer model response, such as a Finite Element Model (FEM) or Computational Fluid Dynamics (CFD) (SAKATA; ASHIDA; ZAKO, 2004; MARTIN; SIMPSON, 2003). Even though different types of Kriging have been developed, like Universal Kriging or Cokriging (ZIMMERMAN *et al.*, 1999), this research focuses on ordinary Kriging, since it is thoroughly covered by the literature, easing its application. The analytical formulation is described by Equation (2.6), whereupon “ $y(x)$ ”

describes the output value, “ $r(x)$ ” a regression model, such as linear or quadratic, and “ $Z(x)$ ” a correlation function.

While the regression model is more traditional, the correlation one describes a relationship between the input and the output by a hyperparameter “ θ ”, which, coupled with a difference between the input and a training sample “ d ”, dictates the weighted importance of an input in its respective output. Therefore, through both variables, the correlation function quantifies how similar or correlated outputs are based on their inputs’ proximity or similarity, being essential for capturing the underlying spatial patterns or trends within the dataset, enabling the Kriging model to make accurate predictions at unsampled locations.

$$y(x) = r(x) + Z(x) \quad (2.6)$$

In similar fashion to ANN, Kriging’s formulation allows it to dictate complex and nonlinear relationships between a large number of inputs and an output. The biggest challenge comes from selecting the correct regression and correlation functions for the system, and then selecting the correct hyperparameters for the architecture. However, due to its popularity, the challenge of hyperparameter tuning can be tackled, with more simple cases being solved by simple optimization methods, such as the ones available in the DACE toolbox (ULAGANATHAN *et al.*, 2015), and more complex cases having traditional layed out techniques (TOAL; BRESSLOFF; KEANE, 2008).

METHODOLOGY

“Engineering is the art of modeling materials we do not wholly understand, into shapes we cannot precisely analyze so as to withstand forces we cannot properly assess, in such a way that the public has no reason to suspect the extent of our ignorance.”

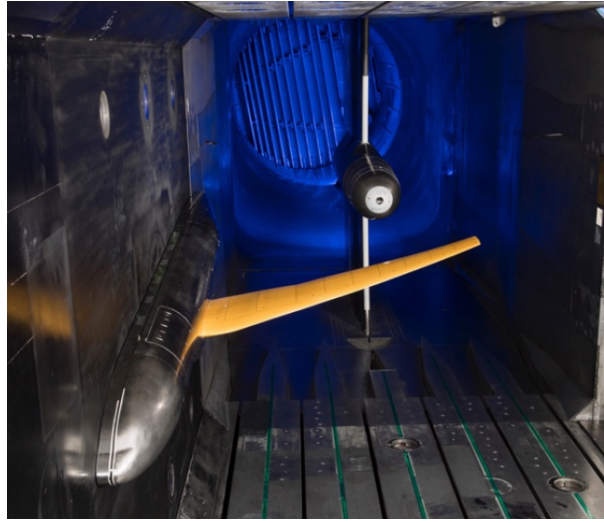
— A. R. Dykes

THIS chapter goes through the methodology used for the development of this work. It dives into the inspiration, modeling and modularity of the structural model used for the static and buckling analysis. It also displays the aerodynamic model used to determine the rigid loads acting on the wingbox, including its V-n diagram. Then, the aeroelastic model used to evaluate possible aeroelastic instabilities on the wingbox is presented. Finally, both the PSO optimization model and the Kriging metamodel used to optimize the wingbox are described in detail, making clear the strategy used to find the local minimum and how to evaluate that the work reached it.

3.1 Structural Model

NASA’s CRM is an open-source aircraft geometry that was developed in 2007-2008 through a partnership between NASA, Boeing, and other industry and government groups, initially used for the validation and assessment of CFD tools (VASSBERG *et al.*, 2008), as exemplified in Figure 11. Over the years, its use branched into all areas of aircraft design, and has been used by many researchers in different studies (RIVERS, 2019; LACY; SCLAFANI, 2016; RIVERS *et al.*, 2019), including the FEM used in this work’s assessment.

Figure 11 – Wind tunnel experiment using the CRM.



Source: Rivers (2019).

The CRM geometry is representative of a typical wide-body transonic transport aircraft, as displayed in Figure 12. Primarily, the CRM wing has a wingspan of $b = 58.76$ m and an aspect ratio of $AR = 9$, resulting in a total wing area of $S = 412.7$ m². The reference area is $S_{ref} = 383.74$ m² and the exposed wing area is $S_{exp} = 337.05$ m². The wing is double tapered with a break at 37% semispan and a taper ratio of $\lambda = 0.533$ inboard of the break and $\lambda = 0.376$ outboard of the break, whilst its reference chord is $c_{ref} = 7.01$ m. The dihedral angle is set at $\Gamma = 8^\circ$ from root to tip. Additionally, the CRM wing is designed for cruising at a Mach number of $M_{cr} = 0.85$, at FL350 ($h_{cr} = 10668$ m), and a lift coefficient of $C_{L_{cr}} = 0.5$. Under standard atmospheric conditions with no temperature offset, this corresponds to a Reynolds number of approximately $Re_{cr} = 4.3 \times 10^7$. The wing and flight reference values are summarized in Table 1.

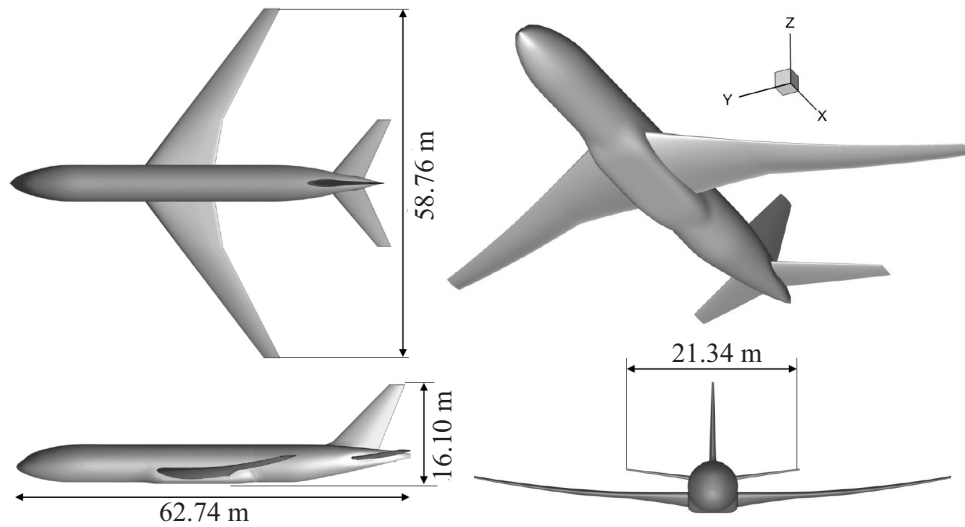
Table 1 – CRM wing and flight properties.

Parameter	Value	Property	Value
b	58.76 m	c_{ref}	7.01 m
AR	9	Γ	8°
S	412.70 m ²	M_{cr}	0.85
S_{ref}	383.74 m ²	h_{cr}	10668 m
S_{exp}	337.05 m ²	$C_{L_{cr}}$	0.5
λ	0.533 - 0.376	Re_{cr}	4.3×10^7

Source: NASA (2012).

As a common reference and baseline, the structural model is based on the CRM's FEM designed on NASTRAN, more specifically its twelfth coarse version, which was retrieved from Vassberg (2012). Its internal structure is a traditional one, composed of 3 I-shaped spars and 17 L-shaped stringers distributed along the chord, including 52 ribs uniformly spaced by 500 mm.

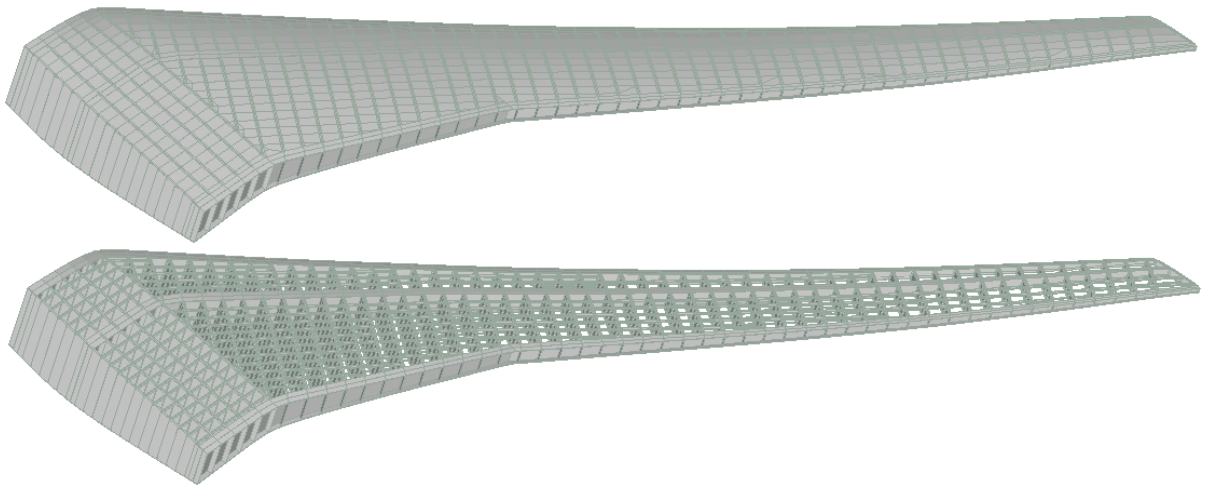
Figure 12 – CRM views.



Source: Fujiwara *et al.* (2018).

The aforementioned components are all modeled as plate elements and composed of aluminum, while mass elements are present for aeroelastic analyses, representing external masses. Figure 13 depicts the FEM model of the wingbox, while Table 2, the model's properties.

Figure 13 – Original FEM.



Source: Elaborated by the author.

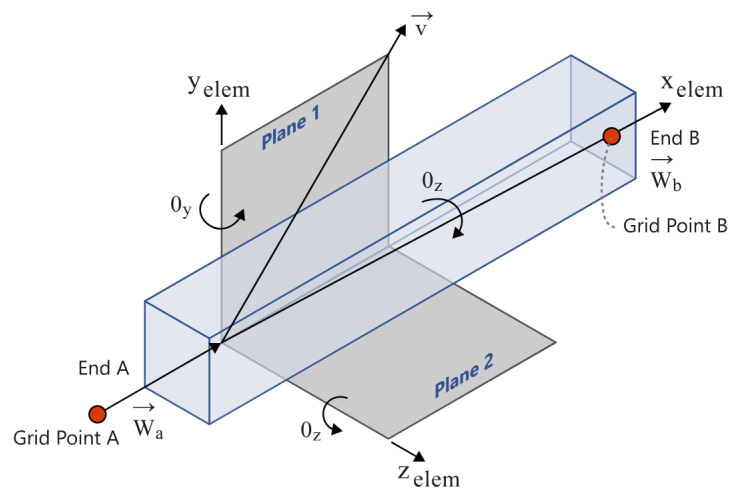
Using some of the original nodes as a baseline to maintain aerodynamic profile and rib spacing, the CRM's internal structure was completely replaced by a truss-based one. Given the necessity to iteratively size the trusses' cross-sections and for a computationally effective global model response instead of a detailed one, line 2-nodal elements represented the trusses. Regarding the properties, bar elements (PBAR) were ideal for this work, since they covered the requirement to input both outer radius and thickness values and are available in a buckling analysis (Figure 14).

Table 2 – Original FEM properties.

Property	Amount
Nodes	6687
Internal elements	7030
Ribs	52
Skin elements	1129
Mass elements	20

Source: Elaborated by the author.

Figure 14 – Coordinate system for a bar element.



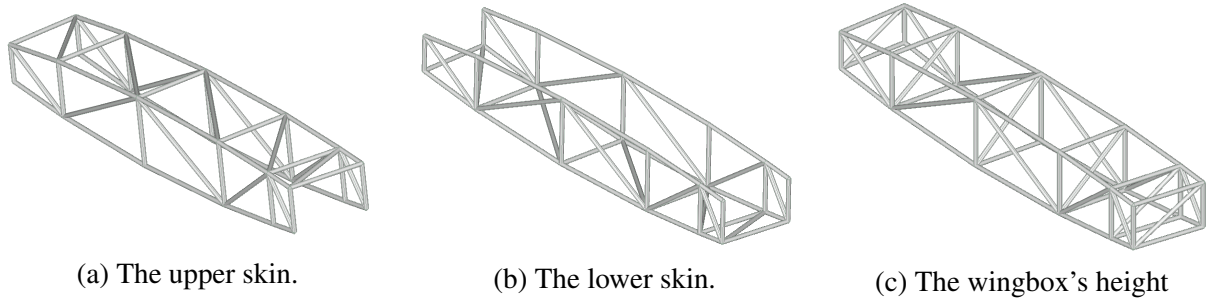
Source: Altair (2021).

Alternating “N” truss patterns were used in the truss-based ribs and between them, in three different directions, parallel to the upper skin, to the lower skin, and to the airfoil’s thickness (Figure 15). The pattern is inspired by the aforementioned B-17 truss-based ribs and spar pattern, with the alternation from rib to rib derived from Silva (2022). It is worth mentioning that the number of nodes per rib depends on the rib’s chord, taking maximum value of 16 at wing root and minimum value of 6 at wing tip.

Furthermore, to account for the joints between trusses, mass elements (CONM2) of 150 g were placed at each node of the model (Figure 16), following the approach proposed by Silva (2022). The specific geometry and correct mass of the joints will not be delved into detail, since the former owes to technological advancements, such as the ones discussed in Subsection 2.1.1, and the latter to not being important to the structural response, only regarding the total weight. However, the mass may be addressed in Section 4.4.2, due to its behavior affecting the dynamic response of the wingbox and, therefore, the aeroelastic model.

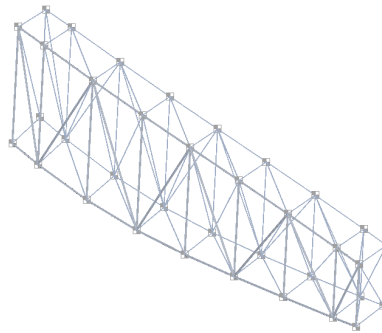
Skin panels were added onto the external surface, represented by plate elements (PSHELL), considering their small thickness when compared to other dimensions, aiming for model represen-

Figure 15 – Truss patterns parallel to.



Source: Elaborated by the author.

Figure 16 – Joints represented by mass elements.



Source: Elaborated by the author.

tativity in the considered NASTRAN analyses. Finally, the truss-based CRM FEM is displayed in Figure 17 and its properties are available in Table 3. It is worth noting that all trusses and skin panels had the mesh size of their original geometry, being that the curve connecting two nodes or a surface between its surrounding trusses, in order to minimize computational cost and reduce the amount of design variables in the optimization process.

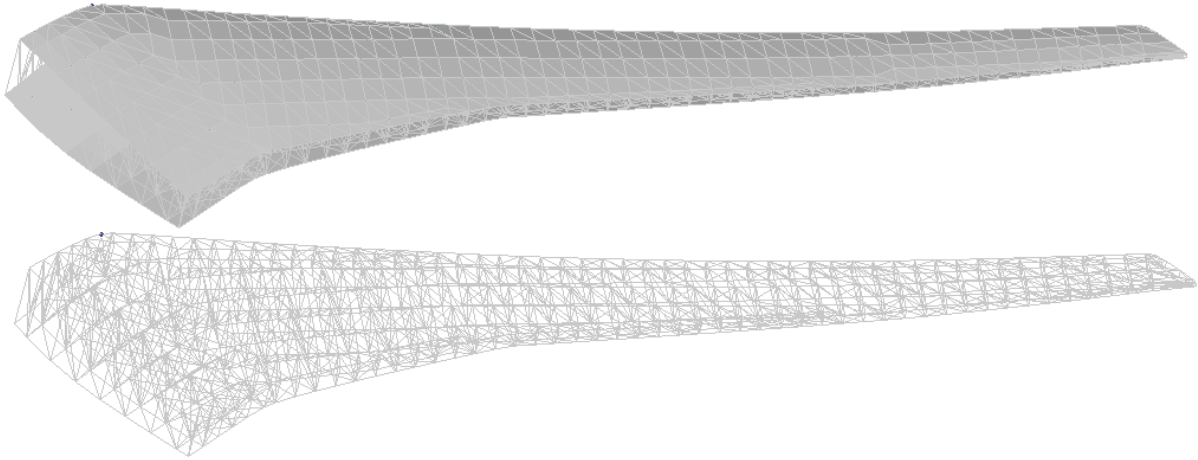
Table 3 – Truss-based FEM properties.

Property	Amount
Nodes	762
Truss elements	3183
Truss-based ribs	52
Skin elements	600
Mass elements	710

Source: Elaborated by the author.

Even though the original CRM used aluminum as the basis for its material properties, adjusting to industry trends - as exemplified by the Boeing 787 majorly composite structure -, composites were predominant in the development of this research. Hence, carbon fiber laminate plates were used in the skin panels, with its material properties being displayed in Table 4.

Figure 17 – Truss-based FEM.



Source: Elaborated by the author.

Table 4 – Carbon fiber laminate plate properties.

Property	Value	Property	Value
E_1	98 GPa	T_1	1314 MPa
E_2	7.9 GPa	C_1	1220 MPa
ν_{12}	0.28	T_2	43 MPa
G_{12}	5.6 GPa	C_2	168 MPa
ρ	1520 kg/m ³	S_{12}	48 MPa

Source: Stanford, Jutte and Wu (2014).

Meanwhile, carbon fiber tubes were used in the trusses. The difference in nomenclature comes from the trusses being modeled as an isotropic material as opposed to the skin's orthotropic nature, since the individual tubes are majorly submitted to loads in the axial direction of their structures, which overpower the importance of other acting loads. Additionally, since the carbon fiber tube's behavior is similar to a fragile material, the maximum combined traction/compression stresses were used as the failure indices in this work. The material properties are displayed in Table 5.

Table 5 – Carbon fiber tube properties.

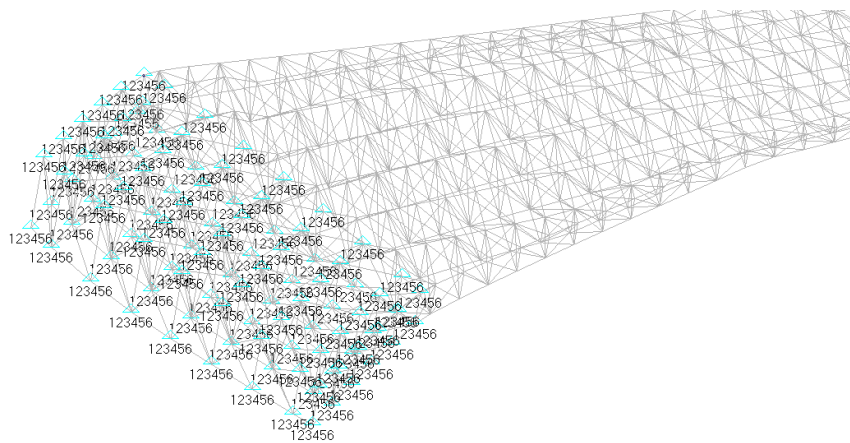
Property	Value
E	180 GPa
ν	0.28
σ_{adm}	550 MPa
ρ	1650 kg/m ³

Source: EXELITE (2014).

It is worth mentioning that, with the use of composites, there also comes the necessity to evaluate the propagation of parametric uncertainties, related to production and manufacturing defects, such as gaps and fiber overlapping, which may negatively affect the composite's properties (GUIMARAES *et al.*, 2017; MESOGITIS; SKORDOS; LONG, 2014). However, since this is not the focus of this study, the manufacturing will be assumed as ideal, not affecting the material's properties.

Furthermore, the boundary conditions for the new FEM had to be established. The constraints from the original FEM were applied, where all degrees of freedom of each node in the wing-fuselage connection were clamped, as depicted in Figure 18. Meanwhile, the applied loads were determined using the aerodynamic model, which is described in more detail in Section 3.2.

Figure 18 – Constraint boundary condition.



Source: Elaborated by the author.

Finally, having the FEM fully developed with its geometry, elements, materials, properties and boundary conditions determined, NASTRAN's SOL101 is initially used in the optimization process (Section 4.3), through the analysis of the structural response constraints that come with its execution. Moreover, the structural model is also used in NASTRAN's SOL105, envisaging to verify the wingbox's structural integrity through a buckling post-analysis (Section 4.4.1). It uses Lanczos' solution method in order to determine the critical eigenvalues and eigenvectors, solving the standard eigenvalue problem by a recursion formula, which transforms the original large-scale problem into a small tridiagonal one that can easily be solved to obtain a small subset of eigenvalues and eigenvectors, thus being a computationally cost-effective solution. Additionally, the structural model is a part of the aeroelastic model used in NASTRAN's SOL145, which is used in order to eliminate the possibility of aeroelastic instabilities inside the flight's envelope (Section 4.4.2).

3.2 Aerodynamic Model

In order to develop the aerodynamic model, the CRM's performance and geometric properties were gathered and displayed in Tables 6 and 7, respectively. The airfoil used in the model was the blunt tail-end (BTE) version of the CRM.65, which is depicted in Figure 19.

Table 6 – Performance properties of the NASA CRM.

Property	Value
MTOW	500000 lbs
h_{cr}	35000 ft
M_{cr}	0.85
V_{cr}	490 knot
Total wing weight	30.29 ton

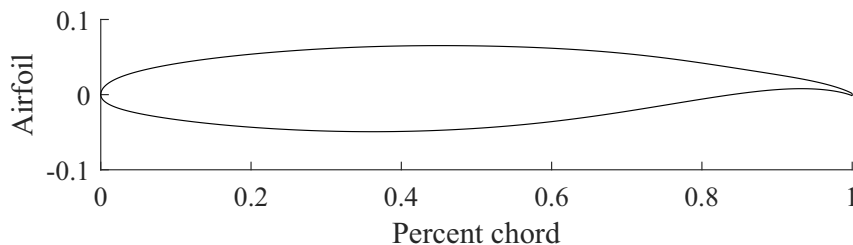
Source: NASA (2012), Kenway, Kennedy and Martins (2014).

Table 7 – Geometric properties of the CRM.

Property	Value
Fuselage width	4.53 m
Semi-wingspan	29.38 m
End of first section semi-wingspan	12.44 m
Wing root chord	12 m
End of first section chord	6.12 m
Wing tip chord	2.4 m
Root-tip sweep wingbox angle	30°
Root-tip Γ	8°
Airfoil profile	CRM.65 BTE

Source: Vassberg (2012), NASA (2012).

Figure 19 – CRM.65 BTE airfoil.

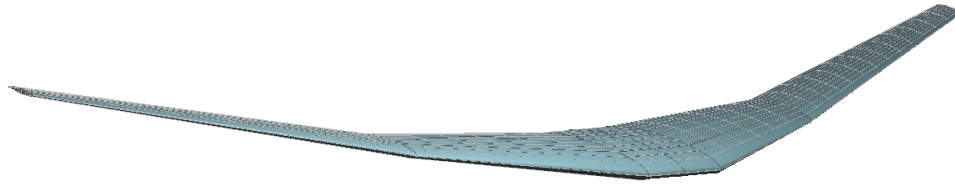


Source: Elaborated by the author.

The aerodynamic model uses XFLR5 as its solver and is based on a fixed-speed inviscid horseshoe vortex analysis, specifically the Vortex Lattice Method (VLM1). It focuses primarily

on the wing of the CRM and, given the aforementioned inputs, the aerodynamic model, including its 426 panels, is presented in Figure 20.

Figure 20 – Aerodynamic model.



The VLM1 analysis is executed and its resulting lift and moment coefficient distributions are extracted, as is each rib's chord. Initially, the area between a rib and the preceding one is determined, as in Equation (3.1). Then, the coefficients are interpolated to the correct positioning of each structural model rib and, through Equations (3.2) and (3.3), the lift force and twisting moment at each “ i ” rib are determined, respectively.

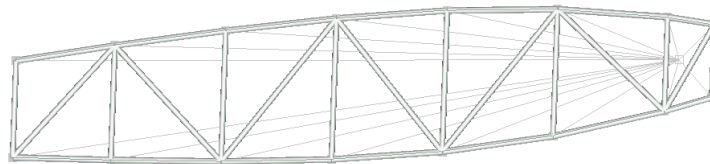
$$S_i = 0.5 [c(y_{i-1}) + c(y_i)] (y_i - y_{i-1}) \quad (3.1)$$

$$L_i = 0.5 \rho_{air_{FL}} V_{cr}^2 C_{L_i} \quad (3.2)$$

$$M_{t_i} = 0.5 \rho_{air_{FL}} V_{cr}^2 C_{M_i} c_i \quad (3.3)$$

Finally, after applying the load factor “ n ” for the considered critical condition, both loads are applied at each truss-based rib's aerodynamic center using an RBE3 element (Figure 21).

Figure 21 – RBE3 element for load application at 25% wing chord.



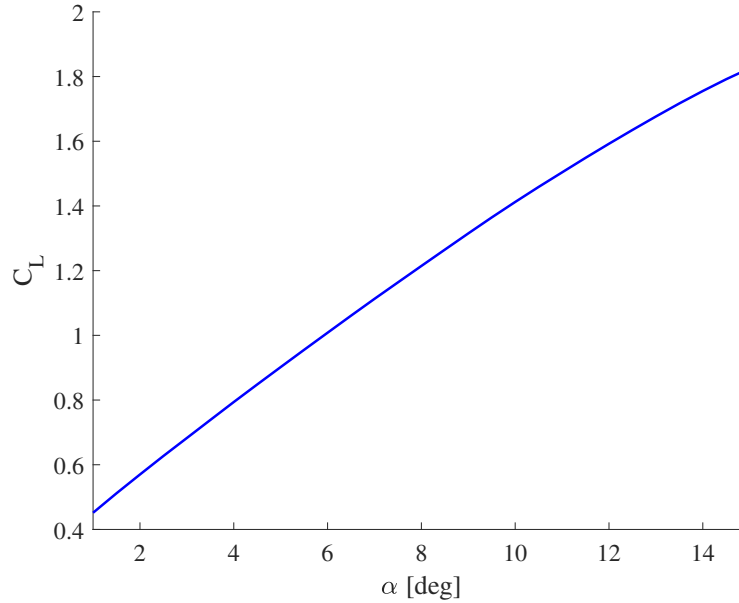
Source: Elaborated by the author.

3.3 V-n Diagram

The V-n diagram is a graph that summarizes an aircraft's structural and aerodynamic limitations, through a correlation between the aircraft's velocity and load factor, which represent the mission's flight envelope. If the aircraft flies outside its envelope, it may suffer catastrophic

damage and, therefore, the diagram displays the critical loads that act upon the structure. For the truss-based CRM, it was developed using FAA's (Federal Aviation Administration) Part 25, regarding airworthiness standards for transport airplanes. Initially, the CRM's airfoil (Figure 19) lift coefficient per angle of attack " α " curve was determined in Figure 22, using XFLR5 as its aerodynamic solver, resulting in a $C_{L\alpha} = 5.76$.

Figure 22 – C_L vs α for the CRM 65.BTE airfoil.



Source: Elaborated by the author.

Then, using the pre-determined V_{cr} and Part 25's Subsection 25.335b, the dive speed $V_d = 612.48$ KEAS was calculated in Equation (3.4).

$$V_d = \frac{V_{cr}}{0.8} \quad (3.4)$$

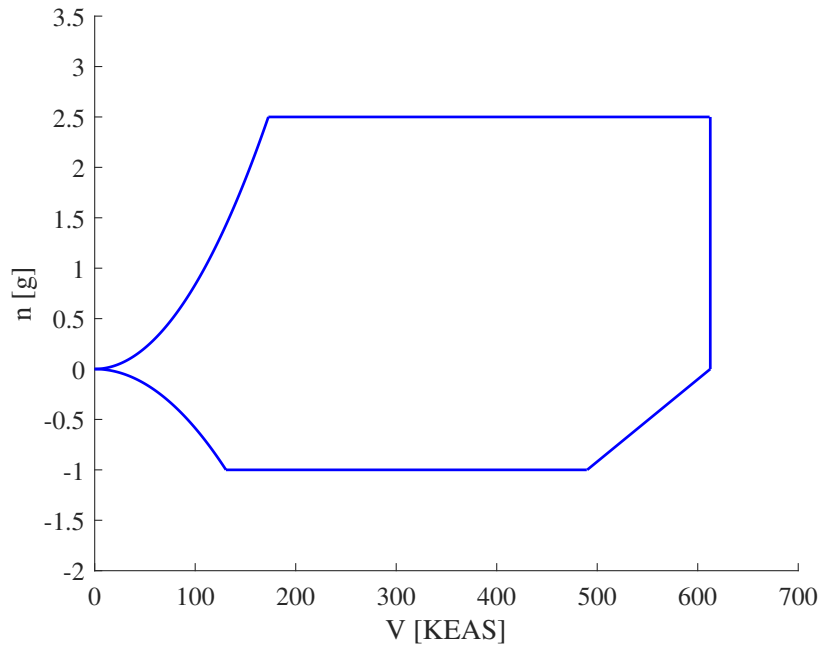
Referencing Part 25's Subsection 25.337, the maneuver load factors were established at $n_{z_{max}} = 2.5$ and $n_{z_{min}} = -1$. The stall load factor curves were determined through Equations (3.5) and (3.6), considering the aforementioned performance (Table 6) and geometric (Table 7) properties of the original CRM, which will also be used for the remaining equations, and establishing $C_{L_{max}} = 3$ inspired from similar aircraft.

$$n_{psl} = \frac{C_{L_{max}} V^2 S_{ref}}{296 \text{ MTOW}} \quad (3.5)$$

$$n_{nsl} = -0.7 n_{psl} \quad (3.6)$$

Finally, the V-n diagram can be displayed in Figure 23.

Figure 23 – V-n diagram.



Source: Elaborated by the author.

In order to offer a complete flight envelope, the static gust lines were also determined, as proposed by Lomax (1996). Initially, the airplane mass ratio in pitch $\mu_g = 77.08$ and gust alleviation factor $K_g = 0.82$ were calculated through Equations (3.7) and (3.8), respectively.

$$\mu_g = \frac{2 \text{ MTOW}}{g \ c_{ref} \ \rho_{cr} \ 0.00194 \ C_{L\alpha} \ S_{ref}} \quad (3.7)$$

$$K_g = \frac{0.88 \ \mu_g}{5.3 + \mu_g} \quad (3.8)$$

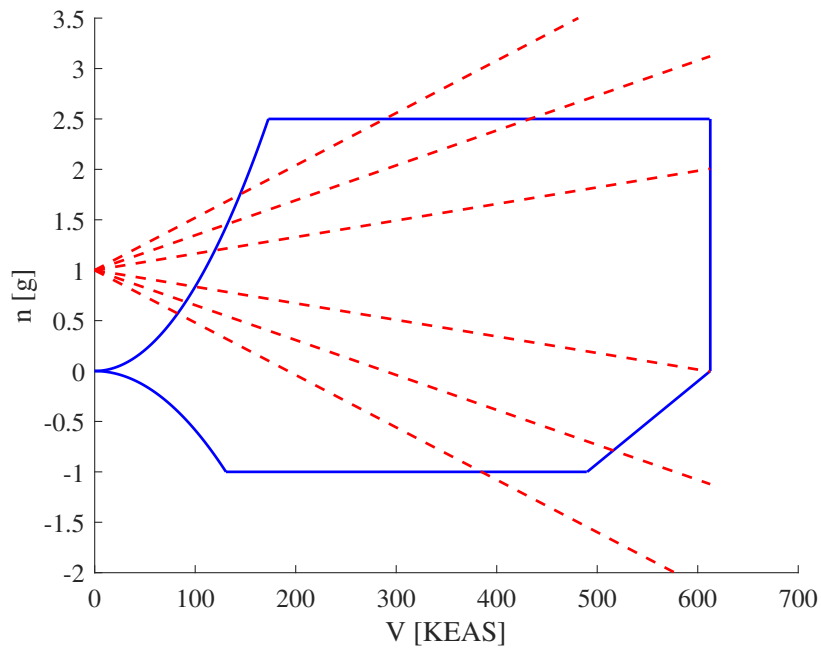
Then, design gust speeds $U_1 = 66$ KEAS, $U_2 = 44$ KEAS, and $U_3 = 20.86$ KEAS were established. Finally, the gust lines were determined using Equation (3.9) and displayed in Figure 24. Since no gust load factors surpassed the preceding V-n diagram, the maneuver load factors remained the critical ones.

$$n_{gusti} = 1 \pm \frac{K_g \ U_i \ V \ C_{L\alpha}}{498 \ \text{MTOW} \ S_{ref}} \quad (3.9)$$

With the flight's envelope determined, the maximum speed $V_{max} = 734.98$ KEAS was calculated through Equation (3.10). The maximum speed and load factor values will be used as inputs in the aerodynamic and aeroelastic model.

$$V_{max} = 1.2 \ V_d \quad (3.10)$$

Figure 24 – V-n diagram with gust lines.



Source: Elaborated by the author.

3.4 Aeroelastic Model

An aeroelastic model was developed in order to verify the wingbox's static and dynamic aeroelastic instabilities, given possible flutter and divergence speeds inside the flight's envelope. Divergence is a static aeroelastic phenomenon that occurs whenever the aerodynamic forces overpower the wing's inertia moment. Meanwhile, flutter is a dynamic aeroelastic phenomenon, self-induced by the resulting oscillations from the interaction between dynamic forces with the wing's structure, consequent from the coalescence of its vibration modes. Hence, divergence is dependent on high velocities to happen, given the resulting lift forces, while flutter takes place at lower speeds and, therefore, is the critical condition.

The model identifies the instabilities via NASTRAN's SOL145, solved by the PKNL method. The PKNL method is an extension of the classical PK method, which performs a general flutter analysis using the Doublet Lattice Method to predict the unsteady aerodynamic loads using an iterative process to determine the reduced frequency considering a defined convergence. The PKNL method modifies the traditional one to include no looping, which uses the linear selection of density ratio, Mach number and velocity in order to extract the eigenvalues, in contrast to the PK method which uses all combinations of the entries. Through the eigenvalues, the frequency and damping for the structure's modes can be identified for each velocity. At the first occasion in which the modes coalesce and a mode's damping turns from a negative to a positive value, aerodynamic flutter occurs.

Initially, the inputs for the aerodynamic flutter analysis had to be gathered. As a reference

value, the $MAC = 7.924$ m was extracted from the aerodynamic model. The density function was determined through the ratio between the air density at cruise flight level and the reference air density, while the Mach number function was constant, represented by the Mach number in cruise condition. In similar fashion, M_{cr} was maintained in the Frequency vs Mach number function, with the frequency discretized in 8 points. The velocity function was discretized by 1 m/s, verifying the full flight envelope until maximum true airspeed V_{max} , which was determined by the aircraft's V-n diagram (Section 3.3). Finally, all inputs necessary in order to develop the aeroelastic model have been determined, being presented in Tables 8 and 9.

Table 8 – Inputs for the aeroelastic model.

Property	Value
MAC	7.924
M_{cr}	0.85
ρ_{cr}	0.3796 kg/m ³
ρ_0	1.225 kg/m ³
V_{max}	378.11 m/s

Source: Elaborated by the author.

Table 9 – Discretized frequency function.

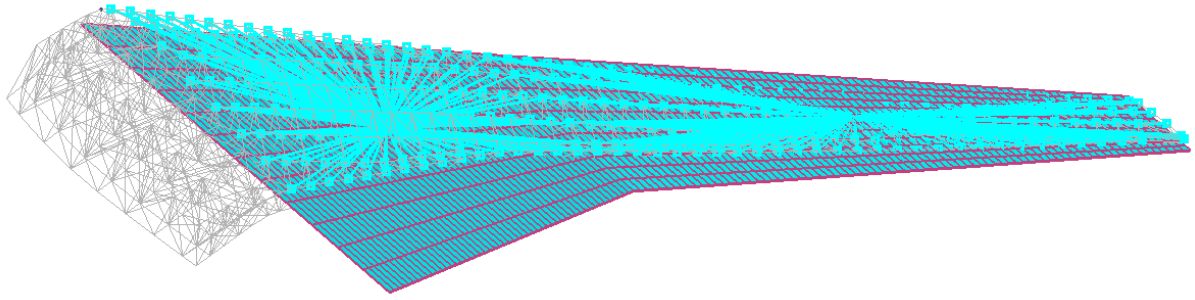
Point	1	2	3	4	5	6	7	8
Frequency [Hz]	0.0001	0.001	0.1	0.5	1	2	5	10

Source: Elaborated by the author.

With the flutter functions determined, the aerodynamic mesh was created. The wingbox area was extended in order to represent the total wing area, using chord values from Table 7. Then, two sets of panels were designed, with the first section taking into account 612 panels and the second a total of 960. Finally, two surface splines were created through the connection between the structural mesh, represented by the upper skin nodes, and the aforementioned aerodynamic panels. The final aeroelastic model can be seen in Figure 25.

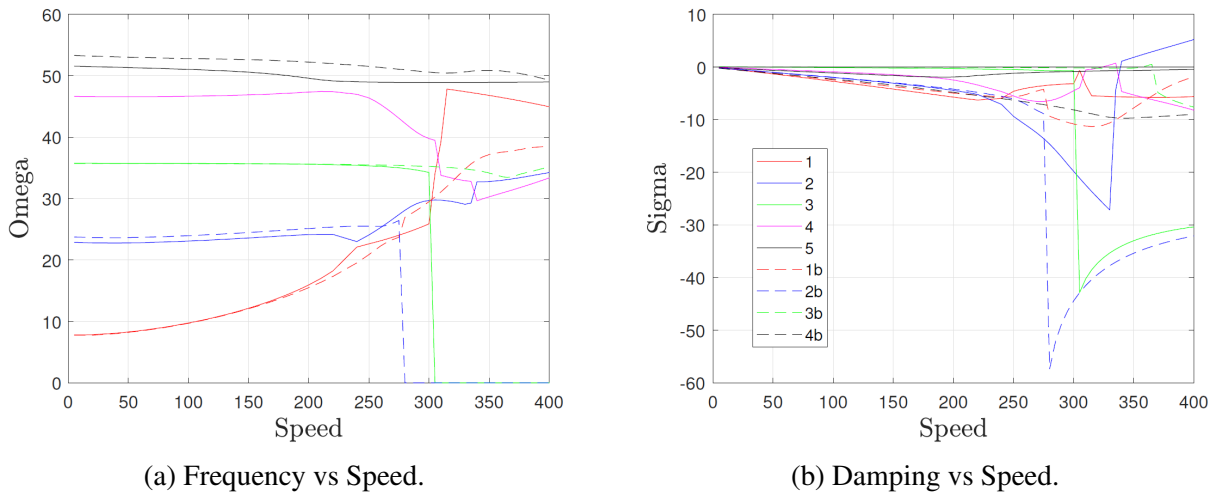
With the model fully developed, an in-house MATLAB code executes SOL145. Then, the routine reads the resulting file extension .f06, extracting the key informations necessary in order to develop a V-g-f diagram, which initially relates velocity and frequency and then velocity and damping, allowing to observe the wing's behavior and find possible aeroelastic instabilities inside the flight's envelope. Figure 26 exemplifies that process using the first 5 modes the original CRM wing, with flutter identified at 340 m/s.

Figure 25 – Aeroelastic model.



Source: Elaborated by the author.

Figure 26 – 5 modes CRM flutter analysis comparison.



Source: Pena (2019).

3.5 Optimization Model

This work consists of a single-objective optimization, aiming to minimize the structural weight of the wingbox. As discussed in Section 3.1, the optimization is integrated with NASTRAN. Thus, an in-house algorithm writes the code with the necessary information to fully develop the FEM and eventually executes NASTRAN's SOL101. Then, the routine reads the resulting .f06 file, extracting the maximum combined traction/compression stresses in each truss " σ_{max} ", which are considered to be the main optimization constraints, due to being the material's failure indices. Given that, if the element surpasses its material's limit stress (considering a Factor of Safety $FS = 1.5$), it is proportionally penalized, i.e., it is penalized as much as it surpasses the allowed limit (Table 10).

Initially, three different optimization methods were used: DE, GA, and PSO. The former as proposed by Jr *et al.* (2016) and the others are the conventional built-in functions available

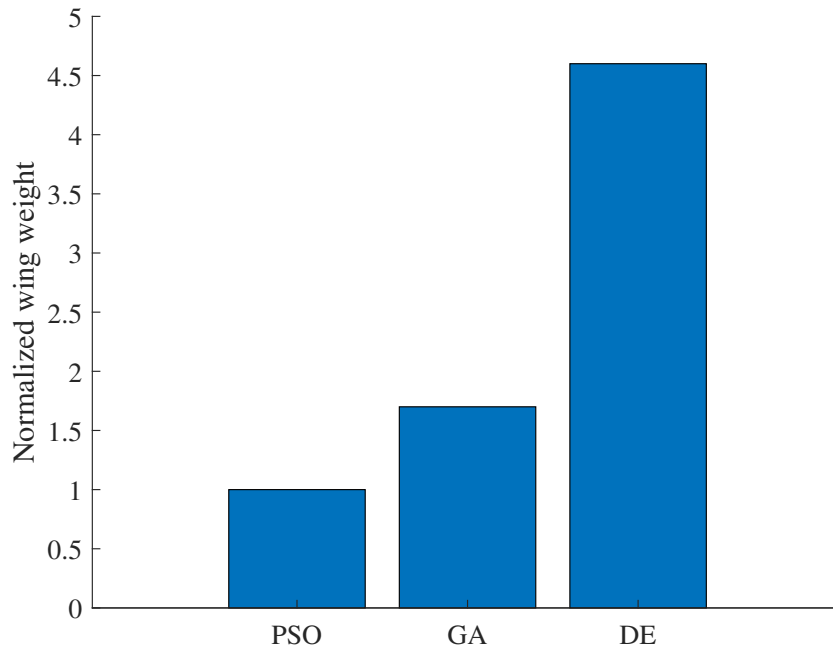
Table 10 – Optimization process proportional penalization.

Level	Amount surpassed	Penalization
Light	$\sigma_{adm}/FS < \sigma_{max} \leq 1.1 \sigma_{adm}/FS$	300 kg
Medium	$1.1 \sigma_{adm}/FS < \sigma_{max} \leq 1.25 \sigma_{adm}/FS$	600 kg
Severe	$1.25 \sigma_{adm}/FS < \sigma_{max}$	1 ton

Source: Elaborated by the author.

on MATLAB. In initial versions of the work, the latter proved to consistently converge quicker and into a better result (Figure 27), while surpassing local optimum results. Thus, it was solely maintained for the rest of the work.

Figure 27 – Comparing optimization methods.



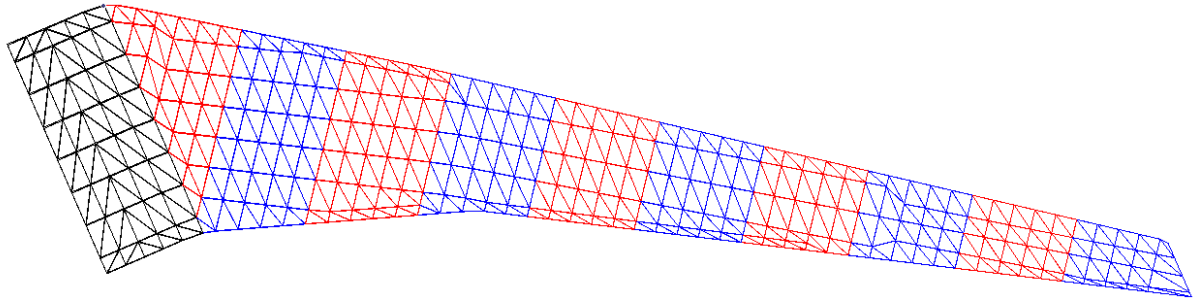
Source: Elaborated by the author.

The design variables include the thickness and outer radius of each optimizable element. It is worth noting that, due to having both nodes clamped, constrained elements are not included in the optimization process. Both variables are discretized, accounting for manufacturing constraints, with the former by 2 mm and the latter by 5 mm, as proposed by Silva (2022). Throughout the optimization, the algorithm generates a population of different individuals with combinations of truss elements, given the maximum and minimum bounds for the design variables, which are evolved over the optimization in each generation.

The wingbox was structurally divided into 10 different sections, with the first one including the first 8 truss-based ribs and the rest including each subsequent 5 truss-based ribs,

aiming for a different maximum outer radius and thickness for each section, given the expected structural response. Figure 28 displays the structural sections contrasting in red and blue, with constrained elements, which are not included in the optimization process, in black.

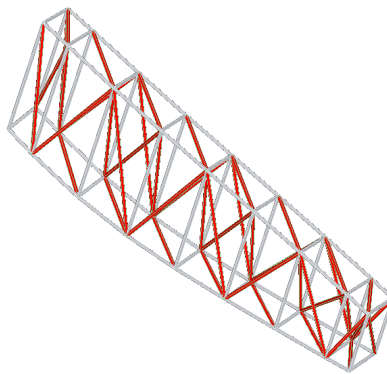
Figure 28 – Structural sections.



Source: Elaborated by the author.

The minimum outer radius and thickness bounds are constant throughout all structural sections, with the latter at 2 mm. However, as an exception, through a minimum value of 0 mm thickness for elements unnecessary to guarantee that the wingbox aerodynamic profile is ensured, the algorithm includes the removal of elements also considered unnecessary for the structural response. Still regarding elements passive of deletion, very thin trusses are also removed from the optimization process, which are the trusses with thicknesses smaller or equal to 10% of their outer radius. Figure 29 displays the concept in detail.

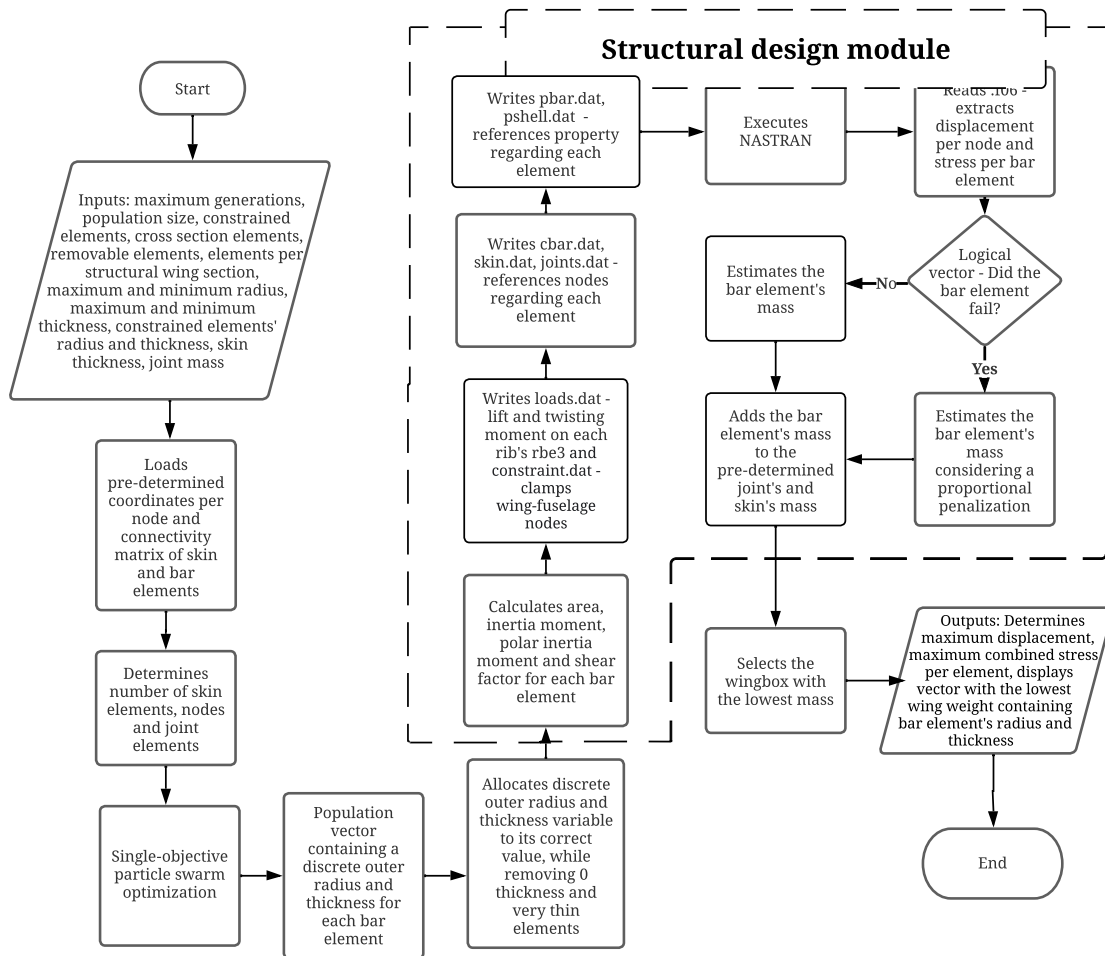
Figure 29 – Removable (red) and necessary (grey) elements considering minimum aerodynamic profile.



Source: Elaborated by the author.

Finally, after generating the truss population, writing the FEM, executing SOL101, extracting the maximum combined stresses, and considering the penalization of failed trusses, the final wingbox empty weight can be considered as the objective function for the optimization, and the wingbox with the lowest mass is the local minimum. The optimization flowchart is depicted in Figure 30.

Figure 30 – Flowchart of the optimization process.



Source: Elaborated by the author.

3.6 Metamodel

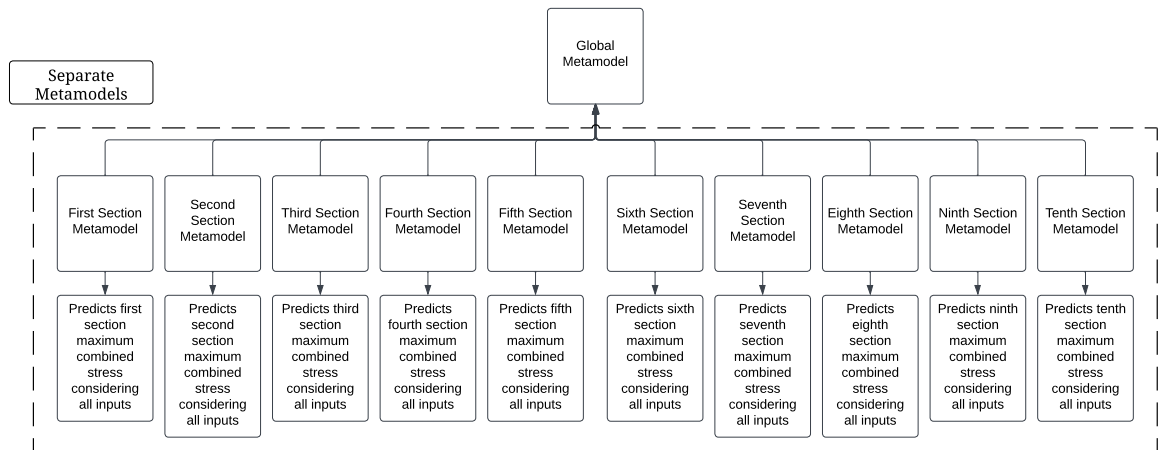
One of the biggest challenges in this work is the computational time. Since both the outer radius and thickness of each optimizable truss were design variables, the population size, number of iterations and model execution time to reach convergence were costly. Moreover, in order to determine the maximum bounds for each structural section (minimum bounds were varied considering removability), considering the different possibilities, a considerable number of optimization cycles would be needed for a representative result which allowed for the best fit possible. Hence, the project of a simplified metamodel in order to determine the maximum bounds came up.

Instead of accounting for each individual truss, the simplified model fixes the same outer radius and thickness for all trusses in a structural section (Subsection 3.1), reducing the amount of variables considerably. Then, a metamodel is used to replace the costly execution of

NASTRAN's SOL101, predicting the maximum σ_{max} for each structural section. The global metamodel consists of 10 separate metamodels, in which each one is able to predict the maximum σ_{max} of its respective structural section.

Traditionally, the algorithm would execute the linear static solution and read each trusses' failure indices, determining whether the truss should be penalized or not. In the simplified model, the routine would execute SOL101, extract each element's σ_{max} , organize the stresses in their corresponding structural section and, if the section's maximum σ_{max} surpasses the allowable, penalize the whole section. In the separate metamodel, which follows the simplified model logic, the new algorithm predicts the section's maximum σ_{max} considering the outer radius and thickness inputs and, if surpassed, proportionally penalizes the whole section. With 10 separate metamodels present, to account for the 10 structural sections, the global metamodel is able to predict the final mass considering the initial mass established by the trusses' geometry and material and the final mass after each section's proportional penalization. The global metamodel is depicted in Figure 31.

Figure 31 – Global metamodel.



Source: Elaborated by the author.

Considering the objective of the metamodel, its complexity, and the amount of variables, Kriging (Subsection 2.3.4), using the DACE toolbox (ULAGANATHAN *et al.*, 2015), was selected for the development of the metamodel. Initially, the training and validation samples had to be created. The training samples contained the input outer radius and thickness for each section and the output maximum σ_{max} for each section. Meanwhile, the validation samples also extracted the proportional penalization and final wingbox mass envisaging result analysis. It is important that the grouped samples are different, not to create a bias within the model.

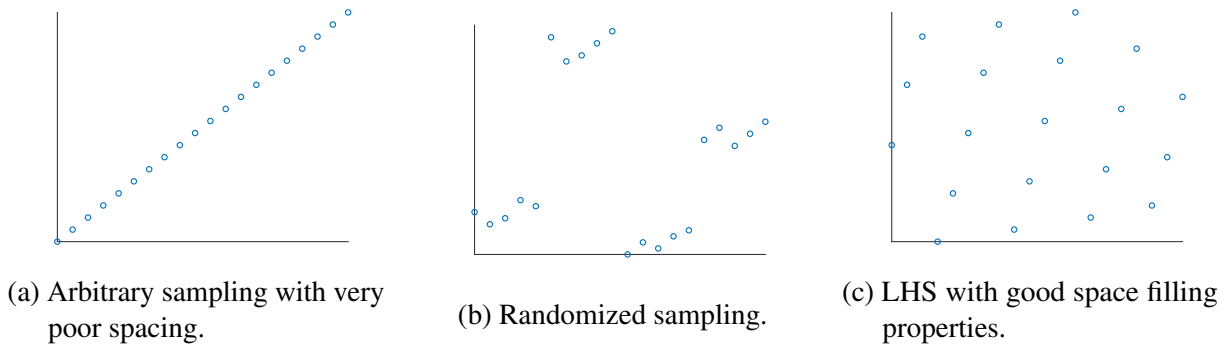
Then, the regression and correlation functions between the inputs and the predicted outputs had to be determined, as well as the hyperparameters. With the selected functions and the training samples, each separate metamodel was created and, subsequently, used for the prediction

of each validation sample section's maximum σ_{max} .

Finally, the predicted results are evaluated by the Mean Square Error (MSE) between the validation sample and the predicted maximum σ_{max} . Additionally, 3 other metrics were used to verify the effectiveness of the metamodel: if it could correctly predict which sections would be penalized and which ones would not (Condition 1), if it could exactly predict the proportional penalization (Condition 2), and the MSE between the validation sample and the predicted final mass.

Latin Hypercube Sampling (LHS) (WYSS; JORGENSEN, 1998) was selected to generate the training and validation samples. It is a random sample generator method, effective in covering the sampling space with a small number of samples, efficiently being representative with a low computational cost. Hence, LHS is ideal for stochastic problems (OLSSON; SANDBERG, 2002), such as the one presented. Initially, the range of each input is divided into intervals of equal probability, based on the number of inputs. For example, in this problem the 10 structural sections have 2 design variable, thus each input's range is divided into 20 intervals. For each interval of each input, one sample point is chosen at random. In this research, if a outer radius has a range from 5 to 25 being discretized by 5 mm, it would divide the input in 5 intervals, with an equal chance of being selected at random. Finally, the sampled points from each parameter are then combined to form multi-dimensional training and validation samples. Therefore, each sample is unique across each dimension, which helps in evenly covering the entire parameter space. The benefits provided by LHS are displayed in Figure 32.

Figure 32 – Exemplifying the advantages of LHS.

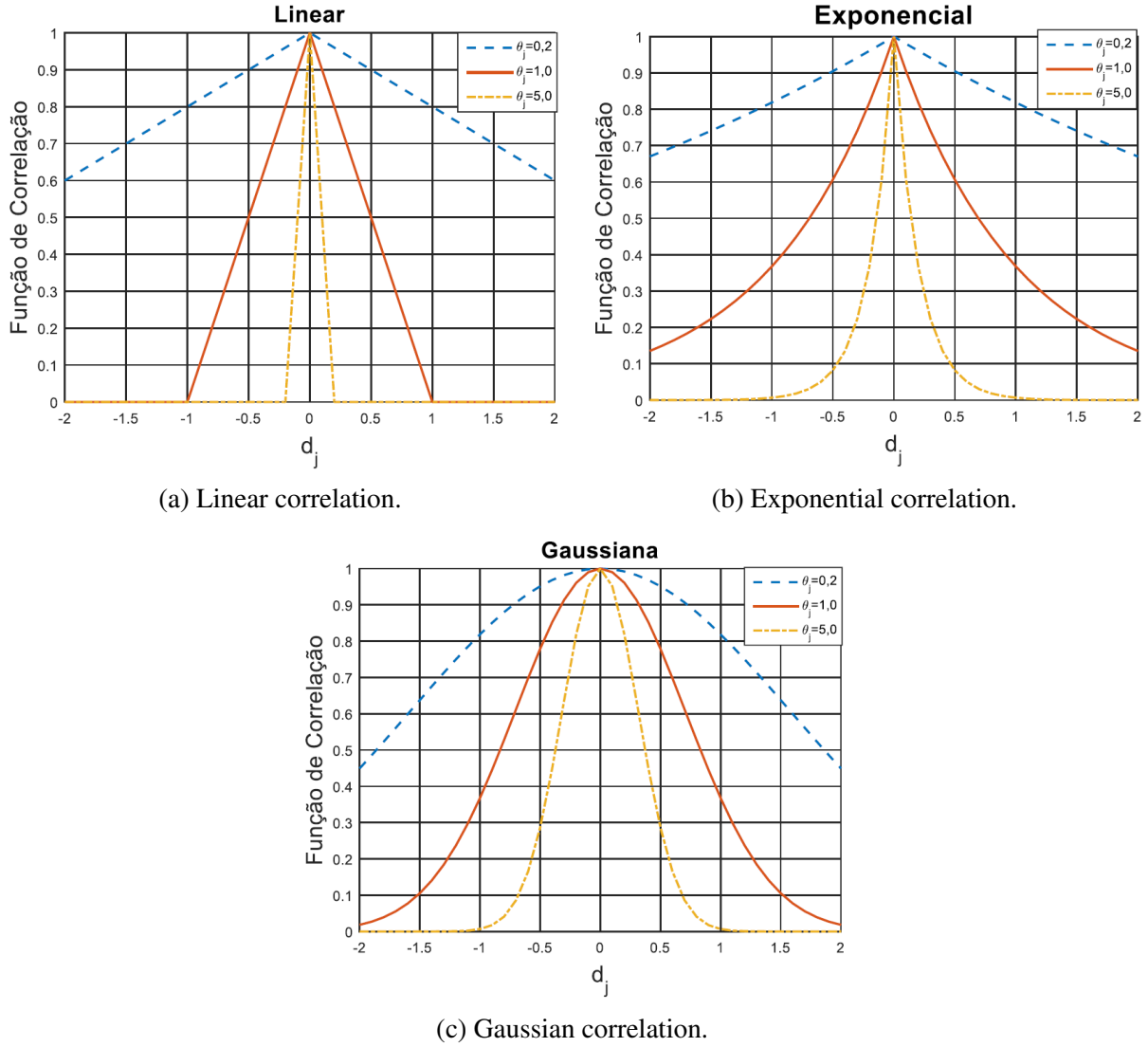


Source: Elaborated by the author.

The DACE toolbox comes with 3 possibilities for its regression function and 5 possibilities for its correlation function. Hence, 15 different combinations may be used in order to develop the metamodel, including constant, linear and quadratic regression combined with linear, spherical, cubic, exponential and gaussian correlations. The correlation functions are made up of coefficients denominated hyperparameters, which indicate the intensity of the correlation between one of the inputs and the predicted output. Therefore, the number of hyperparameters and inputs is the same. While the hyperparameter “ θ ”, coupled with the difference between a

sample input “ j ” and a vector inside the project space, dictates the impact, the function describes the behavior of the correlation. The concept is depicted in Figure 33.

Figure 33 – Correlation functions for $-2 \leq d_j \leq 2$ and $\theta = 0.5, 1$ and 5 .



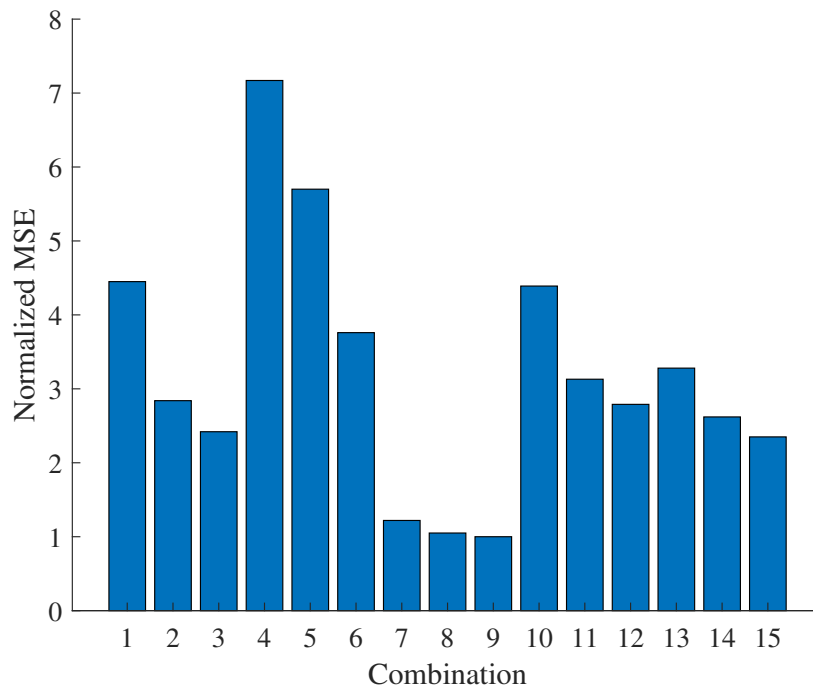
Source: Barbosa *et al.* (2021).

In order to select the best possible combination, 14000 training samples and 1400 validation samples were created, with the ratio recommended by Toal, Bressloff and Keane (2008). The training samples number represent the maximum a 16 GB RAM memory computer with an Intel® Core™ i7-3770 processor handles, which was the machine used in this work. Then, all 15 combinations were used to create one separate metamodel, with its hyperparameters optimized using DACE's toolbox.

The toolbox a rough optimizer which takes into account upper and lower bounds for each hyperparameter, which is only used for this part of the metamodel process. The upper and lower bounds for each combination were narrowed down through a steady process by trying

all 15 of them from 500 samples up until 14000, discretized by 500. At the maximum number of training samples, the combinations were compared through the aforementioned maximum σ_{max} MSE, in order to select the best one. The normalized results are displayed in Figure 34, with the combination number considering the following sequence: constant (1), linear (2) and quadratic (3) regressions combined with linear (1), spherical (2), exponential (3), cubic (4) and gaussian (5) correlations. Therefore, through the rest of the metamodel process, the exponential correlation (Figure 33b) with a quadratic regression was selected.

Figure 34 – Normalized MSE for all 15 combinations.

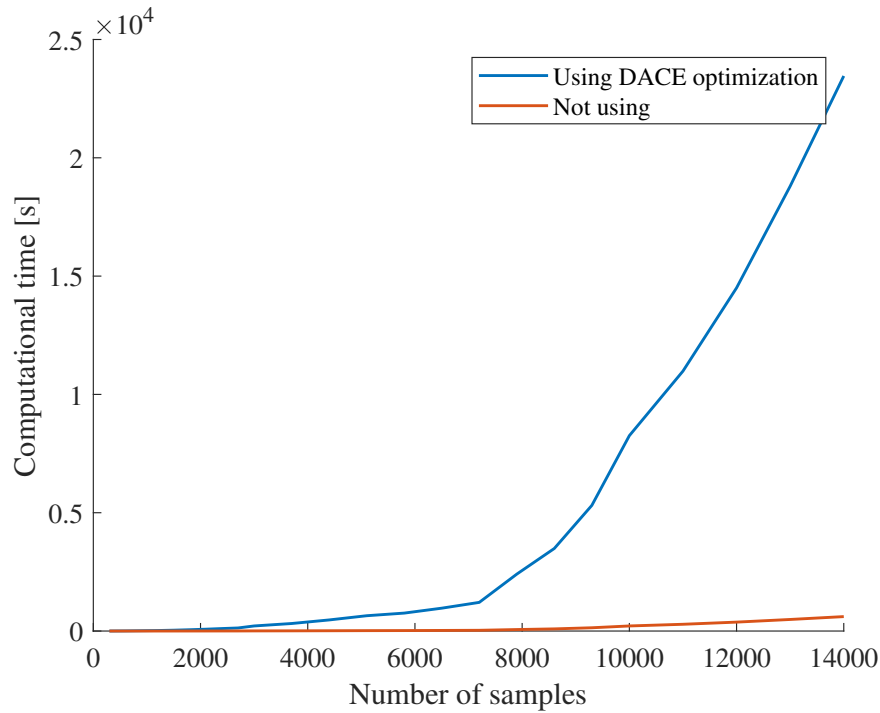


Source: Elaborated by the author.

The computational time taken to generate one separate metamodel using the chosen combination can be seen in Figure 35. It is worth noting that, for the latter stages of the metamodel development, the DACE toolbox optimization method will not be used, and the hyperparameter values will be given, which decreases the computational time to 2.6% of the original value.

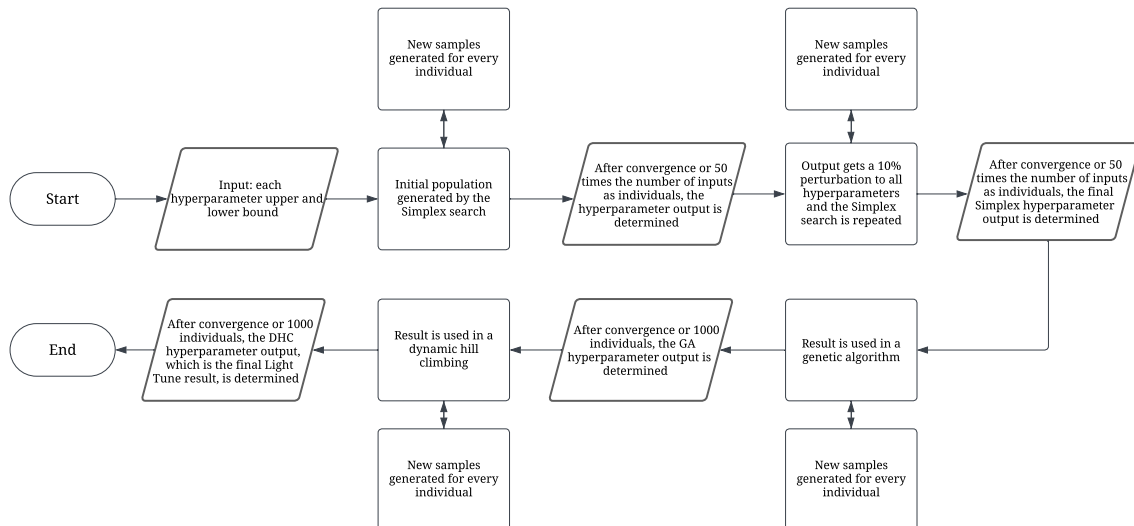
With the chosen combination and the validation method (MSE by maximum σ_{max}), the next step was to correctly determine the hyperparameters, using a more complex optimization process. Initially, the Light Tune proposed by Toal, Bressloff and Keane (2008) was considered, which involved first a Simplex search for 50 times the number of inputs, followed by a perturbation of 10% of the result, subsequently repeating the Simplex search with the new individual, then 1000 individuals go through GA, finally obtaining the result after 1000 individuals go through a Dynamic Hill Climbing (DHC), all the while generating new samples for each individual. Even though this process (Figure 36) yields an exceptional result, it is computationally costly and, therefore, some updates were made.

Figure 35 – Computational time for the chosen combination.



Source: Elaborated by the author.

Figure 36 – Light Tune.

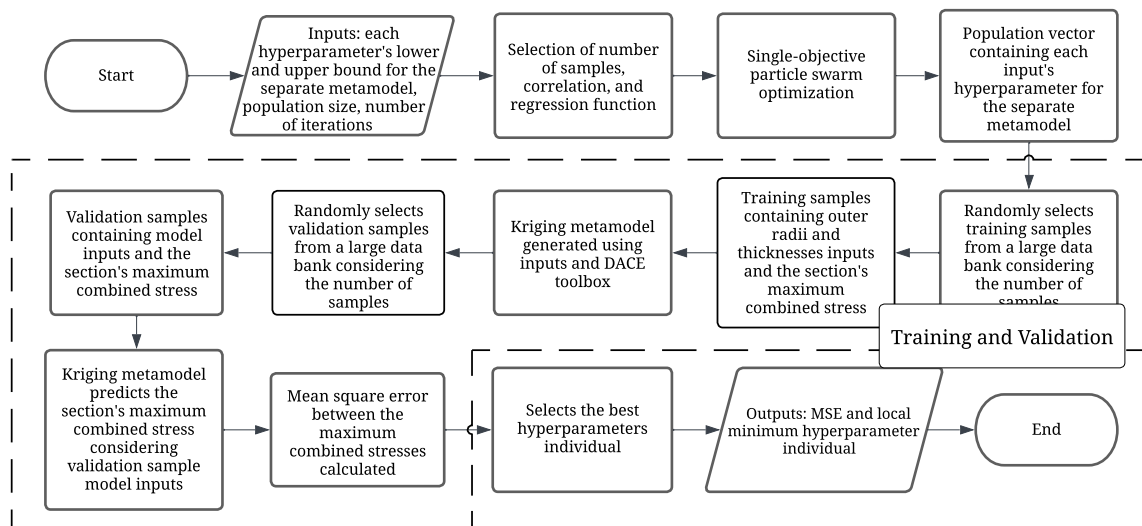


Source: Elaborated by the author.

Taking the Light Tune as inspiration, a Lightning Tune was developed: 500 individuals of the hyperparameters would go through a PSO optimization process, with a population size of 10 and 50 iterations. Firstly, GA was used, but the result got stuck at a local optimum, which did

not happen with PSO. Regarding the new samples for each individual, the approach would be impractical, due to the high amount of samples needed for this metamodel, which was identified in the previous step. Hence, since for a 16 GB RAM memory computer with a Intel® Core™ i7-3770 processor the maximum number of samples that could be used at a time during a PSO optimization process decreases from 14000 to 8000, 80000 new training samples and 8000 new validation samples were created. Then, from the 80000 training samples, 8000 would be randomly selected using MATLAB's *randsample* function. This ensured that all 10 individuals in an iteration would visit a high amount of new samples, as recommended. The Lightning Tune is depicted in Figure 37.

Figure 37 – Lightning Tune.

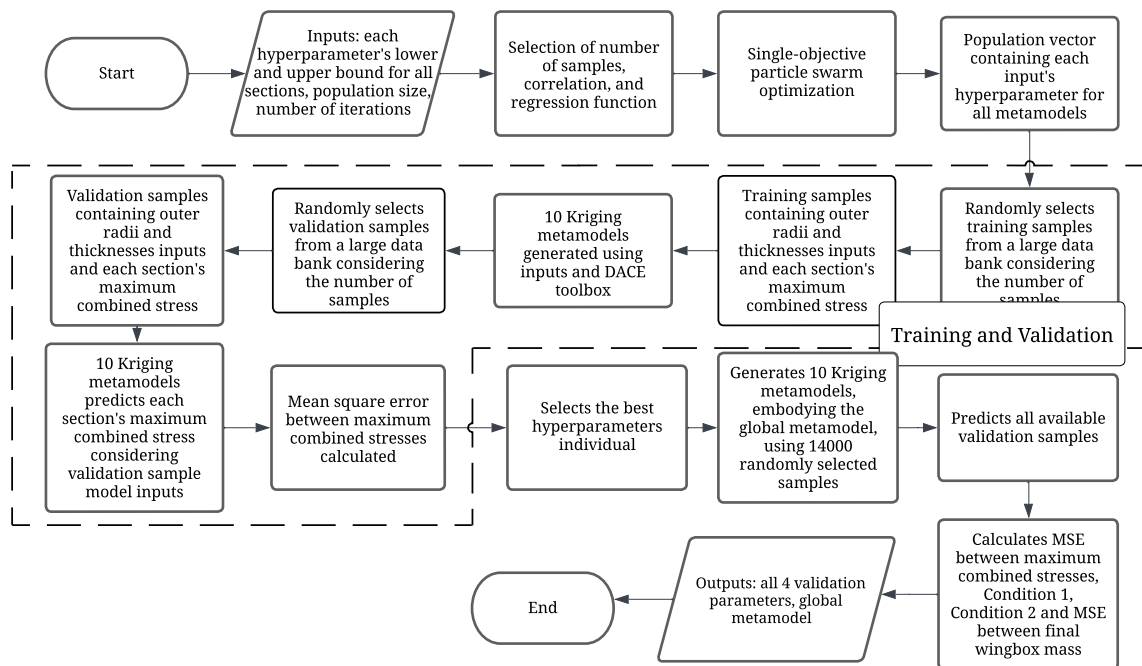


Source: Elaborated by the author.

The Lightning Tune would initially take place for each separate section, which allowed to narrow down the lower and upper bounds for each hyperparameter. Then, the Extra Lightning Tune, with an increase in population size to 20, due to convergence issues stemmed from a 10 times increase in the number of inputs, and a final increase to 14000 training samples after the tuning process, resulted in the final global metamodel, which can be observed in Figure 38.

The global metamodel is able to predict the maximum σ_{max} for all structural sections and apply the correct proportional penalizations and, once developed, it was used in order to determine the maximum bounds for each structural section in the optimization process. It is worth mentioning that, due to the section penalization now representing a larger number of variables, the proportional penalization was updated in order to have a heavier weight on the final mass, as displayed in Table 11.

Figure 38 – Extra Lightning Tune.



Source: Elaborated by the author.

Table 11 – Metamodel proportional penalization.

Level	Amount surpassed	Penalization
Light	$\sigma_{adm}/FS < \sigma_{max} \leq 1.1 \sigma_{adm}/FS$	1 ton
Medium	$1.1 \sigma_{adm}/FS < \sigma_{max} \leq 1.25 \sigma_{adm}/FS$	2 tons
Severe	$1.25 \sigma_{adm}/FS < \sigma_{max}$	3 tons

Source: Elaborated by the author.

RESULTS AND RESULTS' ANALYSIS

“Strive for perfection in everything you do. Take the best that exists and make it better. When it does not exist, design it.”

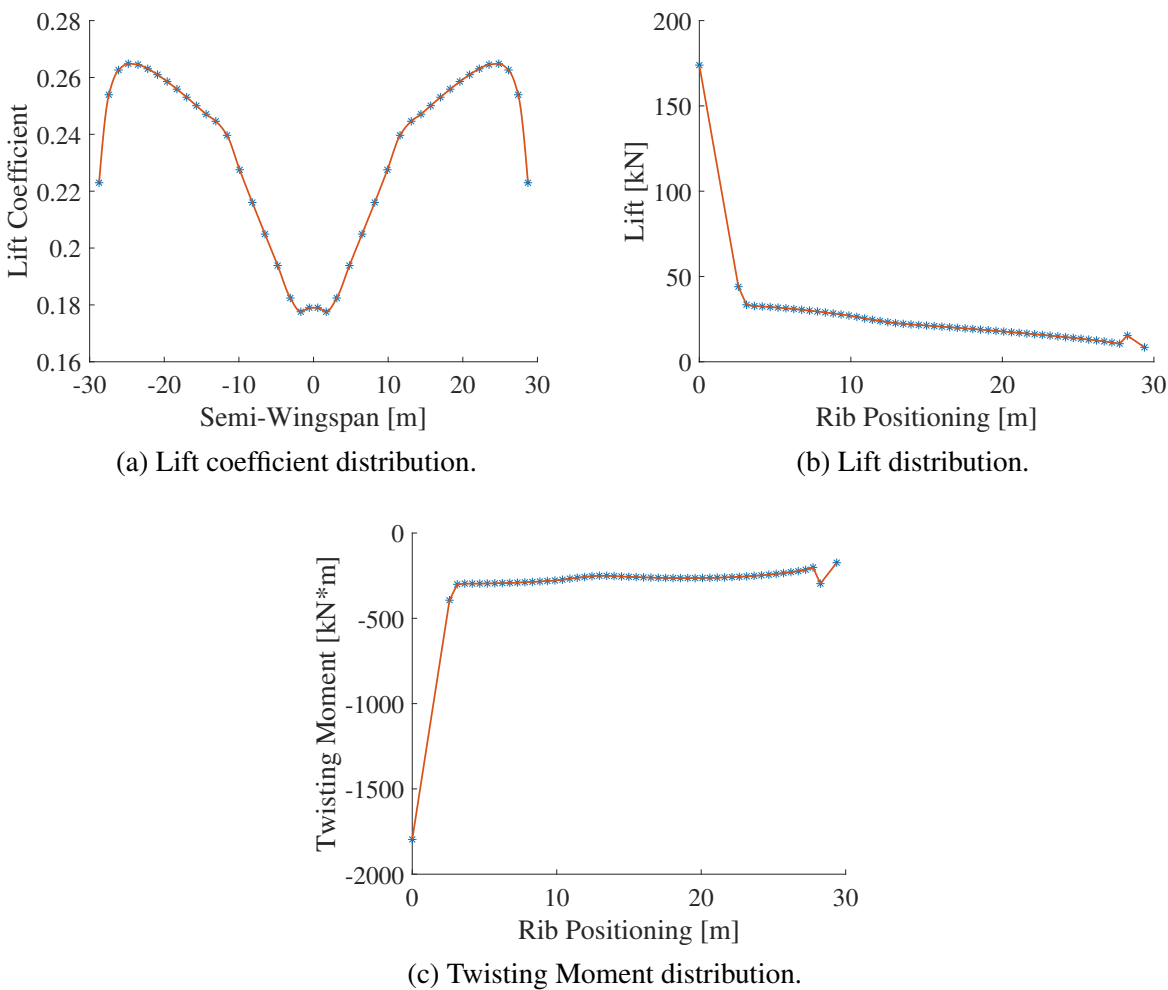
— Sir Henry Royce

THIS chapter displays the main results obtained in this work. Initially, the acting loads on the wingbox are presented and applied as boundary conditions. Then, the metamodel is developed and evaluated, with its output determining the aforementioned inputs for the optimization model. In turn, the PSO model optimizes the wingbox in order to minimize its weight considering structural constraints. Finally, buckling and aeroelasticity post-analyses verify the structural integrity and aeroelastic instabilities of the wingbox inside the flight envelope.

4.1 Loads

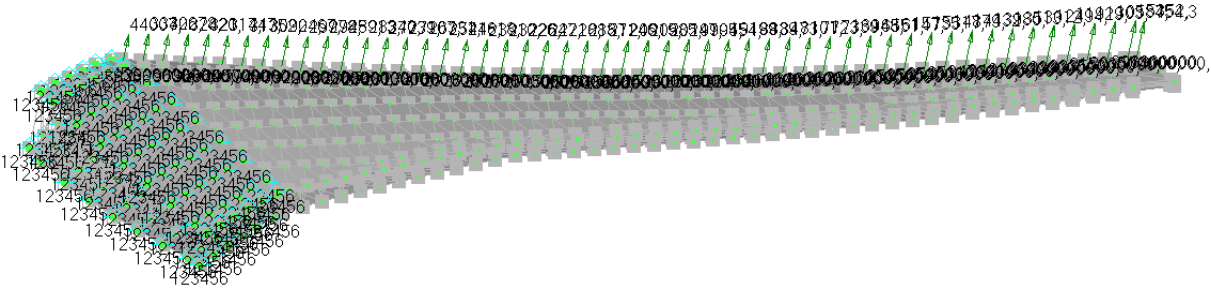
As identified in Figure 24, the +2.5 g maneuver load factor is the critical static sizing condition. Using the aerodynamic model developed in Section 3.2, the total lift coefficient, lift force, and twisting moment acting on the wing in maneuver condition were calculated by the VLM1 analysis and distributed throughout each of the wingbox's truss-based ribs' aerodynamic centers. The results were obtained for an angle of attack of 0° , considered as a hypothesis for the trimmed condition. Given that, the resulting distributions are depicted in Figures 39, whereupon each marker represents a truss-based rib. Therefore, with all boundary conditions determined, the loads were applied to the structural model, as displayed in Figure 40.

Figure 39 – Loads obtained for the maneuver condition.



Source: Elaborated by the author.

Figure 40 – Loads and constraints applied to the FEM in maneuver condition.

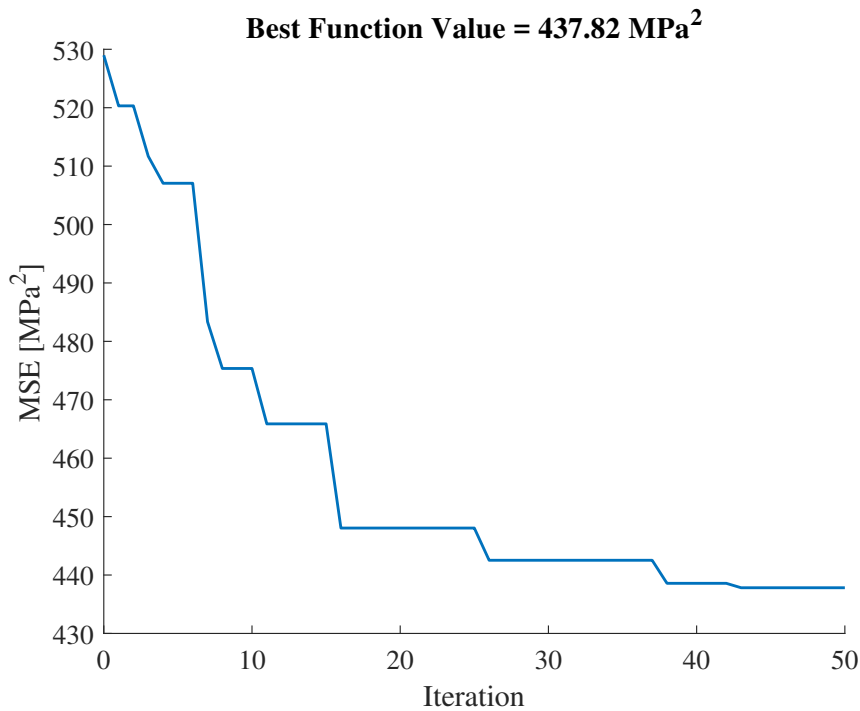


Source: Elaborated by the author.

4.2 Metamodel

As discussed in Section 3.6, initially, the Lightning tune (Figure 37) for all 10 structural sections was executed. Firstly, using LHS, 80000 training samples and 8000 validation samples were created. The samples included outer radii from 10 mm to 180 mm and thicknesses from 2 mm to 68 mm, not yet allowing the removal of trusses in this work's development. Then, using the optimal combination of an exponential correlation and a quadratic linear regression, each separate Kriging metamodel's hyperparameters were optimized. PSO was the method used for the optimization and, for each separate metamodel, 50 iterations of a population size of 10 were cycled through. Each individual randomly selected 8000 of the training samples, created the metamodel - using the training samples, the design variables and the optimal function combination -, randomly selected 800 validation samples containing the real outputs, predicted the structural section's maximum σ_{max} and calculated the MSE between them. The behavior of all 10 optimizations was similar to the one displayed in Figure 41.

Figure 41 – Hyperparameter optimization of separate metamodel 4 - Lightning Tune.



Source: Elaborated by the author.

While 500 individuals were not enough to reach a local minimum, they were sufficient enough in order to determine the global metamodel's (Figure 31) lower and upper hyperparameter bounds. Each individual costed 22 seconds and, consequently, each optimization lasted 6 hours. The resulting hyperparameters can be seen in Tables 12 and 13, whereupon " θ_{r_i} " and " θ_{t_i} " describe the structural section i 's hyperparameter for outer radius and thickness, respectively. Meanwhile, the resulting MSE for each structural section's maximum σ_{max} are displayed in Figure 42.

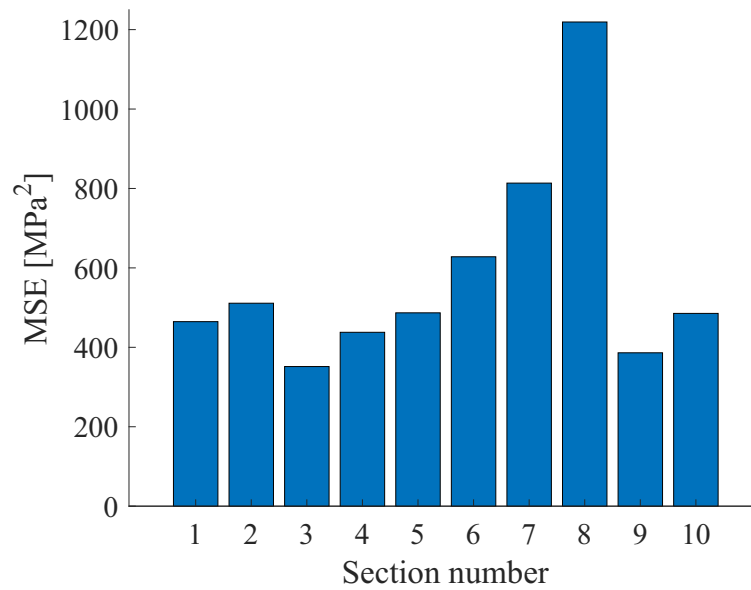
Table 12 – Outer radius hyperparameters for each separate metamodel (K_n) - Lightning Tune.

K	θ_{r_1}	θ_{r_2}	θ_{r_3}	θ_{r_4}	θ_{r_5}	θ_{r_6}	θ_{r_7}	θ_{r_8}	θ_{r_9}	$\theta_{r_{10}}$
1	2.04	9E-2	3E-4	2E-4	4E-4	1E-5	5E-4	1E-4	4E-4	4E-4
2	6E-2	2.31	8E-3	2E-3	1E-4	1E-4	2E-5	3E-5	2E-5	5E-4
3	4E-3	3E-2	2.21	5E-3	2E-4	5E-4	3E-4	5E-4	2E-4	1E-4
4	3E-5	3E-3	2E-2	2.79	3E-2	6E-3	3E-4	4E-4	2E-4	4E-5
5	4E-4	3E-4	5E-4	4E-2	1.5	1E-2	5E-5	1E-5	1E-5	2E-4
6	2E-4	4E-4	2E-4	8E-4	8E-2	2.83	8E-3	5E-5	4E-4	1E-5
7	1E-4	1E-4	3E-4	3E-4	5E-4	2E-2	2.26	7E-2	7E-4	2E-4
8	2E-4	4E-5	3E-4	1E-5	2E-4	6E-5	7E-2	2.72	6E-2	3E-4
9	3E-4	6E-5	3E-4	2E-4	3E-4	7E-5	2E-4	9E-2	1.64	7E-3
10	3E-4	1E-4	7E-5	2E-4	2E-4	1E-4	4E-4	5E-3	7E-2	2.12

Table 13 – Thickness hyperparameters for each separate metamodel (K_n) - Lightning Tune.

K	θ_{t_1}	θ_{t_2}	θ_{t_3}	θ_{t_4}	θ_{t_5}	θ_{t_6}	θ_{t_7}	θ_{t_8}	θ_{t_9}	$\theta_{t_{10}}$
1	1.71	7E-2	3E-4	4E-4	9E-5	4E-4	2E-4	4E-4	1E-5	2E-4
2	5E-2	1	1E-3	1E-3	1E-4	1E-5	4E-4	4E-4	3E-5	4E-4
3	8E-4	1E-2	1.42	2E-3	4E-3	5E-4	7E-5	1E-4	5E-4	5E-4
4	4E-4	4E-3	8E-3	1.27	1E-2	1E-3	5E-4	1E-4	4E-4	4E-4
5	3E-4	2E-4	4E-4	4E-2	1.4	1E-3	4E-4	1E-3	2E-4	4E-4
6	7E-5	3E-4	5E-4	1E-3	4E-2	0.98	3E-3	6E-4	1E-4	2E-5
7	4E-4	5E-4	2E-4	2E-4	1E-4	6E-3	1.15	9E-3	4E-4	1E-4
8	4E-4	3E-4	1E-4	9E-5	2E-4	7E-4	8E-3	0.57	6E-3	1E-4
9	1E-4	5E-4	8E-5	1E-4	4E-4	8E-5	1E-3	7E-3	1.16	9E-3
10	5E-4	1E-4	1E-4	4E-4	2E-4	4E-4	2E-4	5E-4	8E-3	1.75

Figure 42 – MSE for each separate metamodel.



Source: Elaborated by the author.

Considering values lower than 1E-3 as neglectable, other than the inputs of the structural section itself, mainly the previous 2 and the next 2 structural influence the prediction of maximum σ_{max} for an structural section. As evidenced by the hyperparameters of the structural section itself, the outer radius values have a heavier weight in the resulting output. The mean MSE for the separate metamodels is 578.42 MPa², i. e., ± 24.05 MPa. Sections with a lower number of following sections, such as the ones in the root and tip of the wing, have a lower MSE, due to being influenced by a smaller amount of hyperparameters. The exception would be the third one, which has the lowest MSE, having a high contrast to its alternate section 8, which has the highest MSE. This occurs due to intrinsic bias in the training samples when compared to the validation ones, which will be highlighted in the final results for the global metamodel.

With the determined hyperparameters for the separate metamodels, the Lightning Tune was concluded, and then, the Extra Lightning Tune (Figure 38) took place. Initially, the aforementioned results were used in order to determine the lower and upper bounds for the hyperparameters of all 10 metamodels that make up the global metamodel, which were displayed in Tables 14 to 17.

It is worth mentioning that a pattern was established into the lower and upper bounds, envisaging to combat sample bias. Given that, some previously determined hyperparameters had to be adjusted in order to be used as an initial population for the following optimization process. Then, a PSO for 50 iterations and 20 population size - doubled due to a higher amount of design variables - was executed, having all 200 hyperparameters as design variables, and aiming to minimize the mean MSE of all 10 structural section's maximum σ_{max} .

Table 14 – Outer radius hyperparameters lower bounds for the global metamodel per metamodel (K_n) - Extra Lightning Tune.

K	θ_{r_1}	θ_{r_2}	θ_{r_3}	θ_{r_4}	θ_{r_5}	θ_{r_6}	θ_{r_7}	θ_{r_8}	θ_{r_9}	$\theta_{r_{10}}$
1	1.5	1E-3	5E-5	1E-5	1E-5	1E-5	1E-5	1E-5	1E-5	1E-5
2	5E-3	1.5	1E-3	5E-4	1E-5	1E-5	1E-5	1E-5	1E-5	1E-5
3	5E-5	5E-3	1.5	1E-3	5E-4	1E-5	1E-5	1E-5	1E-5	1E-5
4	1E-5	5E-5	5E-3	1.5	1E-3	5E-4	1E-5	1E-5	1E-5	1E-5
5	1E-5	1E-5	5E-5	5E-3	1.5	1E-3	5E-4	1E-5	1E-5	1E-5
6	1E-5	1E-5	1E-5	5E-5	5E-3	1.5	1E-3	5E-4	1E-5	1E-5
7	1E-5	1E-5	1E-5	1E-5	5E-5	5E-3	1.5	1E-3	5E-4	1E-5
8	1E-5	1E-5	1E-5	1E-5	1E-5	5E-5	5E-3	1.5	1E-3	5E-4
9	1E-5	1E-5	1E-5	1E-5	1E-5	1E-5	5E-5	5E-3	1.5	1E-3
10	1E-5	1E-5	1E-5	1E-5	1E-5	1E-5	1E-5	5E-5	5E-3	1.5

Table 15 – Thickness hyperparameters lower bounds for the global metamodel per metamodel (K_n) - Extra Lightning Tune.

K	θ_{t_1}	θ_{t_2}	θ_{t_3}	θ_{t_4}	θ_{t_5}	θ_{t_6}	θ_{t_7}	θ_{t_8}	θ_{t_9}	$\theta_{t_{10}}$
1	0.75	1E-3	5E-5	1E-5	1E-5	1E-5	1E-5	1E-5	1E-5	1E-5
2	1E-3	0.75	1E-3	5E-5	1E-5	1E-5	1E-5	1E-5	1E-5	1E-5
3	5E-5	1E-3	0.75	1E-3	5E-5	1E-5	1E-5	1E-5	1E-5	1E-5
4	1E-5	5E-5	1E-3	0.75	1E-3	5E-5	1E-5	1E-5	1E-5	1E-5
5	1E-5	1E-5	5E-5	1E-3	0.75	1E-3	5E-5	1E-5	1E-5	1E-5
6	1E-5	1E-5	1E-5	5E-5	1E-3	0.75	1E-3	5E-5	1E-5	1E-5
7	1E-5	1E-5	1E-5	1E-5	5E-5	1E-3	0.75	1E-3	5E-5	1E-5
8	1E-5	1E-5	1E-5	1E-5	1E-5	5E-5	1E-3	0.75	1E-3	5E-5
9	1E-5	1E-5	1E-5	1E-5	1E-5	1E-5	5E-5	1E-3	0.75	1E-3
10	1E-5	1E-5	1E-5	1E-5	1E-5	1E-5	1E-5	5E-5	1E-3	0.75

Table 16 – Outer radius hyperparameters upper bounds for the global metamodel per metamodel (K_n) - Extra Lightning Tune.

K	θ_{r_1}	θ_{r_2}	θ_{r_3}	θ_{r_4}	θ_{r_5}	θ_{r_6}	θ_{r_7}	θ_{r_8}	θ_{r_9}	$\theta_{r_{10}}$
1	3.5	0.15	1E-3	5E-4	5E-4	5E-4	5E-4	5E-4	5E-4	5E-4
2	0.15	3.5	0.15	1E-3	5E-4	5E-4	5E-4	5E-4	5E-4	5E-4
3	5E-3	0.15	3.5	0.15	1E-3	5E-4	5E-4	5E-4	5E-4	5E-4
4	5E-4	5E-3	0.15	3.5	0.15	1E-3	5E-4	5E-4	5E-4	5E-4
5	5E-4	5E-4	5E-3	0.15	3.5	0.15	1E-3	5E-4	5E-4	5E-4
6	5E-4	5E-4	5E-4	5E-3	0.15	3.5	0.15	1E-3	5E-4	5E-4
7	5E-4	5E-4	5E-4	5E-4	5E-3	0.15	3.5	0.15	1E-3	5E-4
8	5E-4	5E-4	5E-4	5E-4	5E-4	5E-3	0.15	3.5	0.15	1E-3
9	5E-4	5E-4	5E-4	5E-4	5E-4	5E-4	5E-3	0.15	3.5	0.15
10	5E-4	5E-4	5E-4	5E-4	5E-4	5E-4	5E-4	5E-3	0.15	3.5

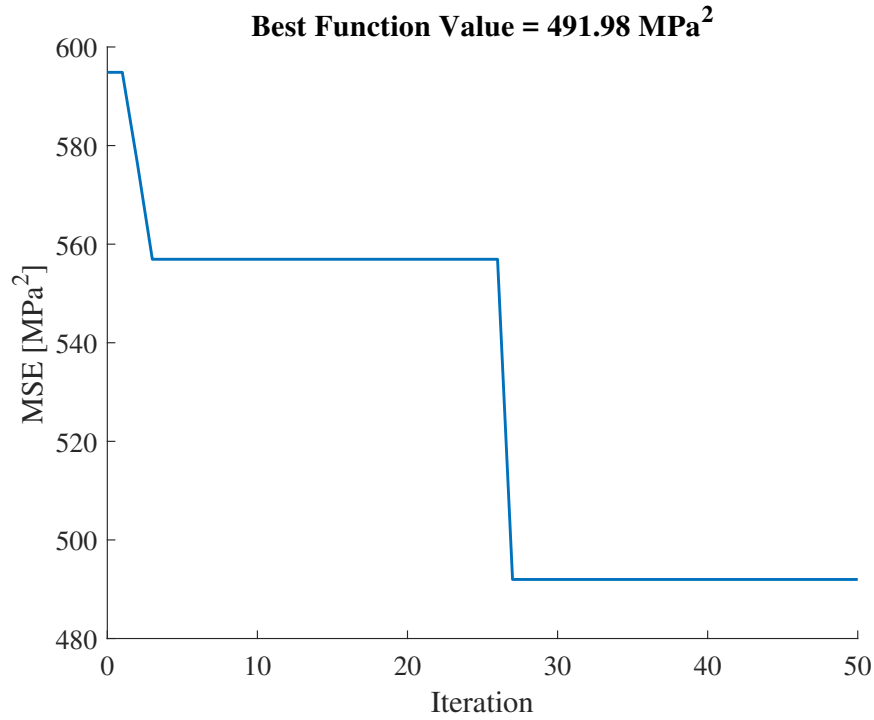
Table 17 – Thickness hyperparameters upper bounds for the global metamodel per metamodel (K_n) - Extra Lightning Tune.

K	θ_{t_1}	θ_{t_2}	θ_{t_3}	θ_{t_4}	θ_{t_5}	θ_{t_6}	θ_{t_7}	θ_{t_8}	θ_{t_9}	$\theta_{t_{10}}$
1	2	0.1	1E-3	5E-4	5E-4	5E-4	5E-4	5E-4	5E-4	5E-4
2	0.1	2	0.1	1E-3	5E-4	5E-4	5E-4	5E-4	5E-4	5E-4
3	1E-3	0.1	2	0.1	1E-3	5E-4	5E-4	5E-4	5E-4	5E-4
4	5E-4	1E-3	0.1	2	0.1	1E-3	5E-4	5E-4	5E-4	5E-4
5	5E-4	5E-4	1E-3	0.1	2	0.1	1E-3	5E-4	5E-4	5E-4
6	5E-4	5E-4	5E-4	1E-3	0.1	2	0.1	1E-3	5E-4	5E-4
7	5E-4	5E-4	5E-4	5E-4	1E-3	0.1	2	0.1	1E-3	5E-4
8	5E-4	5E-4	5E-4	5E-4	5E-4	1E-3	0.1	2	0.1	1E-3
9	5E-4	5E-4	5E-4	5E-4	5E-4	5E-4	1E-3	0.1	2	0.1
10	5E-4	5E-4	5E-4	5E-4	5E-4	5E-4	5E-4	1E-3	0.1	2

The optimization process lasted 4 days and 4 hours, with a costly 360 seconds per individual, increased due to the creation of 10 metamodels per individual as opposed to the one

beforehand. It is displayed in Figure 43, with the resulting hyperparameters available in Tables 18 and 19. As a pattern was established given the previous result (Tables 12 and 13), the behavior was similar, with a higher influence of the previous 2 and next 2 sections - other than the current section - and the outer radii values on the outputs.

Figure 43 – Hyperparameter optimization of the global metamodel - Extra Lightning Tune.



Source: Elaborated by the author.

Table 18 – Outer radius hyperparameters for the global metamodel per metamodel (K_n) - Extra Lightning Tune.

K	θ_{r_1}	θ_{r_2}	θ_{r_3}	θ_{r_4}	θ_{r_5}	θ_{r_6}	θ_{r_7}	θ_{r_8}	θ_{r_9}	$\theta_{r_{10}}$
1	2.41	0.13	1E-3	1E-5	4E-4	3E-5	5E-4	3E-4	1E-4	2E-4
2	7E-2	2.09	6E-2	4E-4	1E-5	5E-4	1E-5	2E-5	3E-4	4E-4
3	5E-3	8E-2	2.3	6E-3	9E-4	5E-4	1E-4	5E-4	7E-5	3E-4
4	3E-5	3E-3	6E-2	2.74	4E-2	9E-4	1E-4	4E-4	2E-4	5E-4
5	4E-4	2E-4	2E-3	0.11	2.41	3E-2	1E-4	3E-4	5E-4	3E-4
6	6E-5	9E-5	5E-4	4E-3	9E-2	2.86	6E-2	7E-4	3E-4	4E-4
7	5E-5	2E-5	4E-4	5E-4	3E-3	4E-2	2.39	4E-2	7E-4	5E-4
8	1E-5	3E-4	2E-4	4E-4	1E-4	5E-3	0.14	1.79	6E-2	7E-4
9	4E-4	5E-4	3E-4	5E-4	2E-4	4E-4	2E-4	5E-2	2.9	2E-2
10	8E-5	1E-4	2E-4	4E-4	5E-4	5E-4	5E-4	5E-3	4E-2	3.23

Source: Elaborated by the author.

Table 19 – Thickness hyperparameters for the global metamodel per metamodel (K_n) - Extra Lightning Tune.

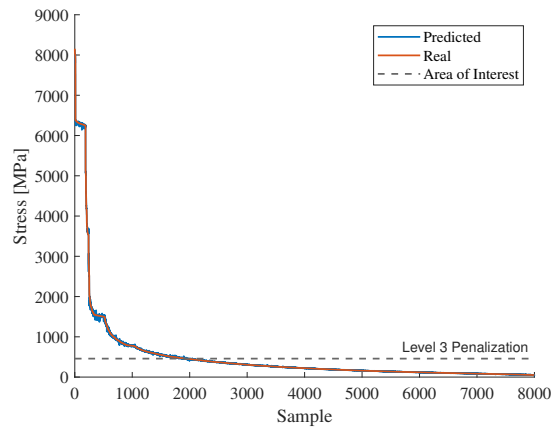
K	θ_{t_1}	θ_{t_2}	θ_{t_3}	θ_{t_4}	θ_{t_5}	θ_{t_6}	θ_{t_7}	θ_{t_8}	θ_{t_9}	$\theta_{t_{10}}$
1	1.74	9E-2	6E-4	3E-4	3E-5	3E-4	6E-5	4E-4	1E-5	4E-4
2	8E-2	1.09	3E-3	4E-4	9E-5	1E-5	1E-5	1E-5	7E-5	5E-4
3	5E-5	8E-2	1.12	1E-3	6E-4	4E-4	2E-4	4E-4	2E-4	3E-4
4	2E-4	9E-3	6E-2	0.79	7E-2	8E-4	6E-5	4E-4	1E-5	2E-4
5	4E-4	7E-5	9E-4	2E-2	1.71	8E-2	1E-3	3E-4	4E-4	4E-4
6	1E-4	3E-4	2E-4	9E-4	6E-2	1.47	3E-3	7E-4	3E-4	1E-5
7	4E-5	1E-4	1E-4	5E-4	2E-4	4E-2	1.14	1E-2	4E-4	9E-5
8	2E-4	2E-4	3E-4	3E-4	4E-4	5E-4	8E-2	1.19	1E-2	5E-4
9	4E-4	5E-4	4E-4	1E-4	4E-4	2E-4	5E-5	3E-2	1.29	4E-2
10	5E-4	4E-4	5E-4	4E-4	2E-4	4E-4	4E-4	9E-4	7E-2	1.91

Source: Elaborated by the author.

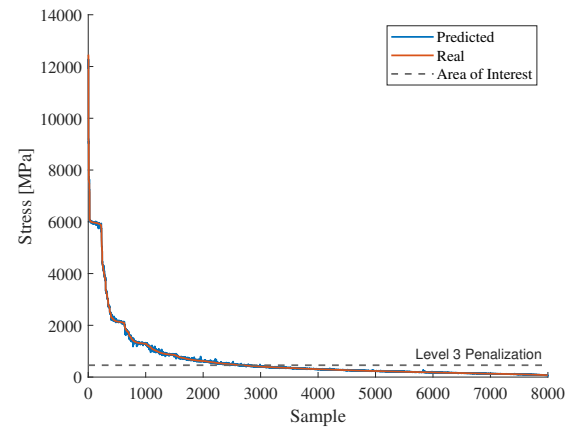
With the hyperparameters determined, coupled with the optimal combination and 14000 random training samples, they were used to create the global metamodel, which was verified by all 8000 available validation samples. Then, the verification would be assessed by 4 conditions: if the mean structural section's maximum σ_{max} MSE is lower than 500 MPa², if both Condition 1 and 2 occurred lower than 5% of times, and if the wing weight MSE is lower than 1 ton². Additionally, it was also verified if the mean structural section's maximum σ_{max} MSE in the Area of Interest (AoI) is lower than 100 MPa². It is the sampling zone whereupon were present stresses lower than 458.33 MPa, i. e, the maximum allowable (Table 5) divided by the FS and multiplied by the level 3 penalization (Table 10). Higher stress values would be attached to the same penalization no matter their magnitude, not being as important to the analysis. For a better result visualization of predicted stresses and wing weights, the samples were reordered in descending order, as to resemble a function. The verification results are displayed in Figures 44 to 47.

(Intentionally left in blank)

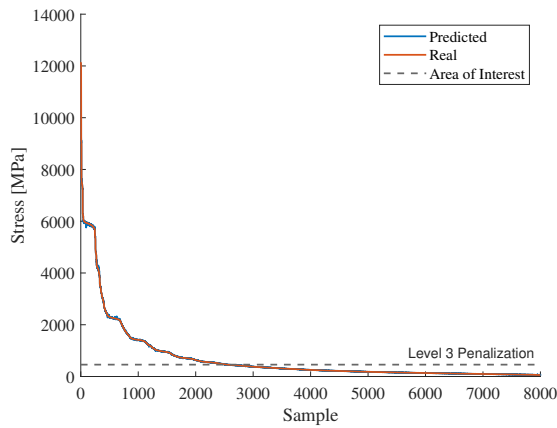
Figure 44 – Each structural section's maximum σ_{max} prediction contrasted with the real value (Sections 1-6).



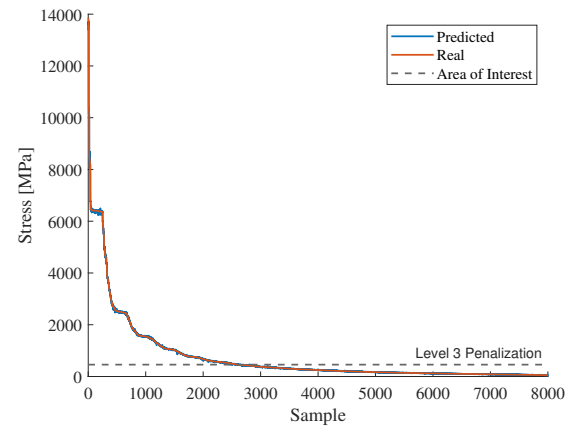
(a) Structural section 1.



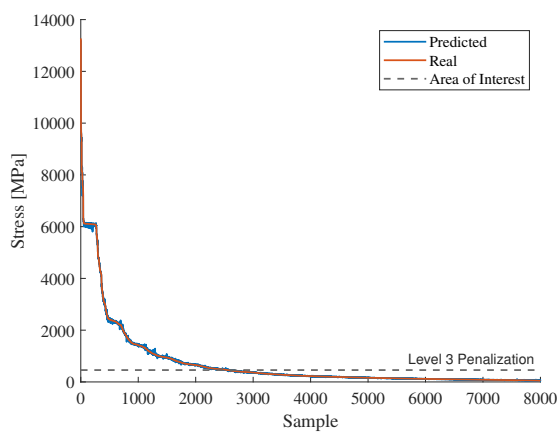
(b) Structural section 2.



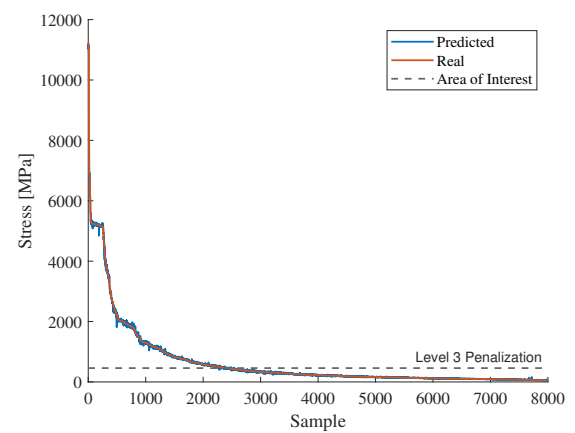
(c) Structural section 3.



(d) Structural section 4.

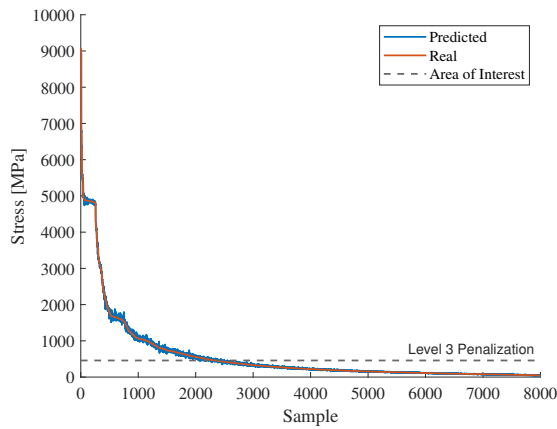


(e) Structural section 5.

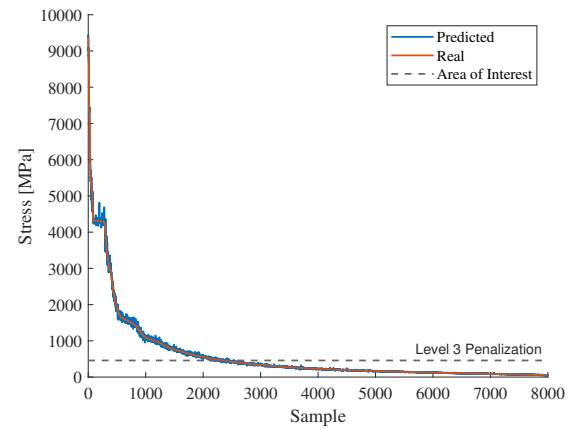


(f) Structural section 6.

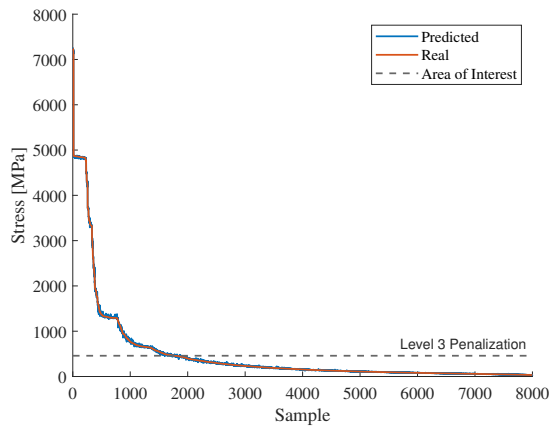
Figure 44 – Each structural section's maximum σ_{max} prediction contrasted with the real value (Sections 7-10).



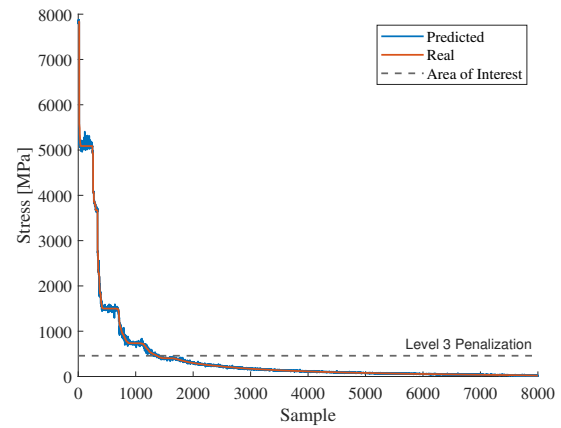
(g) Structural section 7.



(h) Structural section 8.



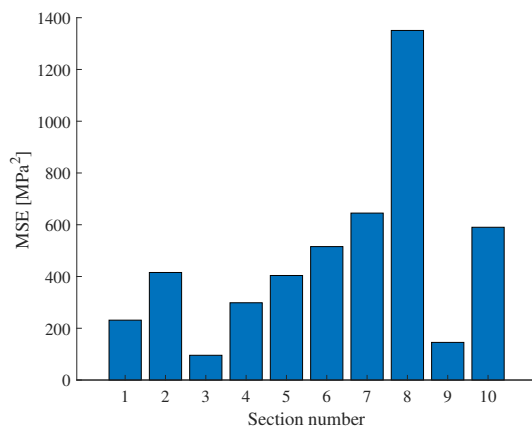
(i) Structural section 9.



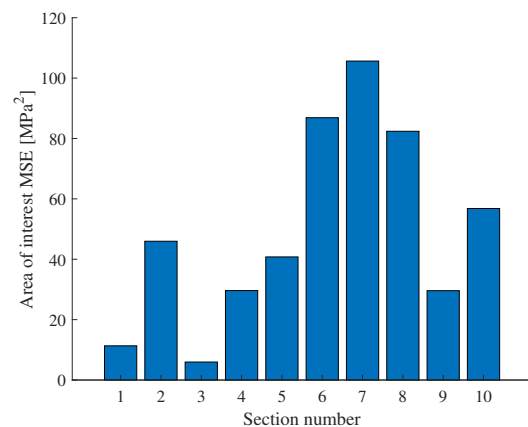
(j) Structural section 10.

Source: Elaborated by the author.

Figure 45 – Each structural section's maximum σ_{max} MSE.



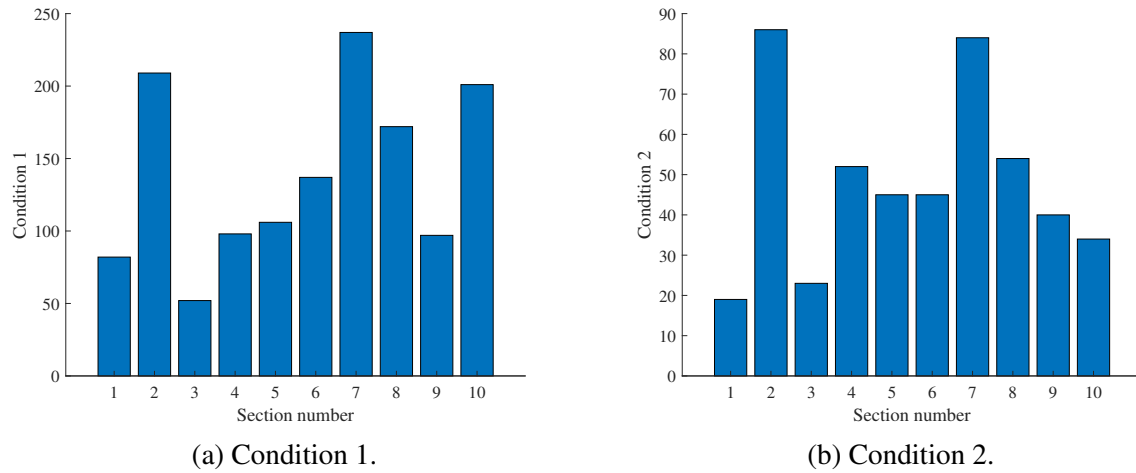
(a) All samples.



(b) Area of Interest.

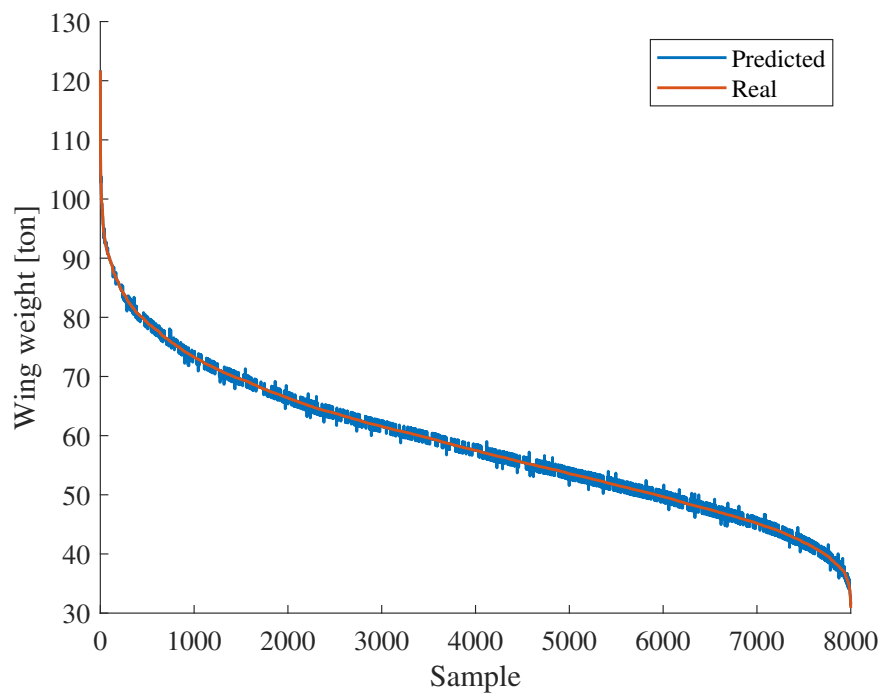
Source: Elaborated by the author.

Figure 46 – Global metamodel verification by conditions 1 and 2.



Source: Elaborated by the author.

Figure 47 – Global metamodel wing weight prediction contrasted with the real value.



Source: Elaborated by the author.

The main results are organized in Table 20, ensuring that the global metamodel has passed the requirements, being verified as able to predict each structural section's maximum σ_{max} , apply the correct penalizations and determine the final wing weight. Throughout the development of the global metamodel, a subsequent decrease in the objective function of 14.94% and 4.63%

was observed, highlighting the efficiency of the tuning process. Higher maximum σ_{max} MSEs take place in higher stress values, which explain some of the sample bias, as highlighted by the 89.45% dropoff of mean structural section's maximum σ_{max} MSE in the AoI. Coupled with that, Conditions 1 and 2 display the effectiveness of the global metamodel in predicting the penalization, which is key in predicting the final wing weight correctly, allowing the global metamodel to perform its role in establishing the optimization process structural section's maximum bounds of outer radius and thickness.

Table 20 – Global metamodel requirements (Req) verification.

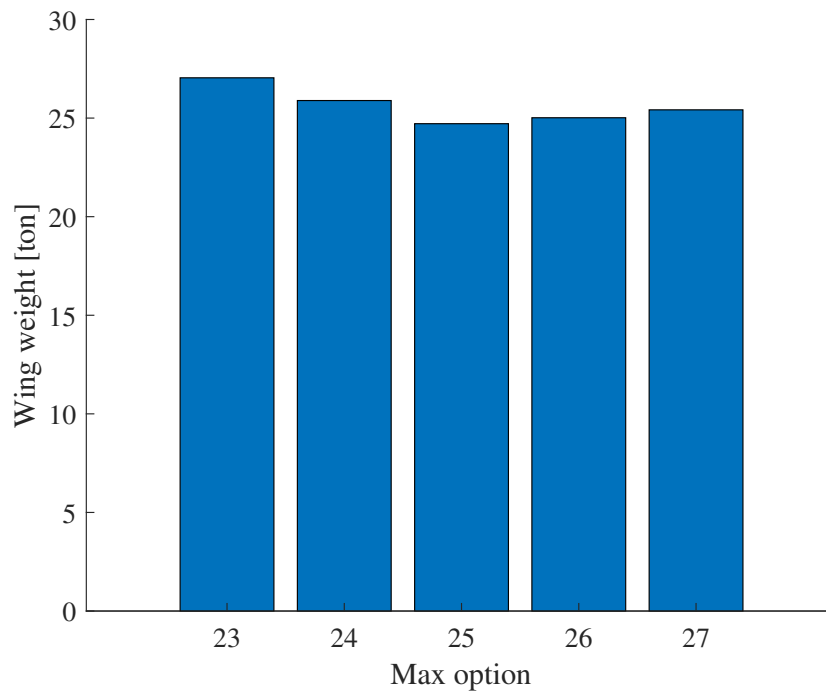
	Stress MSE	Stress MSE in AoI	Condition 1	Condition 2	Weight MSE
Req	500 MPa ²	100 MPa ²	5%	5%	1 ton ²
Result	469.19 MPa ²	49.9 MPa ²	2.96%	1.1%	0,02 tons ²
Passed?	Yes	Yes	Yes	Yes	Yes

Source: Elaborated by the author.

With the global metamodel developed, the maximum bounds for each structural section in the optimization process were determined. Initially, all 10 separate metamodels are loaded into the optimization process. Then, the design variables, which include the outer radius and thickness of each structural section, are generated. The upper bounds value would change for each optimization process, denominated as options. The maximum option references the upper bound for the root structural section, which it would decrease by one until the tip section. All maximum options tested were in the aforementioned sampling space, and, as an example, option 35 would be the maximum upper bound, with 180 mm outer radius and 68 mm thickness, and for each subsequent option, the outer radius would decrease in 5 mm and the thickness in 2 mm (SILVA; GUIMARÃES; CASTRO, 2023; SILVA, 2022). The lower bounds were all 2, since no elements are removable yet. Moreover, the design variables are used to predict each structural section's maximum σ_{max} and determine the initial wing weight, then the penalizations are evaluated, and finally, the final wing weight is determined. The PSO method was maintained and, for each maximum option tested, 250 iterations with a population size of 100 were enough for convergence. The final wing weight for the 5 best maximum options evaluations is displayed in Figure 48.

The lowest achieved wing weight was 24.71 tons. Therefore, maximum option 25, with a maximum outer radius of 130 mm and maximum thickness of 48 mm in the root structural section, was used in the optimization process. Even though the considerable size of over 700 MB for each metamodel takes about 40 seconds in total to load in the beginning of the optimization process, it is worth mentioning that each individual costed 0.024 seconds, displaying the efficiency of the global metamodel regarding computational time.

Figure 48 – Wing weight for the 5 best maximum options evaluations.

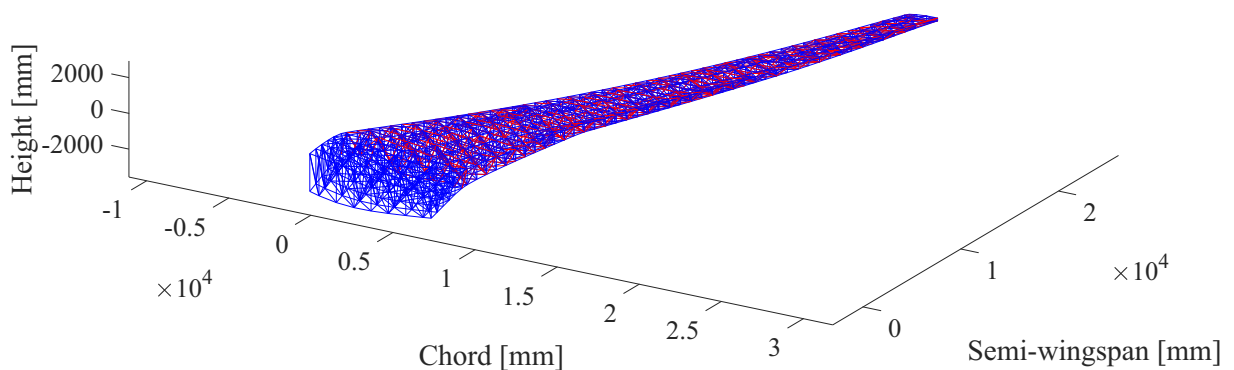


Source: Elaborated by the author.

4.3 Optimization

First and foremost, the inputs for the single-objective particle swarm optimization had to be determined. The number of variables was set as double the amount of optimizable trusses, since the algorithm optimizes both their outer radius and thickness. It is worth noting that the number of optimizable trusses is smaller than the number of trusses in the FEM, because clamped trusses had a fixed outer radius and thickness, since both their nodes could not be displaced. In addition, the elements needed to maintain minimum aerodynamic profile were specified, since they could not be removed (Figure 49).

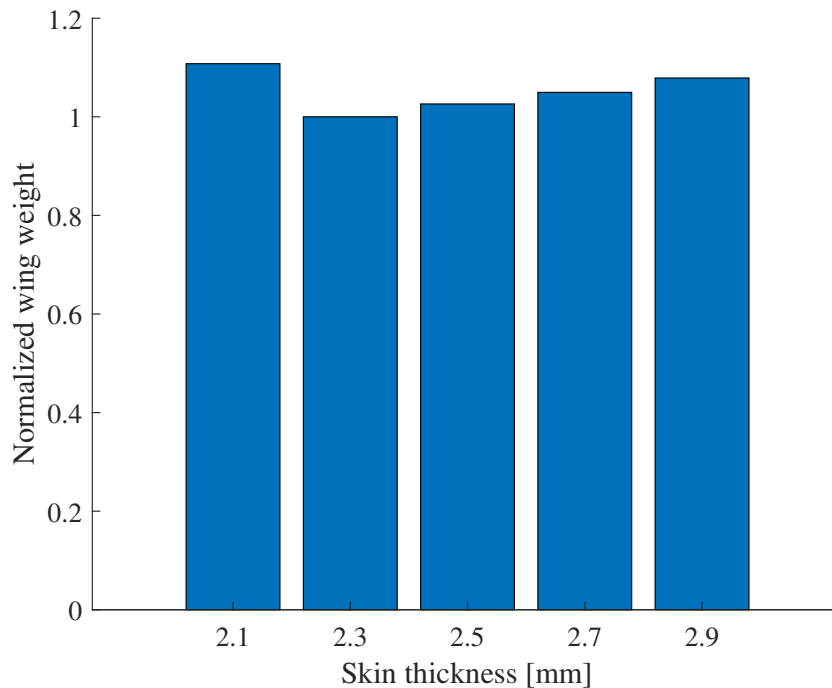
Figure 49 – Removable elements.



Source: Elaborated by the author.

Furthermore, the discrete values for the outer radius and thickness were defined. As proposed by Silva, Guimarães and Castro (2023) and Silva (2022), outer radius values were evenly spaced by 5 mm, while thickness values by 2 mm. The maximum outer radius and thickness both varied according to each structural wingbox section's expected structural response, with the maximum outer radius decreasing by 5 mm in each section from root to tip and the maximum thickness decreasing by 2 mm in each section from root to tip. The maximum value was determined in Section 4.2 through a Kriging metamodel of the simplified optimization model. Both the minimum outer radius and thickness were a constant 2 mm throughout the sections, taking exception to removable elements, which had a minimum thickness of 0 mm. Additionally, even though the thickness of the skin panels was maintained at 2.3 mm, since it is not part of the optimization process, it is fitted to the best possible result considering the aforementioned upper and lower design variable values (Figure 50). Also, the mass of each joint was set at 150 g (SILVA; GUIMARÃES; CASTRO, 2023; SILVA, 2022).

Figure 50 – Skin thickness fit to the best possible.



Source: Elaborated by the author.

The optimization process' population size was initially set at 100, given that, over the course of the development of this work, it was noticed that a smaller number of individuals per iteration would not hinder the optimization process, whilst allowing it to converge faster, i.e., the optimization process benefited from a high number of iterations rather than population size. Nonetheless, at 3000 iterations, the result displayed signs of convergence, exhibiting the need of an increase in population size, with a swarm size increment to 500. All inputs that were needed to run the optimization cycle can be seen in Table 21. The optimization problem is as follows:

Table 21 – Optimization parameters.

Parameter	Value
Number of variables	5460
Constrained trusses	453
Constrained trusses' outer radius	5 mm
Constrained trusses' thickness	1 mm
Optimizable trusses	2730
Trusses with possible removal	1051
Skin's thickness	2.3 mm
Joint's mass	150 g
Iterations	3000 - 1000
Population size	100 - 500

$$\text{Optimization problem} : \begin{cases} \min(W_{wing}) \\ \mathbf{x} : [r_{i_{ext,tube}}, t_{i_{tube}}] \quad \text{for } i = 1, 2, \dots, N \\ r_{i_{ext,tube}} = 10, 15, 20, \dots, 130 \quad [\text{mm}] \\ t_{i_{tube}} = 2, 4, 6, \dots, 48 \quad [\text{mm}] \end{cases}$$

Given the inputs to run the cycle, the outputs specified in Figure 30 could be obtained and displayed in Table 22. The total time of 2152000 seconds, through the course of both steps of the optimization process, initially at 100 and later at 500 population size, shows that each individual takes about 2.69 seconds to be optimized. That displays an increase of 2.67 seconds per individual when compared to the metamodel, mainly due to the time consumed by the NASTRAN execution.

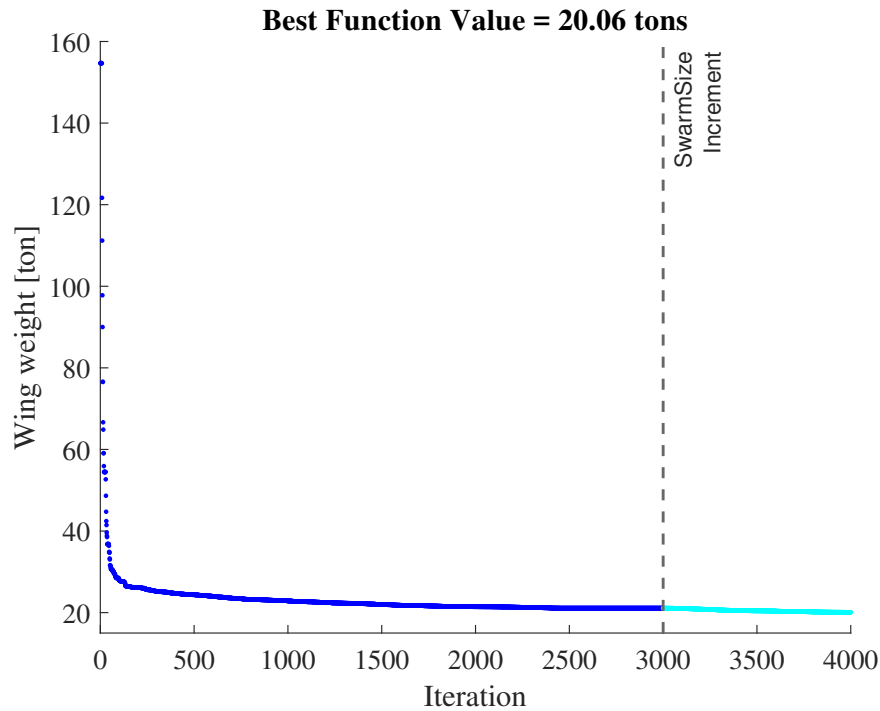
Table 22 – Optimization results.

Parameter	Value
Total time	24 days and 21 hours
Number of elements removed	171
Maximum displacement	2134.71
Maximum combined stress	366.65 MPa
Minimum wing weight	20.06 tons

Source: Elaborated by the author.

The evolution of the function value over the iterations is shown in Figure 51. As mentioned previously, the population size increment allowed the wing weight to escape a local minimum, which was reached with the smaller initial population size. With the aid of the increase, displayed in the graph through the dashed line, the wing weight decreased in additional 1.04 tons through 1000 iterations.

Figure 51 – Optimization process convergence.

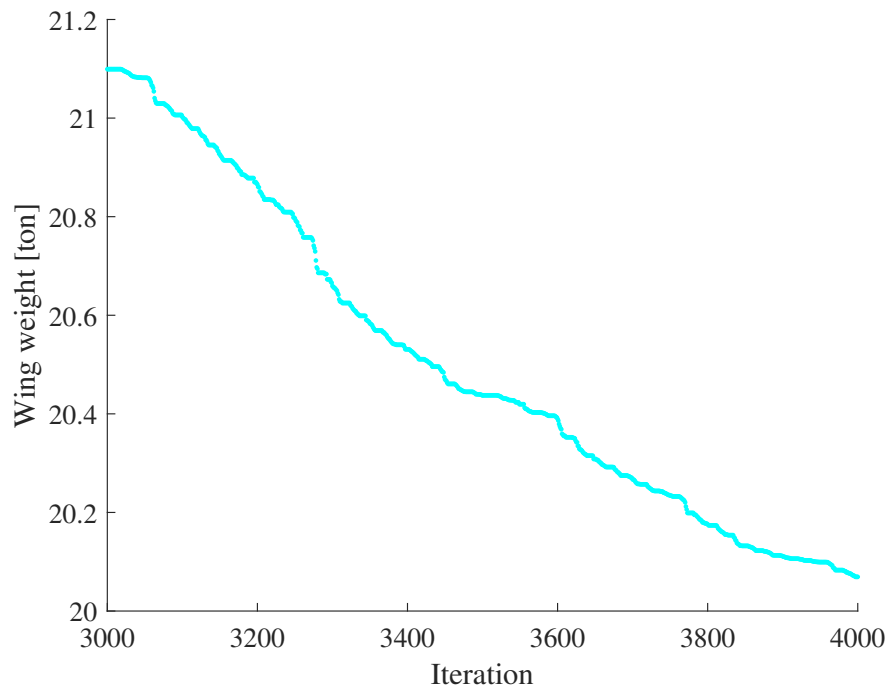


Source: Elaborated by the author.

As is evident in the lack of convergence in the last iterations of Figure 51, the local minimum has not yet been found. Nevertheless, although computationally costly (from 269 s to 1345 s per iteration), the last increase in population size decreased the wing's weight in 1.04 tons, with the process being detailed in Figure 52. Even with the possible convergence of the fitness value with a population size of 500, another increase in population size may allow more considerable weight losses, eventually reaching the 15.05 tons of the original CRM wingbox (Table 6). However, the computational cost is still a challenge in order to reach this possibility.

(Intentionally left in blank)

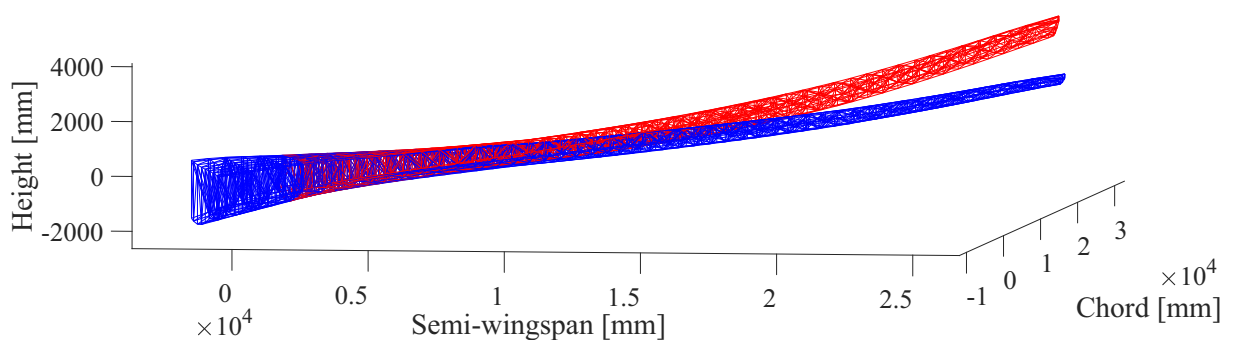
Figure 52 – Detailed optimization process with a population size of 500.



Source: Elaborated by the author.

The wingbox's displacement may be observed in Figure 53, displaying the structure's stiffness, with its maximum value taking place at wing tip, as expected.

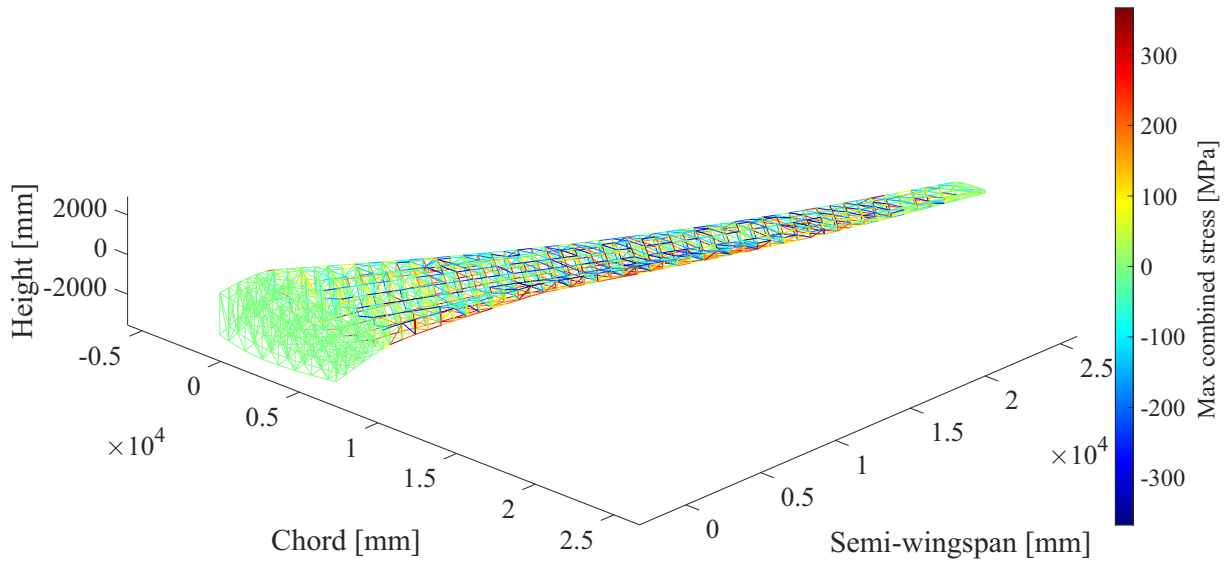
Figure 53 – Optimized wingbox's displacement.



Source: Elaborated by the author.

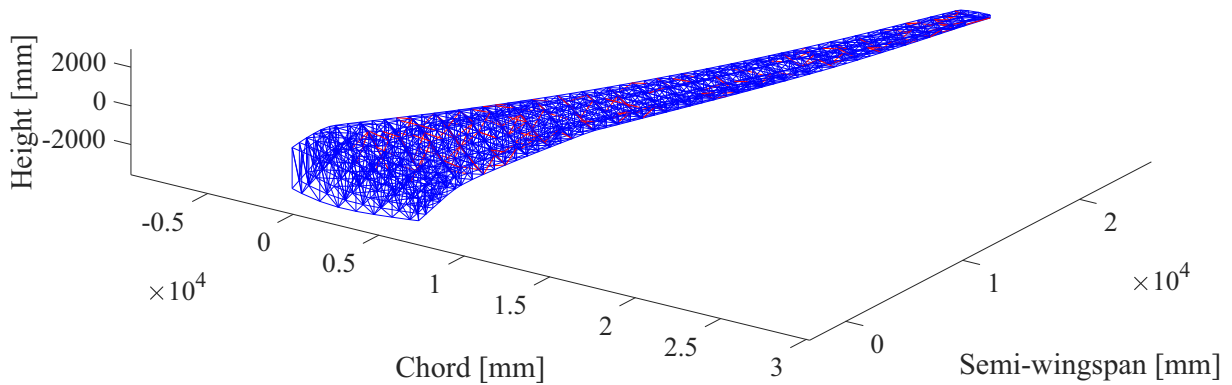
In total, 171 trusses were removed (16.27%) from all across the wingbox, those considered unnecessary for both the aerodynamic profile and structural integrity, allowing to optimize the wingbox's empty weight while staying inside the FS, with no penalized trusses (Figure 54). The wingbox's removed elements are highlighted in the structural mesh by the color red in Figure 55.

Figure 54 – Optimized wingbox's maximum combined stress.



Source: Elaborated by the author.

Figure 55 – Optimized wingbox's removed elements.



Source: Elaborated by the author.

Additionally, Table 23 displays the distribution of removed elements per structural section. It describes how the removal of elements in the wingbox needs to be refined, given the volume of removal in the 3 closest sections to wing root, which is unexpected considering the structural response.

Table 23 – Number of elements removed per structural section (S_n).

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}
Amount	20	34	29	14	15	9	7	11	12	20
Amount [%]	21.98	23.29	20	13.08	14.29	8.57	7.14	13.25	14.12	23.26

Source: Elaborated by the author.

Table 24 displays the wingbox's mass distribution, whereupon the trusses account for 19.03 tons (94.97%) of the total wing weight. Hence, the optimization of the skin panels' thickness and a different value of joint mass as the one proposed by Silva (2022) could decrease the wingbox's empty weight to an even lower value. Nevertheless, the optimized truss-based NASA CRM wingbox was 5.01 tons heavier than the original wing weight.

Table 24 – Wingbox's mass distribution.

Component	Weight [tons]
Trusses	19.03
Skin panels	0.92
Joints	0.11

Moreover, Table 25 displays the distribution of weight along the wingbox, whereupon Case 1 relates the average weight per number of remaining elements of the structural section after removal and Case 2 per the original number of elements. Even though the weight is not considerably concentrated at wing root, the decreasing Case 1 and Case 2 describe how the average element weight is coherent to the expected structural response, showcasing the optimization process' efficacy.

Table 25 – Weight per structural section (S_n).

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}
Weight [tons]	2.53	3.33	2.89	2.29	1.93	1.79	1.54	1.09	0.91	0.73
Case 1 [kg]	10.63	9.82	8.38	8.74	7.57	6.86	6.29	5.21	4.38	3.63
Case 2 [kg]	9.81	8.93	7.81	8.3	7.15	6.63	6.11	4.95	4.14	3.3

4.4 Post-analyses

4.4.1 Buckling

After obtaining the optimized wingbox design, a post-analysis was conducted to assess the buckling behavior and ensure the structural integrity of the wingbox. NASTRAN's SOL105 was used for this purpose. The post-analysis involved determining the first five eigenvalues using Lanczos' solution method, and the corresponding results are presented in Table 26. The critical instability of the wingbox associated with eigenvalue #1 is visualized in Figure 56.

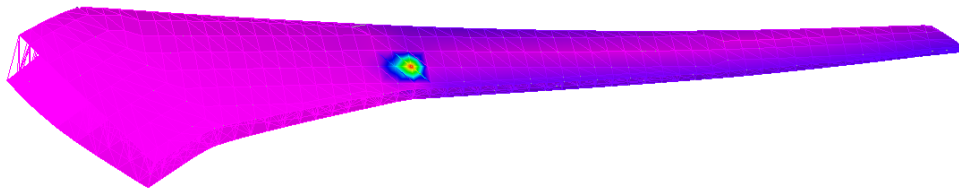
As evident from the results, the optimized wingbox demonstrates significant structural integrity, as it remains well below the critical buckling limit when subjected to the applied loads. Therefore, the wingbox is deemed structurally stable and capable of withstanding the given load conditions without buckling failure.

Table 26 – First five buckling eigenvalues for the optimized wingbox.

Eigenvalue #	Value
1	25.58
2	27.96
3	28.00
4	-32.72
5	-33.14

Source: Elaborated by the author.

Figure 56 – Buckling analysis (eigenvector #1).



Source: Elaborated by the author.

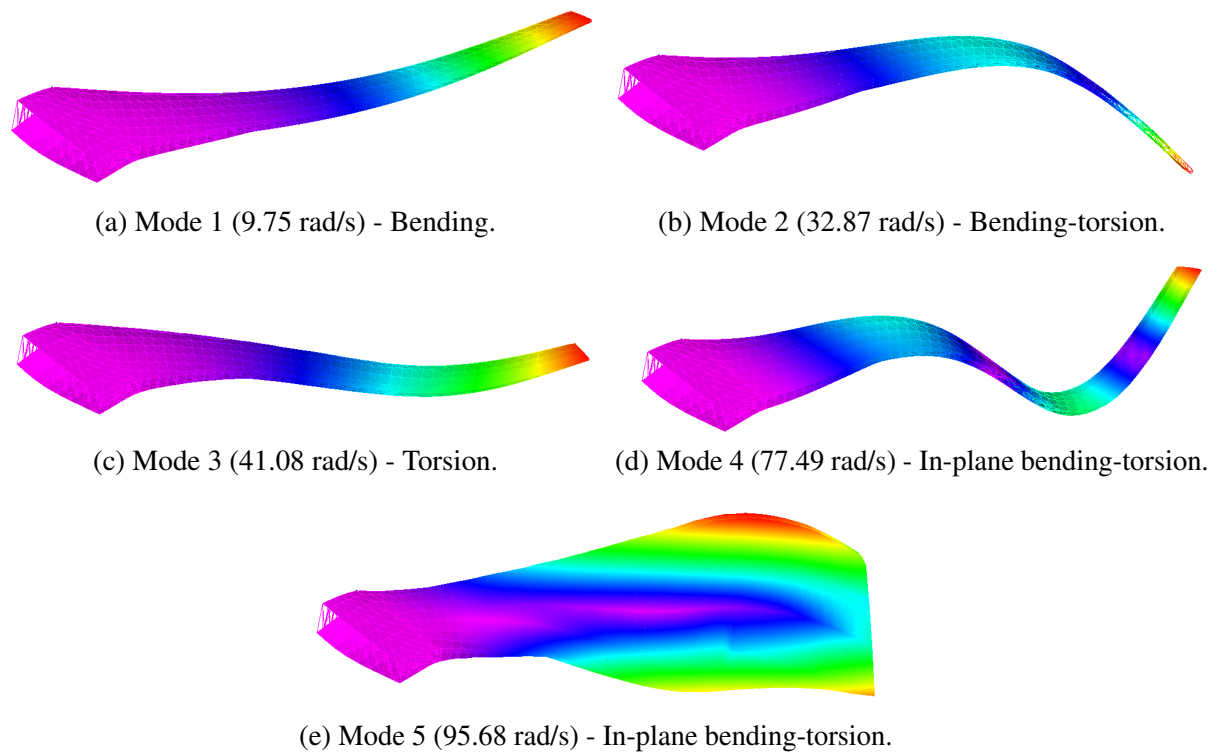
4.4.2 Aeroelasticity

An aeroelastic post-analysis was also conducted to assess the static and dynamic aeroelastic behavior of the wingbox and ensure conformity inside the flight's envelope. Initially, a normal modes (SOL101) analysis on NASTRAN was executed in order to determine the first five natural frequencies and modes of vibration of the optimized wingbox. The results are displayed in Figure 57, in which the behaviors of the modes are identified in the captions, such as their amplitudes in rad/s. The unit allows a comparison to Figure 26, in which most modes increased in amplitude and, apart from modes 2 and 3, increase in distance between each other, due to an increased distributed stiffness of the wingbox.

Moreover, using the aeroelastic model developed in Section 3.4 (Figure 25 and its necessary inputs, highlighted in Tables 8 and 9, NASTRAN's SOL145 was executed. The outputs are displayed in Figure 58, in the form of the aforementioned V-g-f diagram.

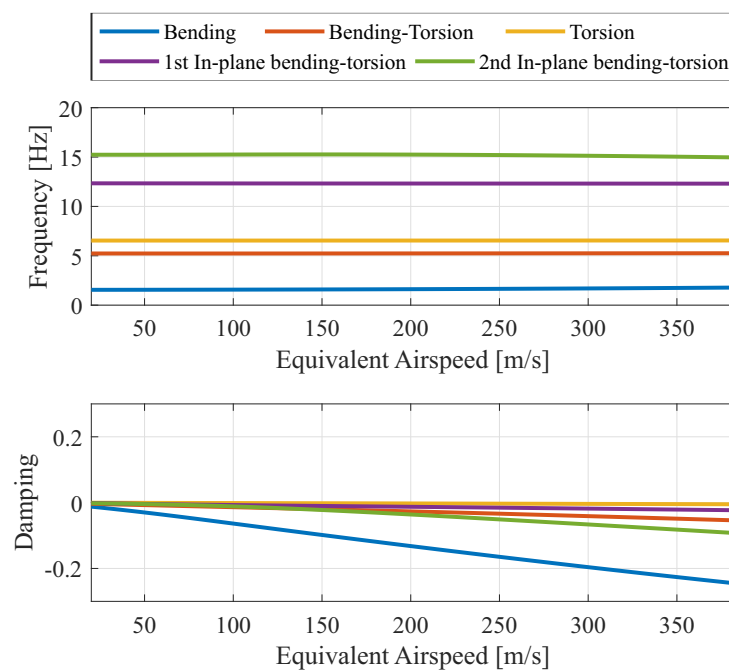
Even though modes 2 and 3 got closer in frequency, they never coalesced inside the flight's envelope. Furthermore, since the damping never turned positive and no modes converged to 0 Hz inside the flight's envelope, the wingbox's possible aeroelastic instabilities have been discarded. Coupled with the structural integrity verified in the buckling analysis and the no penalization of truss elements, the design of the truss-based wingbox has been validated.

Figure 57 – First five modes of vibration for the optimized wingbox.



Source: Elaborated by the author.

Figure 58 – V-g-f diagram for the optimized wingbox.



Source: Elaborated by the author.

CONCLUDING REMARKS

“Aviation is proof that given, the will, we have the capacity to achieve the impossible.”

— Eddie Rickenbacker

THIS chapter describes the conclusions regarding all model’s results, revisiting objectives and the hows and ifs they were fulfilled. Some potential future improvements to this work are also noted.

5.1 General Remarks

This paper presents a new wing design approach. It assesses the concept of a truss-based modular internal wingbox structure applied to a large-scale commercial aircraft model, which is the NASA’s Common Research Model. The results showed that the proposal can be a good strategy in structural design, even with its limitations.

Firstly, the aerodynamic model and V-n diagram were able to determine the critical load boundary conditions for the wingbox. Then, a Kriging metamodel of the simplified optimization model was developed, passing its requirements while improving the time spent per individual considerably as expected, being able to correctly predict the wingbox’s maximum combined stress inside the sample space. The metamodel was able to efficiently determine the maximum thickness and outer radius bounds for the optimization model.

Then, the structural model in NASTRAN was integrated with a PSO in MATLAB, with it’s convergence behavior and final result displaying the effectiveness of the optimization methodology in terms of modularity and reducing wing weight. The optimization model was able to find a non-penalized wingbox with a high percentage of removed elements and, even though the element removal behavior wasn’t coherent, the distribution of wing weight was. Even though it was not lower than the original CRM wingbox weight, the lack of convergence and

potential continuous decrease of wing weight showcase potential for eventually decreasing until the desired point. This is the case due to possible increments in population size, even though they are computationally costly.

Finally, a thorough buckling post-analysis confirmed the structural integrity of the optimized wingbox, indicating that it can withstand the applied loads without experiencing buckling failure. In similar fashion, an aeroelastic post-analysis eliminated the concern for possible flutter and divergence speeds inside the flight's envelope and, hence, the wingbox is structurally and aeroelastically stable.

5.2 Future Perspectives

There are still great potential for developing improvements in the structural model, such as a more optimized spatial arrangement of the structural mesh, with the optimization of not only the existing design variables, but also of the number and position of the truss-based ribs and its truss sections. The evaluation of uncertainties in the manufacturing of the composite plates and tubes and an assessment of a TBW structure - envisaging easing manufacturing issues and analyzing the wing-fuselage connection elements - should also enhance the structural project of this wingbox, as would a deeper mechanical project of the trusses' joints. Due to the large number of design variables in the optimization, the computational time is still a big challenge, hence, the use of metamodels in the complete optimization model may be addressed to make this work more efficient. Kriging may be replaced with ANN in order to tackle the amount of variables.

BIBLIOGRAPHY

AEROVINTAGE. **B-17G Champaign Lady Update: 02/18/2022**. 2022. URL: <<https://www.aerovintage.com/2022/02/18/b-17g-champaign-lady-update-02-18-2022/>>. Citation on page 21.

ALTAIR. **PBAR**. 2021. URL: <https://2021.help.altair.com/2021/hwsolvers/os/topics/solvers/os/pbar_bulk_r.htm>. Citation on page 35.

BAI, Y.; YANG, X. Novel joint for assembly of all-composite space truss structures: conceptual design and preliminary study. **Journal of Composites for Construction**, American Society of Civil Engineers, v. 17, n. 1, p. 130–138, 2013. DOI: <[https://doi.org/10.1061/\(ASCE\)CC.1943-5614.0000304](https://doi.org/10.1061/(ASCE)CC.1943-5614.0000304)>. Citation on page 22.

BARBOSA, J. S.; SICCHIERI, L. C.; DOURADO, A. D. P.; JR, A. A. C.; JR, V. S. Kriging approach dedicated to represent hydrodynamic bearings. **Journal of Engineering for Gas Turbines and Power**, American Society of Mechanical Engineers, v. 143, n. 6, p. 061016, 2021. DOI: <<https://doi.org/10.1115/1.4049307>>. Citation on page 51.

BHATIA, M.; KAPANIA, R.; HOEK, M. van; HAFTKA, R. Structural design of a truss braced wing: potential and challenges. In: **50th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference 17th AIAA/ASME/AHS Adaptive Structures Conference 11th AIAA No.** [S.l.: s.n.], 2009. p. 2147. DOI: <<https://doi.org/10.2514/6.2009-2147>>. Citations on pages 21 and 23.

BHATIA, M.; KAPANIA, R. K.; HAFTKA, R. T. Structural and aeroelastic characteristics of truss-braced wings: A parametric study. **Journal of Aircraft**, v. 49, n. 1, p. 302–310, 2012. DOI: <<https://doi.org/10.2514/1.C031556>>. Citations on pages 21 and 23.

BOEING. 2023. URL: <<https://www.geekwire.com/2023/boeing-wins-425m-in-nasa-backing-to-demonstrate-super-fuel-efficient-airplane/>>. Citation on page 22.

CHEN, X.; XIANG, S.; LIU, C.-L.; PAN, C.-H. Aircraft detection by deep convolutional neural networks. **IPSJ Transactions on Computer Vision and Applications**, Information Processing Society of Japan, v. 7, p. 10–17, 2014. DOI: <<https://doi.org/10.2197/ipsjtcva.7.10>>. Citation on page 29.

EMBRAER. **Future Aircraft Concepts**. 2021. URL: <<https://embraercommercialaviationsustainability.com/concepts/>>. Citations on pages 20 and 21.

EXELITE, E. **Carbon Fiber Tubes**. [S.l.]: Exel Composites, 2014. URL: <https://exelcomposites.com/wp-content/uploads/2020/06/EN_Exelite-Technical-Data-Sheet-2014.pdf>. Citation on page 37.

FINISTAURI, A. D.; XI, F.; WALSH, P. Discretization method for the development of a modular morphing wing. **Journal of Aircraft**, v. 49, n. 1, p. 116–125, 2012. DOI: <<https://doi.org/10.2514/1.C031382>>. Citations on pages 18 and 23.

FONSECA, D.; NAVARESSE, D.; MOYNIHAN, G. Simulation metamodeling through artificial neural networks. **Engineering Applications of Artificial Intelligence**, v. 16, n. 3, p. 177–183, 2003. ISSN 0952-1976. DOI: <[https://doi.org/10.1016/S0952-1976\(03\)00043-5](https://doi.org/10.1016/S0952-1976(03)00043-5)>. Citations on pages 29 and 30.

FRIEDRICH, C.; ROBERTSON, P. A. Hybrid-electric propulsion for aircraft. **Journal of Aircraft**, American Institute of Aeronautics and Astronautics, v. 52, n. 1, p. 176–189, 2015. DOI: <<https://doi.org/10.2514/1.C032660>>. Citation on page 17.

FUJIWARA, G. E.; NGUYEN, N. T.; LIVNE, E.; BRAGG, M. B. Aerostructural design optimization of a flexible wing aircraft with continuous morphing trailing edge. In: **2018 Multidisciplinary Analysis and Optimization Conference**. [S.l.: s.n.], 2018. p. 3571. DOI: <<https://doi.org/10.2514/6.2018-3571>>. Citation on page 34.

GERN, F. H.; NAGHSHINEH-POUR, A. H.; SULAEMAN, E.; KAPANIA, R. K.; HAFTKA, R. T. Structural wing sizing for multidisciplinary design optimization of a strut-braced wing. **Journal of aircraft**, v. 38, n. 1, p. 154–163, 2001. DOI: <<https://doi.org/10.2514/2.2747>>. Citations on pages 21 and 23.

GRAHAM, W. R.; HALL, C. A.; MORALES, M. V. The potential of future aircraft technology for noise and pollutant emissions reduction. **Transport policy**, Elsevier, v. 34, p. 36–51, 2014. DOI: <<https://doi.org/10.1016/j.tranpol.2014.02.017>>. Citation on page 17.

GUIMARAES, T.; PEREIRA, D.; MELLO, W. de; RADE, D. Uncertainty propagation and optimization of the dynamic behavior of tow steered composite plates. In: **Proceedings of the International Conference on Structural Engineering Dynamics**. [S.l.: s.n.], 2017. Citation on page 38.

GUIMARÃES, T. A.; CASTRO, S. G.; CESNIK, C. E.; RADE, D. A. Supersonic flutter and buckling optimization of tow-steered composite plates. **AIAA Journal**, American Institute of Aeronautics and Astronautics, v. 57, n. 1, p. 397–407, 2019. DOI: <<https://doi.org/10.2514/1.J057282>>. Citation on page 17.

GUIMARÃES, T. A.; CASTRO, S. G.; RADE, D. A.; CESNIK, C. E. Panel flutter analysis and optimization of composite tow steered plates. In: **58th AIAA/ASCE/AHS/ASC structures, structural dynamics, and materials conference**. [S.l.: s.n.], 2017. p. 1118. DOI: <<https://doi.org/10.2514/6.2017-1118>>. Citation on page 17.

HEPHAIST. **SR Joint - Precision and Rigidity**. 2022. URL: <<http://www.myostat.ca/imagequalitylabs>>. Citation on page 23.

HERA. **The HERA Project**. 2023. URL: <<https://project-hera.eu/home>>. Citation on page 22.

JR, A. A. C.; LOBATO, F. S.; KOROISHI, E. H.; JR, V. S. Model updating of a rotating machine using the self-adaptive differential evolution algorithm. **Inverse Problems in Science and Engineering**, Taylor & Francis, v. 24, n. 3, p. 504–523, 2016. DOI: <<https://doi.org/10.1080/17415977.2015.1047364>>. Citations on pages 27 and 45.

JR, J. H. S.; HAFTKA, R. T. Preliminary design of composite wings for buckling, strength, and displacement constraints. **Journal of Aircraft**, v. 16, n. 8, p. 564–570, 1979. DOI: <<https://doi.org/10.2514/3.58565>>. Citation on page 17.

JURECKA, F. **Robust design optimization based on metamodeling techniques**. Phd Thesis (PhD Thesis) — Technische Universität München, 2007. Citation on page 29.

JUTTE, C. V.; STANFORD, B.; WIESEMAN, C. D.; MOORE, J. B. Aeroelastic tailoring of the nasa common research model via novel material and structural configurations. In: **52nd aerospace sciences meeting**. [S.l.: s.n.], 2014. p. 0598. DOI: <<https://doi.org/10.2514/6.2014-0598>>. Citation on page 17.

KECHAGIAS, J. D.; TSIOLIKAS, A.; PETOUSIS, M.; NINIKAS, K.; VIDAKIS, N.; TZOUNIS, L. A robust methodology for optimizing the topology and the learning parameters of an ann for accurate predictions of laser-cut edges surface roughness. **Simulation Modelling Practice and Theory**, Elsevier, v. 114, p. 102414, 2022. DOI: <<https://doi.org/10.1016/j.simpat.2021.102414>>. Citation on page 30.

KENWAY, G.; KENNEDY, G.; MARTINS, J. R. Aerostructural optimization of the common research model configuration. In: **15th AIAA/ISSMO multidisciplinary analysis and optimization conference**. [S.l.: s.n.], 2014. p. 3274. DOI: <<https://doi.org/10.2514/6.2014-3274>>. Citation on page 39.

LACY, D. S.; SCLAFANI, A. J. Development of the high lift common research model (hl-crm): A representative high lift configuration for transonic transports. In: **54th AIAA aerospace sciences meeting**. [S.l.: s.n.], 2016. p. 0308. DOI: <<https://doi.org/10.2514/6.2016-0308>>. Citation on page 32.

LI, Z.; LIU, F.; YANG, W.; PENG, S.; ZHOU, J. A survey of convolutional neural networks: analysis, applications, and prospects. **IEEE transactions on neural networks and learning systems**, IEEE, 2021. DOI: <<https://doi.org/10.1109/TNNLS.2021.3084827>>. Citation on page 30.

LIN, D. K.; SIMPSON, T. W.; CHEN, W. Sampling strategies for computer experiments: design and analysis. **International Journal of Reliability and applications**, The Korean Reliability Society, v. 2, n. 3, p. 209–240, 2001. DOI: <<https://koreascience.kr/article/JAKO200111921705473.page>>. Citation on page 29.

LOMAX, T. **Structural Loads Analysis for Commercial Transport Aircraft: Theory and Practice**. [S.l.]: American Institute of Aeronautics and Astronautics, 1996. (AIAA education series). URL: <<https://books.google.com.br/books?id=9YrbswEACAAJ>>. Citation on page 42.

MALLIK, W.; KAPANIA, R. K.; SCHETZ, J. A. Multidisciplinary design optimization of medium-range transonic truss-braced wing aircraft with flutter constraint. In: **54th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference**. [S.l.: s.n.], 2013. p. 1454. DOI: <<https://doi.org/10.2514/6.2013-1454>>. Citations on pages 21 and 23.

MARTIN, J. D.; SIMPSON, T. W. A study on the use of kriging models to approximate deterministic computer models. In: **International design engineering technical conferences and computers and information in engineering conference**. [S.l.: s.n.], 2003. v. 37009, p. 567–576. DOI: <<https://doi.org/10.1115/DETC2003/DAC-48762>>. Citation on page 30.

MASIOL, M.; HARRISON, R. M. Aircraft engine exhaust emissions and other airport-related contributions to ambient air pollution: A review. **Atmospheric Environment**, Elsevier, v. 95, p. 409–455, 2014. DOI: <<https://doi.org/10.1016/j.atmosenv.2014.05.070>>. Citation on page 17.

MESOGITIS, T.; SKORDOS, A. A.; LONG, A. Uncertainty in the manufacturing of fibrous thermosetting composites: A review. **Composites Part A: Applied Science and Manufacturing**, Elsevier, v. 57, p. 67–75, 2014. DOI: <<https://doi.org/10.1016/j.compositesa.2013.11.004>>. Citation on page 38.

NAPOLITANO, M. R.; CHEN, C. I.; NAYLOR, S. Aircraft failure detection and identification using neural networks. **Journal of Guidance, Control, and Dynamics**, v. 16, n. 6, p. 999–1009, 1993. DOI: <<https://doi.org/10.2514/3.21120>>. Citation on page 29.

NASA. **NASA Common Research Model**. 2012. URL: <<https://commonresearchmodel.larc.nasa.gov/>>. Citations on pages 33 and 39.

OLSSON, A. M.; SANDBERG, G. E. Latin hypercube sampling for stochastic finite element analysis. **Journal of Engineering Mechanics**, American Society of Civil Engineers, v. 128, n. 1, p. 121–125, 2002. DOI: <[https://doi.org/10.1061/\(ASCE\)0733-9399\(2002\)128:1\(121\)](https://doi.org/10.1061/(ASCE)0733-9399(2002)128:1(121))>. Citation on page 50.

PENA, J. V. **Aeroelastic calculations on an equivalent beam-based NASA CRM**. [S.l.]: Universidad Carlos III de Madrid, 2019. Citation on page 45.

PETRESCU, R. V. V.; MACHIN, A.; FONTANEZ, K.; ARANGO, J. C.; MARQUEZ, F. M.; PETRESCU, F. I. T. Hydrogen for aircraft power and propulsion. **international journal of hydrogen energy**, Elsevier, v. 45, n. 41, p. 20740–20764, 2020. DOI: <<https://doi.org/10.1016/j.ijhydene.2020.05.253>>. Citation on page 17.

PORNET, C.; ISIKVEREN, A. T. Conceptual design of hybrid-electric transport aircraft. **Progress in Aerospace Sciences**, Elsevier, v. 79, p. 114–135, 2015. DOI: <<https://doi.org/10.1016/j.paerosci.2015.09.002>>. Citation on page 17.

RAO, S. **Engineering Optimization: Theory and Practice**. [S.l.]: Wiley, 2019. URL: <<https://books.google.com.br/books?id=oG21DwAAQBAJ>>. ISBN 9781119454717. Citations on pages 24 and 28.

RIVERS, M. B. Nasa common research model: a history and future plans. In: **AIAA Aviation 2019 Forum**. [S.l.: s.n.], 2019. p. 3725. DOI: <<https://doi.org/10.2514/6.2019-3725>>. Citations on pages 32 and 33.

RIVERS, M. B.; LYNDE, M. N.; CAMPBELL, R. L.; VIKEN, S. A.; CHAN, D. T.; WATKINS, A. N.; GOODLIFF, S. L. Experimental investigation of the nasa common research model with a natural laminar flow wing in the nasa langley national transonic facility. In: **AIAA Scitech 2019 Forum**. [S.l.: s.n.], 2019. p. 2189. DOI: <<https://doi.org/10.2514/6.2019-2189>>. Citation on page 32.

SAKATA, S.; ASHIDA, F.; ZAKO, M. An efficient algorithm for kriging approximation and optimization with large-scale sampling data. **Computer methods in applied mechanics and engineering**, Elsevier, v. 193, n. 3-5, p. 385–404, 2004. DOI: <<https://doi.org/10.1016/j.cma.2003.10.006>>. Citation on page 30.

SALEHINEJAD, H.; SANKAR, S.; BARFETT, J.; COLAK, E.; VALAEE, S. Recent advances in recurrent neural networks. **arXiv preprint arXiv:1801.01078**, 2017. DOI: <<https://doi.org/10.48550/arXiv.1801.01078>>. Citation on page 30.

SGUEGLIA, A.; SCHMOLLGRUBER, P.; BARTOLI, N.; BENARD, E.; MORLIER, J.; JASA, J.; MARTINS, J. R.; HWANG, J. T.; GRAY, J. S. Multidisciplinary design optimization framework with coupled derivative computation for hybrid aircraft. **Journal of Aircraft**, American Institute of Aeronautics and Astronautics, v. 57, n. 4, p. 715–729, 2020. DOI: <<https://doi.org/10.2514/1.C035509>>. Citation on page 17.

SILVA, H. L. Structural and aeroelastic design optimization of truss-based modular wing structures. Universidade Federal de Uberlândia, 2022. DOI: <<http://doi.org/10.14393/ufu.te.2022.345>>. Citations on pages 23, 24, 25, 35, 46, 67, 69, and 74.

SILVA, H. L.; GUIMARÃES, T. A.; CASTRO, S. G. Design and aeroelastic analysis of truss-based modular wing structures. In: **AIAA SCITECH 2023 Forum**. [S.l.: s.n.], 2023. p. 1677. DOI: <<https://doi.org/10.2514/6.2023-1677>>. Citations on pages 18, 67, and 69.

SILVA, H. L.; RESENDE, G. J.; NETO, R. M.; CARVALHO, A. R.; GIL, A. A.; CRUZ, M. A.; GUIMARÃES, T. A. A multidisciplinary design optimization for conceptual design of hybrid-electric aircraft. **Structural and Multidisciplinary Optimization**, Springer, v. 64, n. 6, p. 3505–3526, 2021. DOI: <<https://doi.org/10.1007/s00158-021-03033-8>>. Citation on page 17.

STANFORD, B. K.; JUTTE, C. V. Comparison of curvilinear stiffeners and tow steered composites for aeroelastic tailoring of aircraft wings. **Computers & Structures**, Elsevier, v. 183, p. 48–60, 2017. DOI: <<https://doi.org/10.1016/j.compstruc.2017.01.010>>. Citation on page 17.

STANFORD, B. K.; JUTTE, C. V.; WU, K. C. Aeroelastic benefits of tow steering for composite plates. **Composite Structures**, Elsevier, v. 118, p. 416–422, 2014. DOI: <<https://doi.org/10.1016/j.compstruct.2014.08.007>>. Citations on pages 17 and 37.

STRAGIOTTI, E.; IRISARRI, F.; JULIEN, C. e. a. Efficient 3d truss topology optimization for aeronautical structures. **Structural and Multidisciplinary Optimization**, Springer, v. 67, n. 42, 2024. DOI: <<https://doi.org/10.1007/s00158-024-03739-5>>. Citations on pages 18, 23, and 26.

SVOZIL, D.; KVASNICKA, V.; POSPICHAL, J. Introduction to multi-layer feed-forward neural networks. **Chemometrics and Intelligent Laboratory Systems**, v. 39, n. 1, p. 43–62, 1997. ISSN 0169-7439. DOI: <[https://doi.org/10.1016/S0169-7439\(97\)00061-0](https://doi.org/10.1016/S0169-7439(97)00061-0)>. Citation on page 30.

TANG, D.; CHEN, L.; HU, E.; TIAN, Z. F. A novel actuator controller: Delivering a practical solution to realization of active-truss-based morphing wings. **IEEE Transactions on Industrial Electronics**, IEEE, v. 63, n. 10, p. 6226–6237, 2016. DOI: <<https://doi.org/10.1109/TIE.2016.2580520>>. Citations on pages 18 and 23.

TOAL, D. J.; BRESSLOFF, N. W.; KEANE, A. J. Kriging hyperparameter tuning strategies. **AIAA journal**, v. 46, n. 5, p. 1240–1252, 2008. DOI: <<https://doi.org/10.2514/1.34822>>. Citations on pages 31, 51, and 52.

ULAGANATHAN, S.; COUCKUYT, I.; DESCHRIJVER, D.; LAERMANS, E.; DHAENE, T. A matlab toolbox for kriging metamodeling. **Procedia Computer Science**, Elsevier, v. 51, p. 2708–2713, 2015. DOI: <<https://doi.org/10.1016/j.procs.2015.05.395>>. Citations on pages 31 and 49.

VASSBERG, J.; DEHAAN, M.; RIVERS, M.; WAHLS, R. Development of a common research model for applied cfd validation studies. In: **26th AIAA applied aerodynamics conference**. [S.l.: s.n.], 2008. p. 6919. DOI: <<https://doi.org/10.2514/6.2008-6919>>. Citation on page 32.

VASSBERG, J. C. **Airfoil Geometry: Camber and Thickness Distributions**. [S.l.]: Boeing, 2012. Citations on pages 33 and 39.

WYSS, G. D.; JORGENSEN, K. H. A user's guide to lhs: Sandia's latin hypercube sampling software. 2 1998. DOI: <<https://doi.org/10.2172/573301>>. Citation on page 50.

YE, J.; KYVELOU, P.; GILARDI, F.; LU, H.; GILBERT, M.; GARDNER, L. An end-to-end framework for the additive manufacture of optimized tubular structures. **IEEE Access**, IEEE, v. 9, p. 165476–165489, 2021. DOI: <<https://doi.org/10.1109/ACCESS.2021.3132797>>. Citation on page 22.

ZIMMERMAN, D.; PAVLIK, C.; RUGGLES, A.; ARMSTRONG, M. P. An experimental comparison of ordinary and universal kriging and inverse distance weighting. **Mathematical Geology**, Springer, v. 31, p. 375–390, 1999. DOI: <<https://doi.org/10.1023/A:1007586507433>>. Citation on page 30.