# DEVELOPING AI FRAMEWORK FOR STABILITY/BUCKLING ANALYSIS OF STIFFENED PANELS

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Aerospace Engineering

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**APPROVAL BY BOARD OF EXAMINERS**

______________________

Assistant Professor Gohar Majeed

## CERTIFICATE

This is to certify that the research work described in this thesis is the original work of author(s) and has been carried out under my direct supervision. I have personally gonethrough all the data/results/materials reported in the manuscript and certify their correctness/authenticity. I further certify that the material included in this thesis is not plagiarized and has not been used in part or full in a manuscript already submitted or in the process of submission in partial/complete fulfilment of the award of any other degree from any institution. I also certify that the thesis has been prepared under my supervision according to the prescribed format and I endorse its evaluation for the award of Bachelor of Science in Aerospace Engineering degree through the official procedures of the Institute.

Assistant Professor Gohar Majeed

# AUTHOR’S DECLARATION

We take full responsibility of the research work conducted during BS Thesis titled “Developing AI framework for Stability/Buckling analysis of stiffened panels”. We solemnly declare that the research and development work presented in this Thesis is done solely by us with no significant help from any other person; however, small help wherever taken is duly acknowledged. We have also written the complete thesis by ourselves. Moreover, we have not presented this thesis (or substantially similar research and development work) or any part of the thesis to any other degree awarding institution within Pakistan or abroad.

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# ABSTRACT

Traditional approaches to preliminary structural design in aerospace engineering especially for components like fuselage and wing panels are often labor-intensive, require iterative optimization, and rely heavily on manual calculations. These conventional workflows lead to longer design cycles, increased costs, and inconsistencies in parameter selection. With the rising capabilities of Artificial Intelligence (AI), there is growing potential to modernize and automate such structural design processes, yet AI applications in early-stage aerospace structural sizing remain limited and underexplored.

This research presents the development of an AI-based framework that automates the preliminary design process for flat and curved skin-stringer panels. The framework utilizes a machine learning approach, particularly Random Forest regression to accurately predict key structural and material parameters based on user-supplied design conditions. The input parameters are four for flat panels which are: longer side length, shorter side length, axial load intensity, and transverse load intensity which serve as features for the machine learning model. Similarly, the user input takes four parameters for curved panel design which are: applied compression stress, applied shear stress, allowable hoop stress and radius. The methodology begins with the loading and cleaning of domain-specific datasets (flat and curved panel data), followed by feature selection and filtering to ensure high-quality training samples. Each engineering output parameter (e.g., thickness, stringer dimensions, material classification) is predicted independently. For each parameter, the dataset is filtered to exclude missing values, and the corresponding Random Forest model

is trained using a train-test split strategy to ensure robust learning. Once trained, these models are used to generate predictions for new input values provided by the user.

If the predicted output is categorical such as material type or design status the model reverses label encoding to provide interpretable results. All predicted outputs are compiled into a structured JSON response, which is returned to the user interface for visualization and further use. Additionally, the trained model can generate APDL script files to automate panel modeling in ANSYS environment.

Performance analysis parameters were also calculated including regression coefficient (R), Mean Absolute Error (MAE) and Mean squared error (MSE), for which all the values showed that our model has good accuracy, and the AI tool is producing reliable outputs.

The developed AI framework significantly improves design consistency, reduces lead times, and enhances the integration of AI into traditional aerospace engineering workflows. By automating parameter prediction and simulation code generation, this research contributes toward a more intelligent and efficient approach to early-stage structural design in the aerospace industry.

# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# LIST OF ABBREVIATIONS AND SYMBOLS USED

| | |
|---|---|
| $A_{st}$ | **Stiffener Area** |
| $A_{sk}$ | **Skin Area** |
| **a** | **Longer side of the panel (length)** |
| **b** | **Shorter side of the panel (width)** |
| **N** | **Panel Axial Load Intensity** |
| **L'** | **Effective length** |
| $F_c$ | **Allowable Compression Stress** |
| **t** | **Skin Thicknes** |
| $t_w$ | **Stringer Vertical Web Thickness** |
| $b_w$ | **Depth of the stringer** |
| $b_f$ | **Flange Width of the stringer** |
| $b_r$ | **Rivet Spacing** |
| $b_o$ | **Base Width of the stringer** |
| $b_e$ | **Effective Width** |
| **c** | **Fixity Coefficient** |
| **d** | **Fastener diameter** |
| **s** | **Rivet spacing** |
| ${b_e}'$ | **Total Effective Width** |
| $I_{xx}$ | **Moment of Inertia** |
| $\rho_{xx}$ | **Radius of Gyration** |
| $F_{CC}$ | **Crippling stress** |

| | |
|---|---|
| $N_{all}$ | **Colum Buckling Allowable Load** |
| **£** | **Plasticity Correction Factor** |
| $F_c$ | **Allowable Compression Stress** |
| **M** | **Bending Moment** |
| $f_c$ | **Fuselage Axial Compression Stress on stringer** |
| $f_c$ | **Fuselage Axial Tension Stress on stringer** |
| $F_{c,cr}$ | **Initial Buckling stress under Compression** |
| $F_{s,cr}$ | **Initial Buckling stress under Shear** |
| **p** | **Cabin Pressure** |
| **q** | **Fuselage skin Shear flow** |
| $F_{fat}$ | **Fatigue allowable Compression stress** |
| **R** | **Fuselage Radius** |
| **d** | **Stringer length** |
| **h** | **Stringer spacing** |
| $t_{min}$ | **Minimum thickness** |
| **k** | **Diagonal Skin Tension Factor** |
| $F_{s,all}$ | **Allowable Shear Stress** |
| $f_{st}$ | **Average Stringer stress** |
| **A** | **Cross section Area** |
| **Y** | **Centroid** |
| $k_s$ | **Shear Coefficient** |
| $k_c$ | **Compression Coefficient** |

| | |
|---|---|
| $k_b$ | **Bending Coefficient** |
| **α** | **Diagonal Tension Angle** |
| $\varepsilon_{sk}$ | **Strain skin** |
| $\varepsilon_{st}$ | **Strain Stringer** |
| **E** | **Elastic Limit** |
| $E_t$ | **Tangent Modulus** |
| **μ** | **Poisson's Ratio** |
| $F_e$ | **Elastic Stress** |
| $f_{h,fr}$ | **Fuselage frame circumferential axial stress** |
| $F_{tu}$ | **Ultimate Tensile Strength** |
| $F_{cy}$ | **Compressive Yield Strength** |
| $F_{su}$ | **Ultimate Shear Strength** |
| $F_{bru}$ | **Ultimate Bearing Strength** |
| $E_{fr}$ | **Frame Elastic Modulus** |
| $E_{st}$ | **Skin Elastic Modulus** |
| **c'** | **The distance between stringer neutral axis to the most remote fiber of the Outstanding flange away from skin** |

# 1 INTRODUCTION

The aerospace industry constantly pushes the boundaries of innovation, demanding design of structural components that meet standard criteria for performance, safety, and cost-efficiency. Among these components, fuselage and wing panels are particularly critical because of their direct influence on an aircraft's structural strength and aerodynamic efficiency. Traditionally, the initial design of these parts includes intensive analytical methods, manual calculations, and iterative optimization, which can cause extended development cycles, increased costs, and high inconsistencies in design outputs.

As the aviation sector is rapidly improving and demanding faster, smarter, and reliable design processes, there is a high need to shift from traditional methods to intelligent solutions. Artificial Intelligence (AI) has emerged as a transformative tool in aerospace engineering, offering significant benefits in tasks covering aerodynamic modeling to predictive maintenance. Its ability to process complex datasets, extract essential patterns, and deliver fast and accurate predictions makes it ideal for modernizing design workflows.

A review of existing literature shows several successful AI implementations across various aerospace-structures domains. For example, researchers at the University of London applied neural networks to predict composite ply orientation effects on wing vibrations, On the other hand NASA has explored AI models for structural optimization using Artificial Neural Networks (ANNs). Similarly, in the field of Integrated Vehicle Health Management (IVHM), AI-driven systems have improved predictive maintenance process and reduced costs. With these advancements, the application of

AI particularly in **preliminary structural design of panels** such as flat wing panels and curved fuselage parts are not publicly available in research.

This thesis aims to cover that gap by developing a AI-based framework designed to automate and optimize the initial design of aerospace structural panels. The system takes four user-defined input parameters for flat panels which are given as: longer side length, shorter side length, axial load intensity, and transverse load intensity which serve as features for the machine learning model. Similarly, the user input takes four parameters for curved panel design which are stated as: applied compression stress, applied shear stress, allowable hoop stress and radius. A Random Forest Regressor is trained on domain-specific datasets to predict a range of geometric parameters such as panel thickness, stringer spacing, material selection, and other geometric properties.

A main innovation in this work is the integration of AI predictions with ANSYS APDL (ANSYS Parametric Design Language). The geometric properties predicted by model are programmatically translated into APDL script files, which are used to automatically generate the panel geometry within ANSYS environment in APDL. This enables users to pass manual modeling properties and specifications and directly visualize the designed panel based on AI-driven outputs in APDL. It is important to note that, in the current phase, integration supports **design automation** only structural analysis and simulations are not included but remain a promising direction for future.

By automating the parameter prediction and model generation scenarios, this framework offers a scalable, consistent, and highly efficient solution to preliminary panel design. It marks a significant step toward the integration of intelligent tools in aerospace structural engineering, ultimately making it design efficient and enhancing the reliability of preliminary design decisions

## 1.1 PROBLEM STATEMENT

Current aerospace structural design procedures, particularly for critical components like fuselage and wing panels, are very time-consuming, iterative and resource intensive. These processes depend on intensive analytical calculations, trade-off studies, and iterative optimization loops, which must consider structural integrity, aerodynamic performance, material selection, and regulatory compliance. Each phase in the design procedure from conceptual sizing to final geometry specifications requires extensive manual effort and engineering expertise.

This traditional workflow leads to long design cycles, high costs, delayed production timelines, and slower innovation. The complexity involved in simultaneously balancing many geometric parameters such as load distribution, material compatibility, and geometric constraints further increases the inefficiency. Moreover, the lack of intelligent automation limits scalability and constrains the swiftness of design teams to changing needs.

Although advances in simulation and modeling tools, there remains a significant gap in AI-integrated frameworks that can automate the **initial design** phase particularly for structures like panels. This project deals with that gap by introducing design framework based on machine learning capable of forecasting desired panel specifications based on a set of user-defined inputs. The system then automatically generates ANSYS APDL script files to model the panel geometry, considerably reducing the need for manual coding and design iterations.

## 1.2 PROBLEM-SOLVING STRATEGY

Our project suggests the use of Artificial Intelligence to predict and optimize the preliminary design of aerospace structural panels, exactly for flat and curved fuselage/wing panels. By leveraging Random Forest regression models trained on datasets, we forecast key structural and geometric specifications like skin thickness, stringer spacing, material type, and load distribution characteristics.

This technique effectively systemizes the design process by reducing time spent on repetitive calculations and trade-off studies, improving accuracy, and making it cost efficient while ensuring compatibility with aerospace standards and established design workflows.

## 1.3 IMPORTANCE OF FASTER, OPTIMIZED DESIGN SOLUTIONS

Implementing faster, AI-driven design strategies offer several high-impact benefits to the aerospace industry:

1. **Reduced Development Time**: Machine controlled parameter prediction and direct panel generation eliminates time and cost inefficient manual tasks, fastening ups the design-to-modeling process.
2. **Reduced Budget**: reducing manual input and design revisions decreases engineering hard work, software usage, and computational expenses, by helping to control the overall project budget.

3. **Improved Structural and Aerodynamic Performance**: Optimized initial designs make better decisions on thickness, layout, and material usage ultimately causing lighter, stronger, and more design parameters optimized geometric properties of these parts.
4. **Enhanced Safety and Compliance**: AI-based automation reduces the risk of manual error and helps to meet safety standards, enabling quicker validation without compromising accuracy.
5. **Adaptability to smart Manufacturing**: AI-developed designs are more compatible with latest manufacturing methods such as additive manufacturing and composites, improving manufacturability and production quality.
6. **Focused Engineering Innovation**: By automating manual design stages, engineers are able to more focus on creative problem-solving and innovation, thereby increasing the overall pace of technology and development.

## 1.4 PRIMARY OBJECTIVE

**"To develop an AI-based framework for automating and optimizing the preliminary design of aerospace structural components, specifically fuselage and wing panels."**

This project aims to address the inefficiencies of traditional design workflows by leveraging artificial intelligence and automated modeling. The specific objectives are:

1. **Automate the preliminary structural design process** using machine learning models that predict key engineering and geometric parameters based on limited

user inputs, thereby reducing dependency on manual and iterative analytical methods.

2. **Optimize design parameters**—including panel thickness, stringer dimensions, material type, and load-bearing characteristics—through advanced regression models trained on domain-specific, structured datasets.
3. **Minimize design cycle time** while enhancing design accuracy, consistency, and reliability, ultimately improving overall productivity in aerospace structural design tasks.
4. **Develop and clean comprehensive datasets** representing flat and curved skin-stringer panel configurations, following established aerospace standards for data validity and consistency.
5. **Generate APDL script files** from AI-predicted outputs to directly model the panel geometry in ANSYS, eliminating the need for manual input or script writing during the design stage.
6. **Ensure compliance** with aerospace safety, strength, and weight requirements by training models on data that reflect realistic performance conditions and structural constraints.
7. **Enable integration with FEM tools**, particularly ANSYS Mechanical APDL, to support real-world implementation of AI-generated designs and promote adoption by aerospace design engineers

# 2 LITERATURE REVIEW

AI has been increasingly applied in composite material design and maintenance within the aerospace industry, offering advancements in predictive maintenance, defect detection, and material performance optimization. Numerous studies and implementations focus on AI-driven techniques for monitoring structural health, optimizing composite layups, and improving repair strategies. These applications leverage machine learning algorithms, data analytics, and automation to enhance efficiency, reduce costs, and improve the durability of aerospace components.

However, when it comes to AI applications in structural design, particularly for components like fuselage and wing panels, the available data is significantly limited. While research in this area is undoubtedly progressing, much of it remains unpublished or confined to proprietary projects within aerospace corporations and research institutions. This lack of openly accessible information creates a knowledge gap, restricting widespread innovation and industry-wide adoption of AI-driven structural design methodologies. Bridging this gap through open-access research, collaborative studies, and knowledge-sharing platforms could accelerate advancements in AI-assisted structural design, making aerospace engineering more efficient and cost-effective. The following are the research papers we studied.

Artificial Intelligence Based Aerospace Composite Design

*(Published in 2021 by City, University of London, School of Mathematics, Computer Science & Engineering)*

The paper uses a neural network to predict the effects of composite lamina ply orientation on wing structure vibrations, with data from ABAQUS FEA. A Python script automated data generation, and a MATLAB neural network accurately modeled results. The study shows AI's potential for aeroelastic flutter problems in aerospace, despite project delays and challenges.

The Application of Reasoning to Aerospace Integrated Vehicle Health Management (IVHM):

*(Published by Science Direct in 2019, IVHM Centre, Cranfield University, Bedfordshire, MK43 0AL, United Kingdom)*

This paper emphasizes the role of AI-based reasoning in improving Aerospace Integrated Vehicle Health Management (IVHM) for optimizing maintenance and reducing costs. It highlights gaps in vehicle-level health monitoring and suggests integrating advanced technologies to enhance IVHM effectiveness

An Overview of Systems Engineering Challenges for Designing AI-Enabled Aerospace Systems

*(Presented at the AIAA SciTech Forum, IAA SciTech, 2021)*

The paper emphasizes the need to evolve systems engineering methods for integrating AI, such as machine learning and deep learning, into aerospace missions, addressing challenges in concept development, model-based engineering, and AI validation.

Application of Artificial Neural Networks to the Design Optimization of Aerospace Structural Components

*(Published by NASA, National Aeronautics and Space Administration, Office of Management, Scientific and Technical Information Program, 1993)*

Artificial Neural Networks (ANNs) optimize structural design with fast predictions but face challenges like higher error rates and complex modeling. Improvements include narrowing design ranges and increasing training data. Future work should explore ANNs as expert designers and hybrid AI models for better performance.

## 2.1 GAPS OUR PROJECT ADDRESSES

While AI has made significant progress in various aerospace domains such as composite material optimization, predictive maintenance, and Integrated Vehicle Health Management (IVHM) its application in **preliminary structural design**, particularly for **fuselage and wing panels**, remains underexplored. Most existing design processes still rely on manual calculations, iterative trade-off studies, and time-intensive simulations to determine key design parameters.

Furthermore, many AI-driven tools developed for structural optimization are either **proprietary** or focused on niche applications, limiting their **accessibility and adaptability** across the aerospace industry. There is a notable lack of open, customizable frameworks that can generate real-time design outputs based on user-defined input conditions.

Another significant gap is the **absence of integrated AI systems** that can both predict structural specifications and directly generate simulation-ready models, bridging the gap between data-driven prediction and practical implementation.

Our project addresses these challenges through the development of an **AI-powered framework** that:

1. Automates the **preliminary structural design** of flat and curved fuselage/wing panels using machine learning models trained on domain-specific datasets.

2. Predicts key engineering specifications such as skin thickness, stringer spacing, and material type using **Random Forest Regressors**.

3. Converts model outputs into **ANSYS APDL code**, enabling **automatic panel generation** without manual scripting or modeling.

4. Provides a **lightweight, flexible, and accessible solution** that can be adapted for different structural configurations and extended in future iterations.

5. Lays the foundation for **faster, scalable, and more consistent** structural design processes enhancing industry adoption and reducing reliance on closed-form, black-box solutions.

By addressing these gaps, our project contributes to the modernization of structural design methodologies and advances the practical integration of AI in aerospace engineering.

# 3 METHODOLOGY

This part of the thesis outlines the entire methodology adopted to develop an AI framework for the early-stage structural design of **fuselage and wing panels**, concerning both **flat and curved panel configurations**. The methodology spans from theoretical design principles to data generation, AI model training, and eventual integration with ANSYS APDL for automated geometry generation.

## 3.1 THEORETICAL FRAMEWORK AND DESIGN APPROACH

The framework is grounded in the principles of classical aerospace structural design. Flat and curved panels in fuselage and wing applications are typically reinforced using **skin-stringer-frame** configurations and are subjected to a combination of axial, shear, and pressure loads. The main design goal is to ensure **lightweight construction** while satisfying **stress, buckling, and strength requirements**.

For **flat panels**, classical buckling theory is used to compute **compressive buckling**, **shear buckling**, **panel collapse loads**, and **margins of safety**.

For **curved panels**, additional curvature-dependent formulations are applied, accounting for geometry-induced stress redistributions and stiffener interaction effects. These include **cylindrical shell theory** and **curved panel buckling criteria**, which introduce more complex behavior.

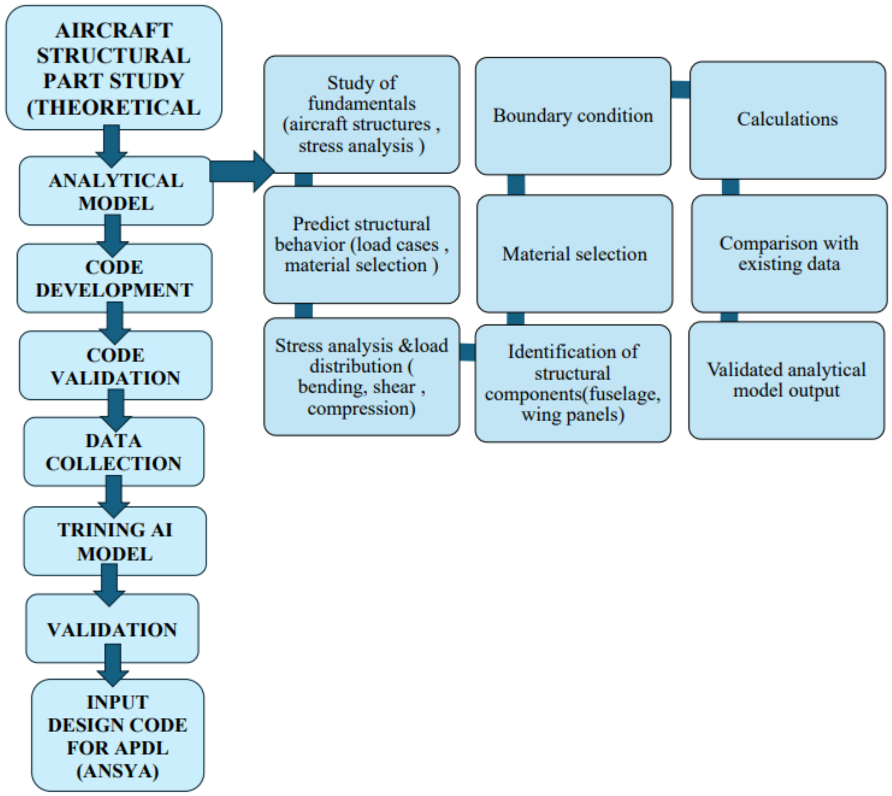



Fig 3-1:Methodology Flowchart

The traditional method requires time-consuming analytical evaluations and iterative sizing based on trade-off studies. Our AI framework aims to **replace this with a predictive model** that can instantly generate feasible design parameters using a trained machine learning pipeline.

## 3.2 FLAT PANEL DESIGN PROCESS

Complete study of the design process for flat plates was done using the theoretical books, it starts from the material configurations and goes up to the calculations of allowable loads and stresses.

### 3.2.1 Step 1: Compute panel dimensions:

We start off the process by identifying all the material properties, from the tables given below, referenced used is linked in the references Airframe Stress Analysis and Sizing by Michael C.Y. Niu

| Specification | QQ-A-250/5 | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Form | Flat sheet and plate | | | | | | | | | |
| Temper | T42 | | | | | | | | | |
| Thickness, in. | 0.008-0.009 | | 0.010-0.062 | | 0.063-0.249 | | 0.250-0.499 | 0.500-1.000 | 1.001-2.000 | 2.001-3.000 |
| Basis | A | B | A | B | A | B | S | S | S | S |
| Mechanical properties: | | | | | | | | | | |
| $F_{tu}$, ksi: | | | | | | | | | | |
| L | 55 | 57 | 57 | 59 | 60 | 62 | 60 | 59 | 58 | 56 |
| LT | 55 | 57 | 57 | 59 | 60 | 62 | 60 | 59 | 58 | 56 |
| $F_{ty}$, ksi: | | | | | | | | | | |
| L | 34 | 35 | 34 | 35 | 36 | 38 | 36 | 36 | 36 | 36 |
| LT | 34 | 35 | 34 | 35 | 36 | 38 | 36 | 36 | 36 | 36 |
| $F_{cy}$, ksi: | | | | | | | | | | |
| L | 34 | 35 | 34 | 35 | 36 | 38 | 36 | 36 | 36 | 36 |
| LT | 34 | 35 | 34 | 35 | 36 | 38 | 36 | 36 | 36 | 36 |
| $F_{su}$, ksi | 33 | 34 | 34 | 35 | 36 | 37 | 36 | 35 | 35 | 34 |
| $F_{bru}^{e}$, ksi: | | | | | | | | | | |
| $(\frac{e}{D} = 1.5)$ | 83 | 86 | 86 | 89 | 90 | 93 | 90 | 89 | 87 | 83 |
| $(\frac{e}{D} = 2.0)$ | 104 | 108 | 108 | 112 | 114 | 118 | 114 | 112 | 110 | 106 |
| $F_{bry}^{e}$, ksi: | | | | | | | | | | |
| $(\frac{e}{D} = 1.5)$ | 48 | 49 | 48 | 49 | 50 | 53 | 50 | 50 | 50 | 50 |
| $(\frac{e}{D} = 2.0)$ | 54 | 56 | 54 | 56 | 58 | 61 | 58 | 58 | 58 | 58 |
| e, percent (S-basis): | | | | | | | | | | |
| LT | 10 | – | d | – | 15 | – | 12 | 8 | d | 4 |
| E, $10^3$ ksi: | | | | | | | | | | |
| Primary | 10.5 | | | | 10.5 | | 10.7 | | | |
| Secondary | 9.5 | | | | 10.0 | | 10.2 | | | |
| $E_c$, $10^3$ ksi: | | | | | | | | | | |
| Primary | 10.7 | | | | 10.7 | | 10.9 | | | |
| Secondary | 9.7 | | | | 10.2 | | 10.4 | | | |
| G, $10^3$ ksi | | | | | | | | | | |
| $\mu$ | 0.33 | | | | | | | | | |
| Physical properties: | | | | | | | | | | |
| $\omega$, lb/in.$^3$ | 0.101 | | | | | | | | | |

Fig 3-2:Mechanical and Physical Properties of Clad 2024-T42 Alloy Sheet and Plate

| Specification | QQ-A-250/4 | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Form | Sheet | | | | | Plate | | | | | | | | | | | |
| Temper | T3 | | | | | T351 | | | | | | | | | | | |
| Thickness, in. | 0.008-0.009 | 0.010-0.128 | | 0.129-0.249 | | 0.250-0.499 | | 0.500-1.000 | | 1.001-1.500 | | 1.501-2.000 | | 2.001-3.000 | | 3.000-4.000 | |
| Basis | S | A | B | A | B | A | B | A | B | A | B | A | B | A | B | A | B |
| Mechanical properties: | | | | | | | | | | | | | | | | | |
| $F_{tu}$, ksi: | | | | | | | | | | | | | | | | | |
| L | 64 | 64 | 65 | 65 | 66 | 64 | 66 | 63 | 65 | 62 | 64 | 62 | 64 | 60 | 62 | 57 | 59 |
| LT | 63 | 63 | 64 | 64 | 65 | 64 | 66 | 63 | 65 | 62 | 64 | 62 | 64 | 60 | 62 | 57 | 59 |
| ST | – | – | – | – | – | – | – | – | – | – | – | – | – | 52 | 54 | 49 | 51 |
| $F_{ty}$, ksi: | | | | | | | | | | | | | | | | | |
| L | 47 | 47 | 48 | 47 | 48 | 48 | 50 | 48 | 50 | 47 | 50 | 47 | 49 | 46 | 48 | 43 | 46 |
| LT | 42 | 42 | 43 | 42 | 43 | 42 | 44 | 42 | 44 | 42 | 44 | 42 | 44 | 42 | 44 | 41 | 43 |
| ST | – | – | – | – | – | – | – | – | – | – | – | – | – | 38 | 40 | 38 | 39 |
| $F_{cy}$, ksi: | | | | | | | | | | | | | | | | | |
| L | 39 | 39 | 40 | 39 | 40 | 39 | 41 | 39 | 41 | 39 | 40 | 38 | 40 | 37 | 39 | 35 | 37 |
| LT | 45 | 45 | 46 | 45 | 46 | 45 | 47 | 45 | 47 | 44 | 46 | 44 | 46 | 43 | 45 | 41 | 43 |
| ST | – | – | – | – | – | – | – | – | – | – | – | – | – | 46 | 48 | 44 | 47 |
| $F_{su}$, ksi | 39 | 39 | 40 | 40 | 41 | 38 | 39 | 37 | 38 | 37 | 38 | 37 | 38 | 35 | 37 | 34 | 35 |
| $F_{bru}$, ksi: | | | | | | | | | | | | | | | | | |
| $(\frac{e}{D} = 1.5)$ | 104 | 104 | 106 | 106 | 107 | 97 | 100 | 95 | 98 | 94 | 97 | 94 | 97 | 91 | 94 | 86 | 89 |
| $(\frac{e}{D} = 2.0)$ | 129 | 129 | 131 | 131 | 133 | 119 | 122 | 117 | 120 | 115 | 119 | 115 | 119 | 111 | 115 | 106 | 109 |
| $F_{bry}$, ksi: | | | | | | | | | | | | | | | | | |
| $(\frac{e}{D} = 1.5)$ | 73 | 73 | 75 | 73 | 75 | 72 | 76 | 72 | 76 | 72 | 76 | 72 | 76 | 72 | 76 | 70 | 74 |
| $(\frac{e}{D} = 2.0)$ | 88 | 88 | 90 | 88 | 90 | 86 | 90 | 86 | 90 | 86 | 90 | 86 | 90 | 86 | 90 | 84 | 88 |
| e, percent (S-basis): | | | | | | | | | | | | | | | | | |
| LT | 10 | – | – | – | – | 12 | – | 8 | – | 7 | – | 6 | – | 4 | – | 4 | – |
| E, $10^3$ ksi | 10.5 | | | | | 10.7 | | | | | | | | | | | |
| $E_c$, $10^3$ ksi | 10.7 | | | | | 10.9 | | | | | | | | | | | |
| G, $10^3$ ksi | 4.0 | | | | | 4.0 | | | | | | | | | | | |
| $\mu$ | 0.33 | | | | | 0.33 | | | | | | | | | | | |
| Physical properties: | | | | | | | | | | | | | | | | | |
| $\omega$, lb/in.$^3$ | 0.101 | | | | | | | | | | | | | | | | |

Fig 3-3: Mechanical and Physical Properties of 2024-TJ Alloy Sheet and Plate

| Specification | QQ-A-250/12 | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Form | Sheet | | | | | Plate | | | | | | | | | | | |
| Temper | T6 and T62 | | | | | T651 | | | | | | | | | | | |
| Thickness, in. | 0.008-0.011 | 0.012-0.039 | | 0.040-0.125 | | 0.126-0.249 | | 0.250-0.499 | | 0.500-1.000 | | 1.001-2.000 | | 2.001-2.500 | | 2.500-3.000 | |
| Basis | S | A | B | A | B | A | B | A | B | A | B | A | B | A | B | A | B |
| Mechanical properties: | | | | | | | | | | | | | | | | | |
| $F_{tu}$, ksi: | | | | | | | | | | | | | | | | | |
| L | – | 76 | 78 | 78 | 80 | 78 | 80 | 77 | 79 | 77 | 79 | 76 | 78 | 75 | 77 | 71 | 73 |
| LT | 74 | 76 | 78 | 78 | 80 | 78 | 80 | 78 | 80 | 78 | 80 | 77 | 79 | 76 | 78 | 72 | 74 |
| ST | – | – | – | – | – | – | – | – | – | – | – | – | – | 70 | 71 | 66 | 68 |
| $F_{ty}$, ksi: | | | | | | | | | | | | | | | | | |
| L | – | 69 | 72 | 70 | 72 | 71 | 73 | 69 | 71 | 70 | 72 | 69 | 71 | 66 | 68 | 63 | 65 |
| LT | 61 | 67 | 70 | 68 | 70 | 69 | 71 | 67 | 69 | 68 | 70 | 67 | 69 | 64 | 66 | 61 | 61 |
| ST | – | – | – | – | – | – | – | – | – | – | – | – | – | 59 | 61 | 56 | 58 |
| $F_{cy}$, ksi: | | | | | | | | | | | | | | | | | |
| L | – | 68 | 71 | 69 | 71 | 70 | 72 | 67 | 69 | 68 | 70 | 66 | 68 | 62 | 64 | 58 | 60 |
| LT | – | 71 | 74 | 72 | 74 | 73 | 75 | 71 | 73 | 72 | 74 | 71 | 73 | 68 | 70 | 65 | 67 |
| ST | – | – | – | – | – | – | – | – | – | – | – | – | – | 67 | 70 | 64 | 66 |
| $F_{su}$, ksi | – | 46 | 47 | 47 | 48 | 47 | 48 | 41 | 44 | 44 | 45 | 44 | 45 | 44 | 45 | 42 | 43 |
| $F_{bru}$, ksi: | | | | | | | | | | | | | | | | | |
| $(\frac{e}{D} = 1.5)$ | – | 118 | 121 | 121 | 124 | 121 | 124 | 117 | 120 | 117 | 120 | 116 | 119 | 114 | 117 | 108 | 111 |
| $(\frac{e}{D} = 2.0)$ | – | 152 | 156 | 156 | 160 | 156 | 160 | 145 | 148 | 145 | 148 | 143 | 147 | 141 | 145 | 134 | 137 |
| $F_{bry}$, ksi: | | | | | | | | | | | | | | | | | |
| $(\frac{e}{D} = 1.5)$ | – | 100 | 105 | 102 | 105 | 103 | 106 | 97 | 100 | 100 | 103 | 100 | 103 | 98 | 101 | 94 | 97 |
| $(\frac{e}{D} = 2.0)$ | – | 117 | 122 | 119 | 122 | 121 | 124 | 114 | 118 | 117 | 120 | 117 | 120 | 113 | 117 | 109 | 112 |
| e, percent (S-basis): | | | | | | | | | | | | | | | | | |
| LT | 5 | 7 | – | 8 | – | 8 | – | 9 | – | 7 | – | 6 | – | 5 | – | 5 | – |
| E, $10^3$ ksi | 10.3 | | | | | 10.3 | | | | | | | | | | | |
| $E_c$, $10^3$ ksi | 10.5 | | | | | 10.6 | | | | | | | | | | | |
| G, $10^3$ ksi | 3.9 | | | | | 3.9 | | | | | | | | | | | |
| $\mu$ | 0.33 | | | | | 0.33 | | | | | | | | | | | |
| Physical properties: | | | | | | | | | | | | | | | | | |
| $\omega$, lb/in.$^3$ | 0.101 | | | | | | | | | | | | | | | | |

Fig 3-4: Mechanical and Physical Properties of 7075 Alloy Sheet and Plate

| Specification | QQ-A-200/11 | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Form | Extrusion (rod, bar, and shapes) | | | | | | | | | | | | |
| Temper | T6, T6510, T6511, and T62 | | | | | | | | | | | | |
| Cross-sectional area, $in^2$ | $\leq 20$ | | | | | | | | | | | | $>20, \leq 32$ |
| Thickness, in. | Up to 0.249 | | 0.250-0.499 | | 0.500-0.749 | | 0.750-1.499 | | 1.500-2.999 | | 3.000-4.499 | | |
| Basis | A | B | A | B | A | B | A | B | A | B | A | B | S |
| Mechanical properties: | | | | | | | | | | | | | |
| $F_{tu}$, ksi: | | | | | | | | | | | | | |
| L | 78 | 82 | 81 | 85 | 81 | 85 | 81 | 85 | 81 | 85 | 81 | 84 | 78 |
| LT | 76 | 80 | 78 | 81 | 76 | 80 | 74 | 78 | 70 | 74 | 67 | 70 | 65 |
| $F_{ty}$, ksi: | | | | | | | | | | | | | |
| L | 70 | 74 | 73 | 77 | 72 | 76 | 72 | 76 | 72 | 76 | 71 | 74 | 70 |
| LT | 66 | 70 | 68 | 72 | 66 | 70 | 65 | 68 | 61 | 65 | 56 | 58 | 55 |
| $F_{cy}$, ksi: | | | | | | | | | | | | | |
| L | 70 | 74 | 73 | 77 | 72 | 76 | 72 | 76 | 72 | 76 | 71 | 74 | 70 |
| LT | 72 | 76 | 74 | 78 | 72 | 76 | 71 | 74 | 67 | 71 | 61 | 64 | 60 |
| $F_{su}$, ksi | 42 | 44 | 43 | 45 | 43 | 45 | 42 | 44 | 41 | 43 | 40 | 41 | 38 |
| $F_{bru}$, ksi: | | | | | | | | | | | | | |
| $(\frac{e}{D} = 1.5)$ | 112 | 118 | 117 | 122 | 117 | 122 | 116 | 122 | 115 | 120 | 109 | 113 | 105 |
| $(\frac{e}{D} = 2.0)$ | 141 | 148 | 146 | 153 | 146 | 153 | 145 | 152 | 144 | 151 | 142 | 147 | 136 |
| $F_{bry}$, ksi: | | | | | | | | | | | | | |
| $(\frac{e}{D} = 1.5)$ | 94 | 99 | 97 | 103 | 96 | 101 | 95 | 100 | 93 | 98 | 89 | 92 | 87 |
| $(\frac{e}{D} = 2.0)$ | 110 | 117 | 115 | 121 | 113 | 119 | 112 | 118 | 110 | 116 | 105 | 110 | 104 |
| e, percent (S-basis): | | | | | | | | | | | | | |
| LT | 7 | – | 7 | – | 7 | – | 7 | – | 7 | – | 7 | | 6 |
| E, $10^3$ ksi: | 10.4 | | | | | | | | | | | | |
| $E_c$, $10^3$ ksi: | 10.7 | | | | | | | | | | | | |
| G, $10^3$ ksi | 4.0 | | | | | | | | | | | | |
| $\mu$ | 0.33 | | | | | | | | | | | | |
| Physical properties: | | | | | | | | | | | | | |
| $\omega$, lb/in.$^3$ | 0.101 | | | | | | | | | | | | |

Fig 3-5:Mechanical and Physical Properties of 7075 Alloy Extrusion

| Alloy | | | | | Hy-Tuf 4330V | D6AC 4335V | AISI 4340 D6AC | AISI 4340 | 0.40C 300M | 0.42C 300M |
|---|---|---|---|---|---|---|---|---|---|---|
| Form | All wrought forms | | | | All wrought forms | | | Bar, forging, tubing | | |
| Condition | Quenched and tempered | | | | Quenched and tempered | | | Quenched and tempered | | |
| Basis | S | S | S | S | S | S | S | S | S | S |
| Mechanical properties: | | | | | | | | | | |
| $F_{tu}$, ksi | 125 | 160 | 180 | 200 | 220 | 220 | 260 | 260 | 270 | 280 |
| $F_{ty}$, ksi | 100 | 142 | 163 | 176 | 185 | 190 | 215 | 215 | 220 | 230 |
| $F_{cy}$, ksi | 109 | 154 | 173 | 181 | 193 | 198 | 240 | 240 | 236 | 247 |
| $F_{su}$, ksi | 75 | 96 | 108 | 120 | 132 | 132 | 156 | 156 | 162 | 168 |
| $F_{bru}$, ksi: | | | | | | | | | | |
| $(\frac{e}{D} = 1.5)$ | 194 | 230 | 250 | 272 | 297 | 297 | 347 | 347 | 414 | 430 |
| $(\frac{e}{D} = 2.0)$ | 251 | 300 | 326 | 355 | 385 | 385 | 440 | 440 | 506 | 525 |
| $F_{bry}$, ksi: | | | | | | | | | | |
| $(\frac{e}{D} = 1.5)$ | 146 | 202 | 230 | 255 | 267 | 274 | 309 | 309 | 344 | 360 |
| $(\frac{e}{D} = 2.0)$ | 175 | 231 | 256 | 280 | 294 | 302 | 343 | 343 | 379 | 396 |
| e, percent: | | | | | | | | | | |
| L | | | | | 10 | – | – | 10 | 8 | 7 |
| T | | | | | 5 | – | – | – | – | – |
| E, $10^3$ ksi: | 29.0 | | | | | | | | | |
| $E_c$, $10^3$ ksi: | 29.0 | | | | | | | | | |
| G, $10^3$ ksi | 11.0 | | | | | | | | | |
| $\mu$ | 0.32 | | | | | | | | | |
| Physical properties: | | | | | | | | | | |
| $\omega$, lb/in.$^3$ | 0.283 | | | | | | | | | |

Fig 3-6:Mechanical and Physical Properties of Low-Alloy Steel

After these material properties we identify area ratio from the given table:

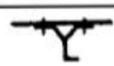
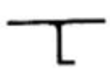
| | IDEAL* | | PRACTICAL DESIGN | |
|---|---|---|---|---|
| PANEL TYPE | $\frac{A_{st}}{A_{sk}}$ | EFFICIENCY | $\frac{A_{st}}{A_{sk}}$ | EFFICIENCY |
|  | 2.16 | 1.23 | 0.5 | — |
|  | 1.3 | 1.03 | 0.5 | 0.82 |
|  | 1.47 | 0.911 | 0.5 | 0.68 |
|  | 1.28 | 0.793 | 0.5 | 0.58 |

Fig 3.3-7:Stiffened Panel Efficiencies

After this the $\frac{N}{L'}$ ratio is identified from the following plots, these are different for different materials:

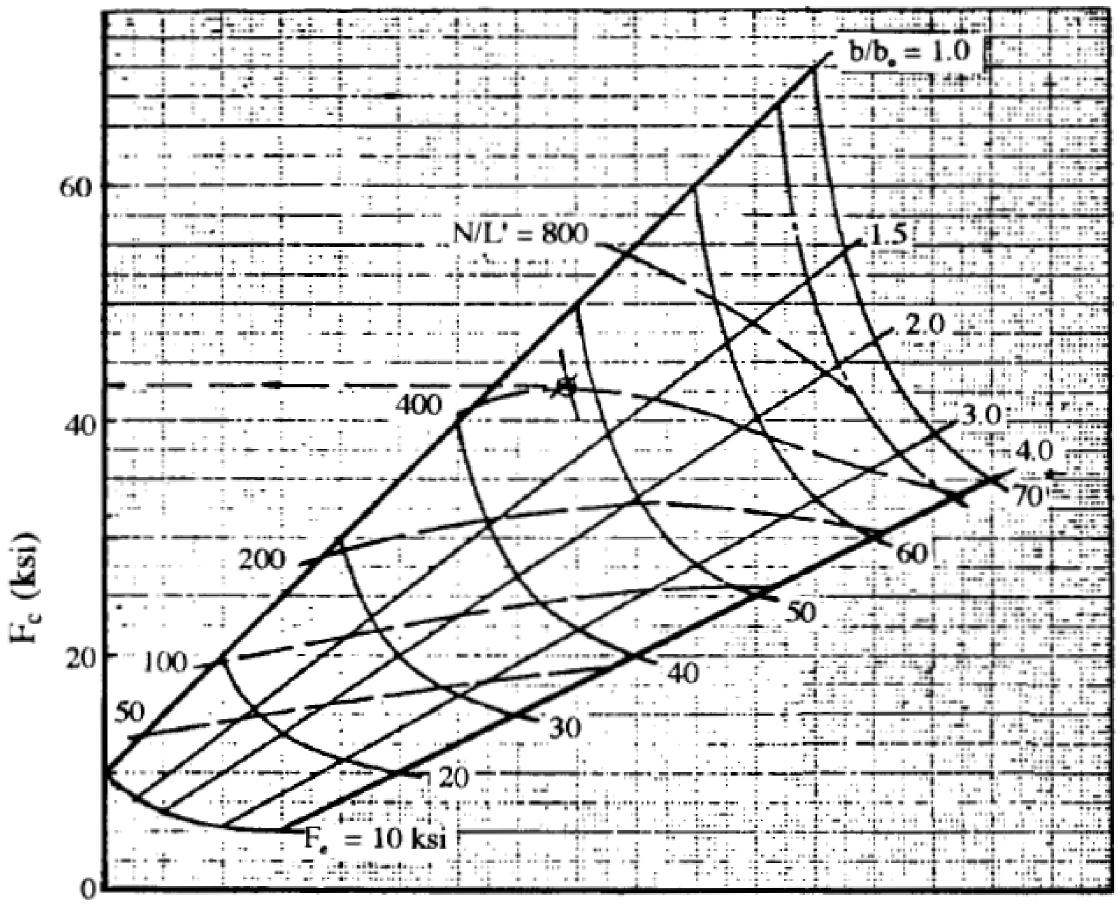



Fig 3-8:Design Curves for Stringer-Skin Panels($\frac{A_{st}}{A_{sk}} = 0.5$)

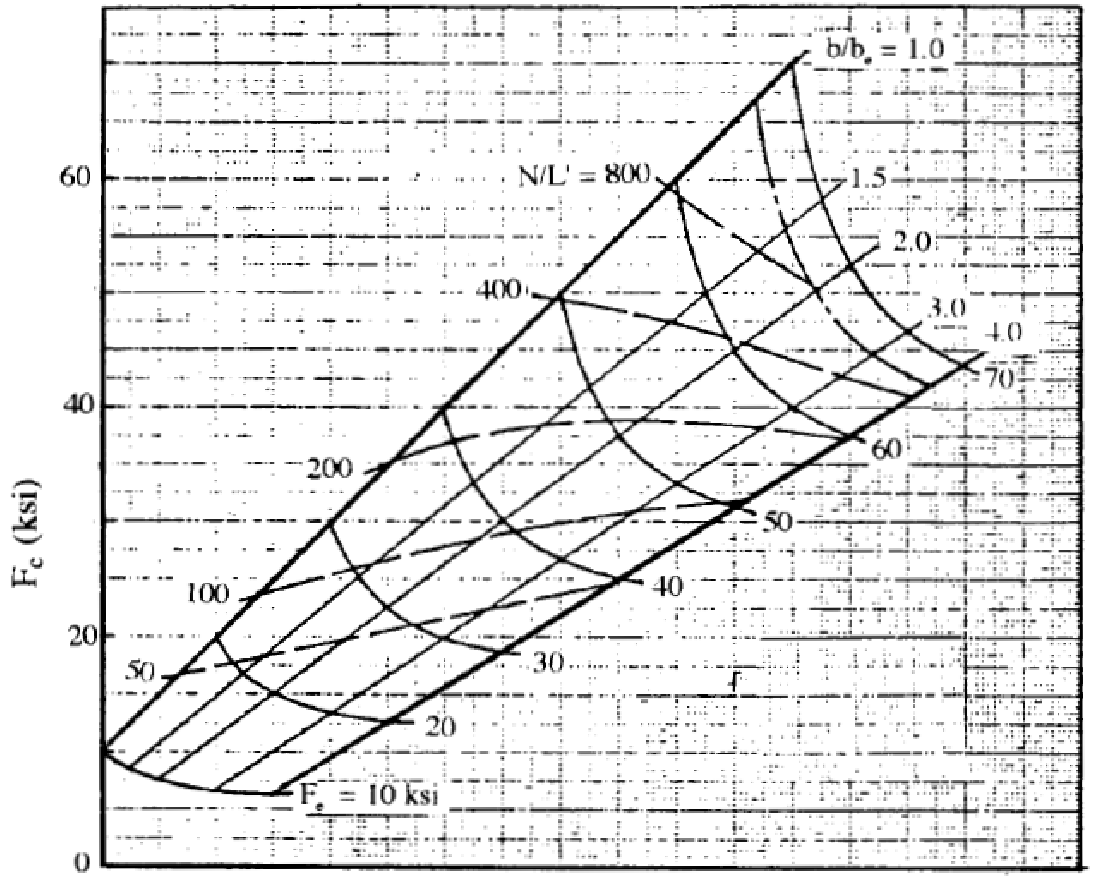



Fig 3-9:Design Curves for Stringer-Skin Panels ($\frac{A_{st}}{A_{sk}} = 1$)

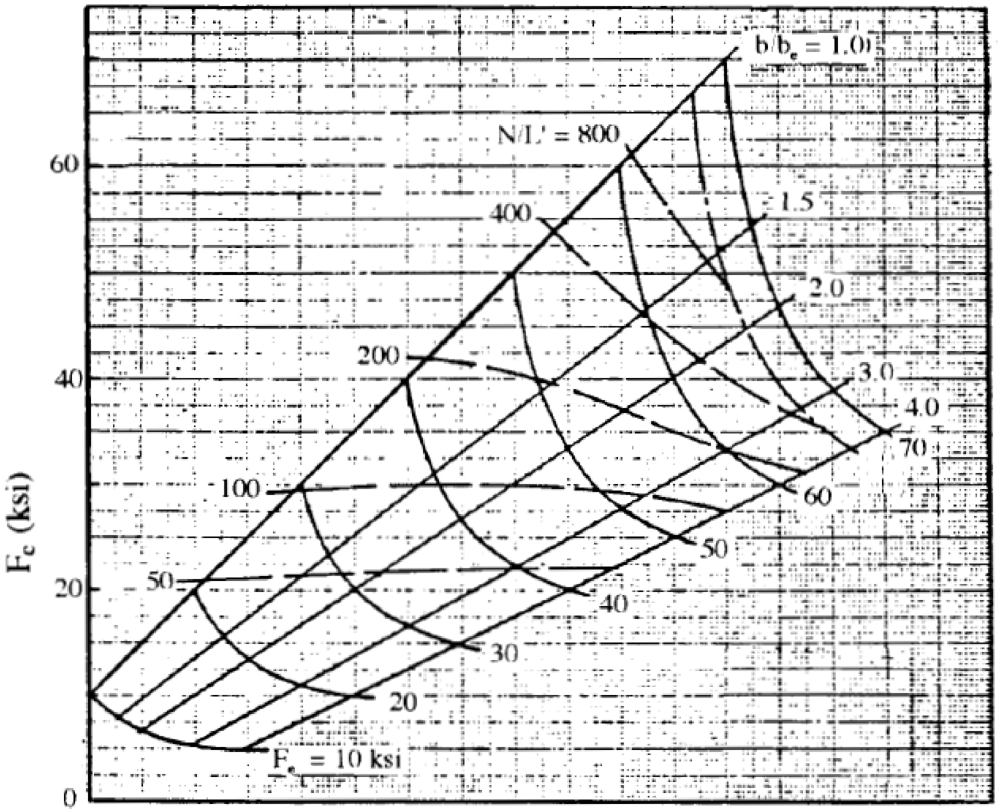



Fig 3-10:Design Curves for Integrally Stiffened Panels ($\frac{A_{st}}{A_{sk}} = 0.5$)

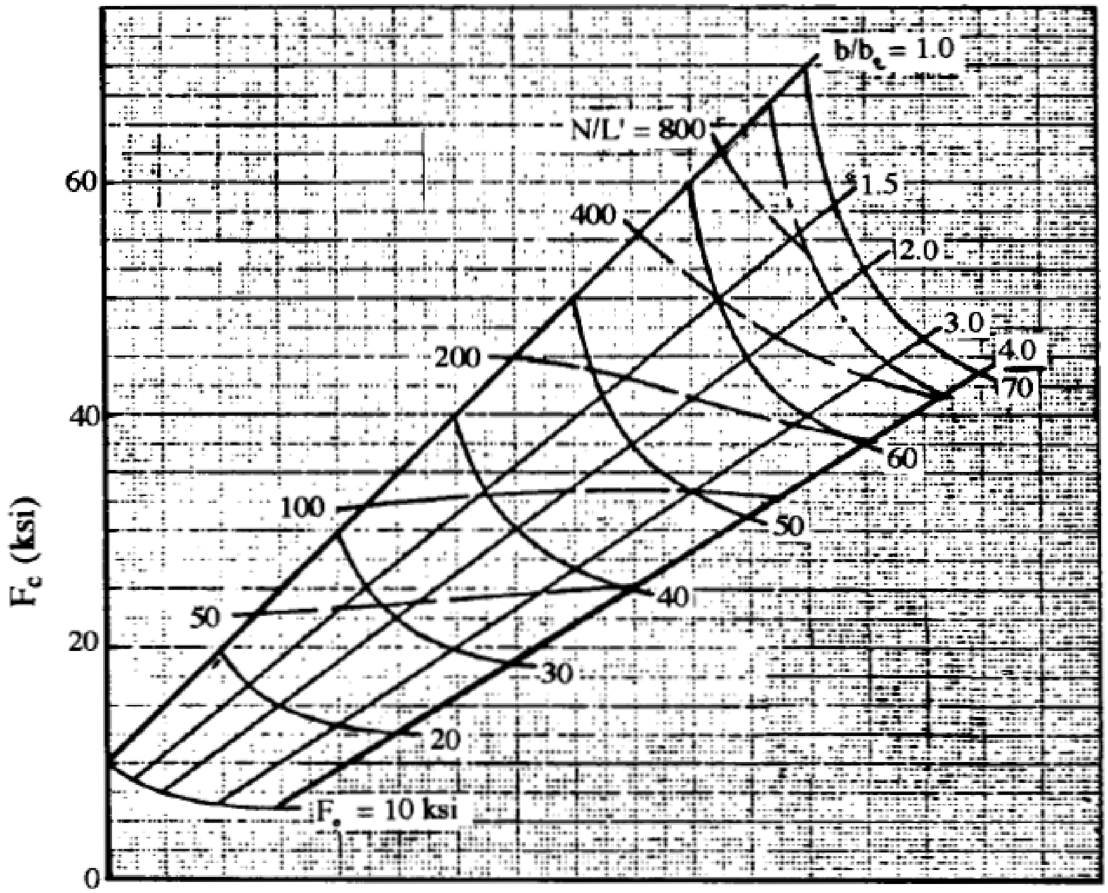



Fig 3-11:Design Curve .for Integrally Stiffened Panels ($\frac{A_{st}}{A_{sk}} = 1$)

$\frac{b}{b_e}$ is also identified from the same plots and further on these calculations are done:

$$t = \frac{N\left(\frac{b}{b_c}\right)}{F_c\left[1 + \left(\frac{A_{st}}{A_{sk}}\right)\left(\frac{b}{b_c}\right)\right]}$$

$$t_a = 0.7t$$

$$A_{st} = \left(\frac{A_{st}}{A_{sk}}\right)(bt)$$

$$b_w = \left[\left(\frac{b_w}{t_w}\right)\left(\frac{A_{st} - 2b_a t_a}{1.327}\right)\right]^{\frac{1}{2}}$$

$$\left.\begin{array}{l} t_w = \frac{b_w}{\frac{b_w}{t_w}} \\ b_f = 0.327 \times b_w \\ t_f = t_w \end{array}\right\}\text{all from the figure given below}$$

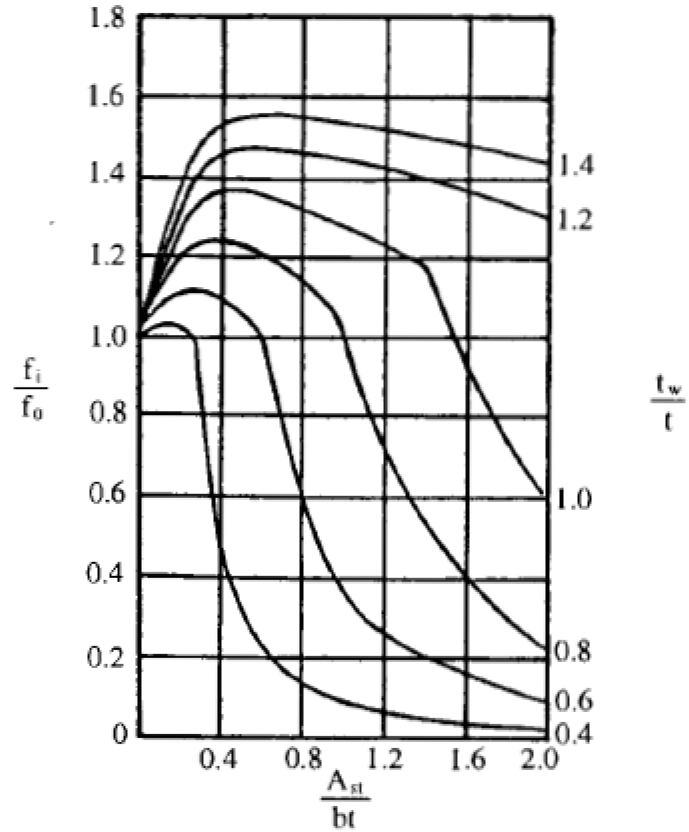



Fig 3-12:Initial Buckling Stress of a Skin-Stringer Panel

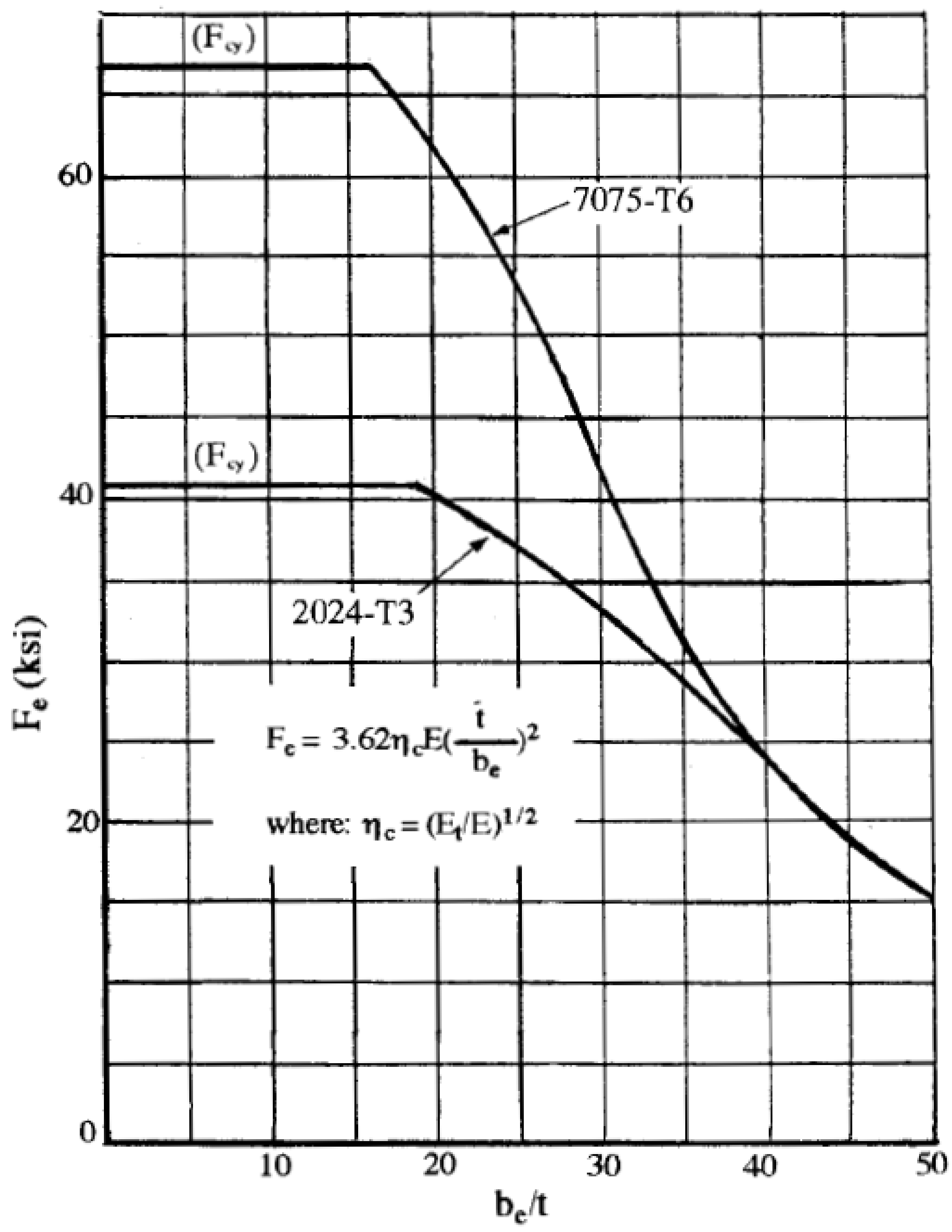



Fig 3-13:Effective Width for 2024 and 7075 Skins

$$b_e = \left(\frac{b_e}{t}\right) t$$

The ratio $\frac{b_e}{t}$ is found from the figure above and $b_e$ is found out, the next step is to find out $t_a$ using the figure below:

| Elements | Design practice |
|---|---|
| $\frac{b_a}{t_a}$ | 10 or less |
| $\frac{b_w}{t_w}$ | 18 – 22 |
| $\frac{b_f}{t_f}$ | 6 – 8 |
| $\frac{A_{st}}{A_{sk}}$ | 0.5 |
| $t_a$ | 0.7t |
| $\frac{b_f}{b_w}$ | 0.4 |

Fig 3-14:Practical Dimensions

After this The above optimum element dimensions are then checked against the practical Dimensions and then shown on a schematic diagram as shown below:

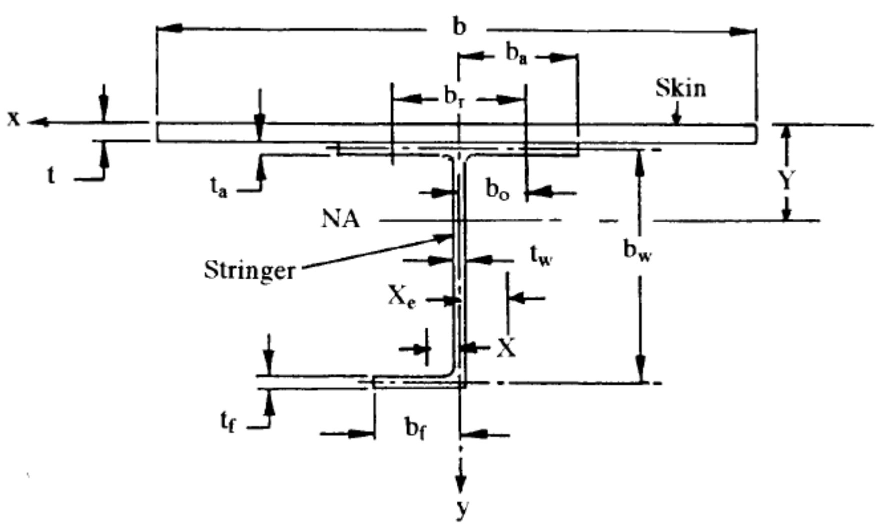



Fig 3-15:Panel Geometry configuration

### 3.2.2 Step 2: Effective width of the skin (be) and panel section properties:

Rivet spacing is calculated using the decided diameter of the fastener and furthermore edge distance is calculated by using the formula and further calculations are done:

$$e = 2d + \frac{1}{16}$$

Rivet spacing is calculated:

$$\mathrm{b_r} = 2 \times \mathrm{b_o}$$

Total Effective width is given by:

$$b_e{}' = b_e + b_r$$

Furthermore, all Panel section properties are calculated including A, Y, $I_{xx}$, $\rho_{xx}$,L',$\frac{L'}{\rho_{xx}}$ and hence crippling stress is calculated:

$$\mathrm{F_{cc}} = \frac{\sum \ \mathrm{b_n t_n \ F_{ccn}}}{\sum \ \mathrm{b_n t_n}}$$

And then the Colum Buckling Allowable Panel load is calculated using:

$$\mathrm{N_{all}} = \frac{\mathrm{F_c \ A}}{\mathrm{b}}$$

### 3.2.3 Step 3: Checking Plasticity Correction factor

$$£ = \frac{\pi^2}{\left(\frac{L'}{\rho_{xx}}\right)^2}$$

Furthermore, we calculate the ratio again and see our design margins by comparing the critical stress values.

$$\frac{A_{sk}}{A_{sk} + A_{st}}$$

New total effective width is found out and all the steps are repeated until the value of allowable load is conserved.

### 3.2.4 Step 4: Panel Beam Column Bending (up-bending)

Firstly, the arbitrary value of $f_c$ is assumed and using the section properties in Step 2 the total axial load is found.

$$P = f_c \times A$$

After this Poisson's ratio is calculated.

$$\mu_{\mathrm{T}} = \frac{\mathrm{PL}^2}{\mathrm{E_t I_{xx}}}$$

The next step is to input fixity factor and then calculate moment.

$$M = \mathrm{w_0\ L^2}$$

After this the bending compression stress is calculated using:

$$\mathrm{f_b} = \frac{\mathrm{MY}}{\mathrm{I_{xx}}}$$

The maximum compression stress (in skin) is given by:

$$\mathrm{f_c + f_b}$$

In case this total is greater than the allowable stress calculated before, all the steps pf Step 4 are repeated until it is within the design parameter. Different iterations are made, assuming different values for $f_c$.

### 3.2.5 Step 5: Panel Beam Column Bending (down-bending)

Assume $\mathrm{f_c = F_{b,c'}}$ [calculated in Step 4 and put this equal to the allowable panel beam-column between supports for which the take the tangent modulus, $\mathrm{E_t}$ of plate (skin) from Figures used before and set $f_c = F_c$. Panel section properties (full skin width, b and others) from Step 2.

Again, find out the total axial load.

$$P = f_c \times A$$

After this Poisson's ratio is calculated.

$$\mu_T = \frac{PL^2}{E_t I_{xx}}$$

The next step is to input fixity factor and then calculate moment.

$$M = w_0 \, L^2$$

The bending compression stress (in stringer outstanding flange) is:

$$f_b = \frac{M(bw - Y)}{I_{xx}}$$

The compression stress (critical in stringer outstanding flange) given by,

$$f_c + f_b$$

Is calculated and compared to the crippling stress from step 2, if it's close and lies within the design range, no further iterations are required.

### 3.2.6 Step 6: Final summary

The allowable load taken is the lowest load as determined from Step 2 through Step 5. The maximum compression stress [from Step 4] is the most critical case which is in the skin (t) of the panel center span with the given transvers loading, acting on it.

The allowable load must lie within the given limitation of load, if it doesn't then the calculations are to be repeated.

In actual design, these values would be considered together with local shear stress in the skin and then the allowable stress is calculated,

### 3.3 CURVED PANEL DESIGN PROCESS

Some values such as cabin pressure, fuselage axial compression stress on stringer, fuselage axial tension stress on stringer, fuselage skin shear flow, allowable fatigue stress, stringer length, stringer spacing and radius and then the thickness is calculated using the formula and material properties from the data tables as shown in the previous design process:

$$t_{\min} = \frac{\mathrm{pR}}{F_{fat}}$$

Use skin thickness, t calculated and determine the skin buckling stress $\mathrm{F}_{\mathrm{c,cr}}$ or $\mathrm{F}_{\mathrm{s},cr}$ using these equations:

$$\mathrm{F}_{c.cr} = \frac{k_c' \eta_{\mathrm{c}} \pi^2 \mathrm{E}}{12(1-\mu^2)} \left(\frac{\mathrm{t}}{\mathrm{h}}\right)^2$$

$$\mathrm{F}_{s.cr} = \frac{k_s' \eta_{\mathrm{c}} \pi^2 \mathrm{E}}{12(1-\mu^2)} \left(\frac{\mathrm{t}}{\mathrm{h}}\right)^2$$

$k_s'$and $k_c'$ are calculating using the following figures:

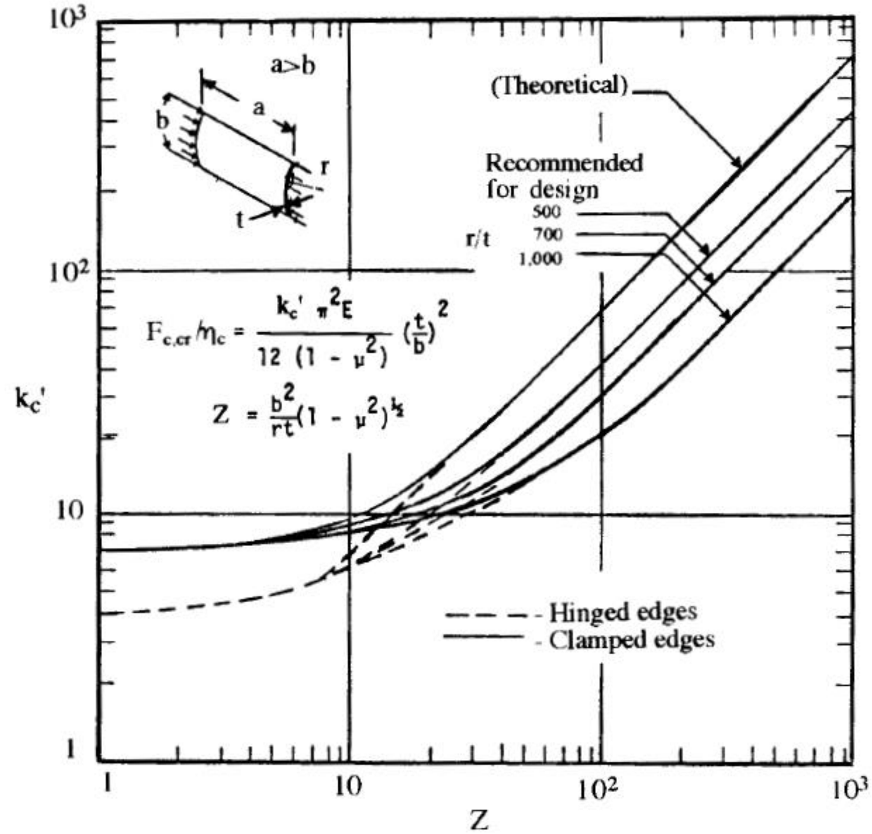



Fig 3-16:Curved Plate Coefficient kc'(Compression)

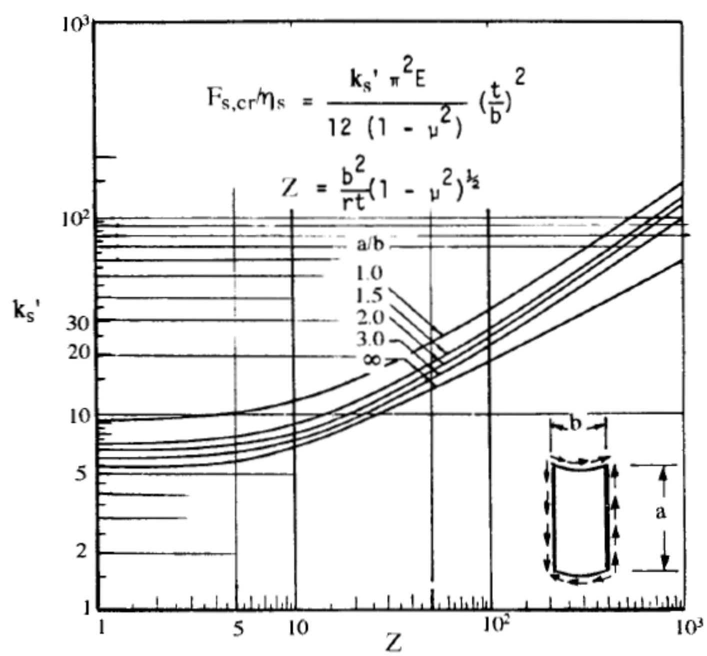



Fig 3-17:Long Curved Plate Coefficient K,' (Shear)- Four Edges are Hinged

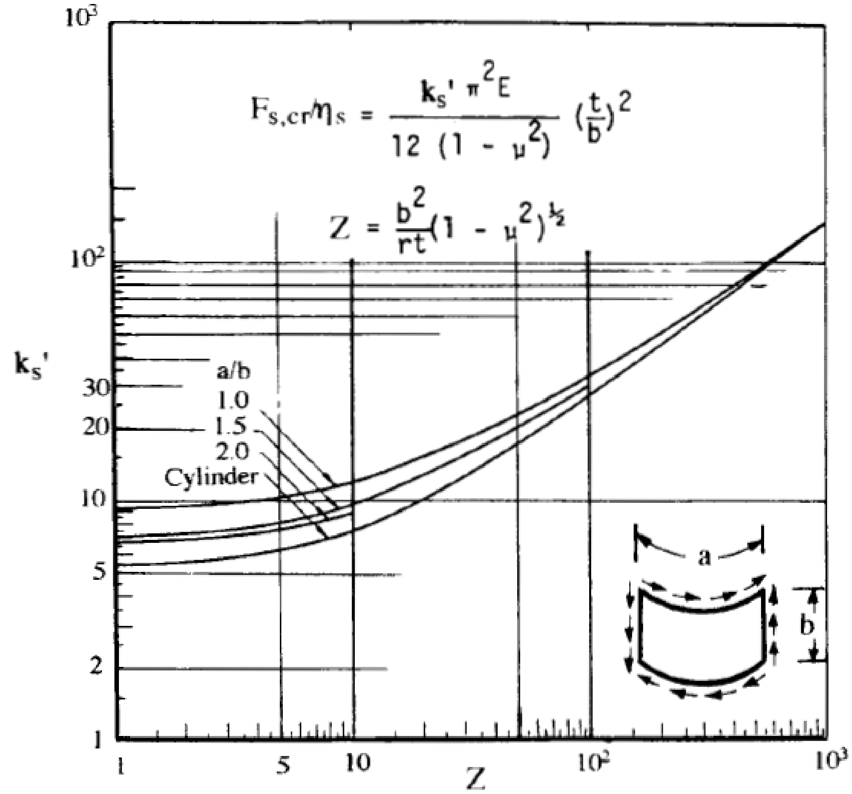



Fig 3-18:Wide Curved Plate Coefficient k.' (Shear) - Four Ec/1;es are Hinged

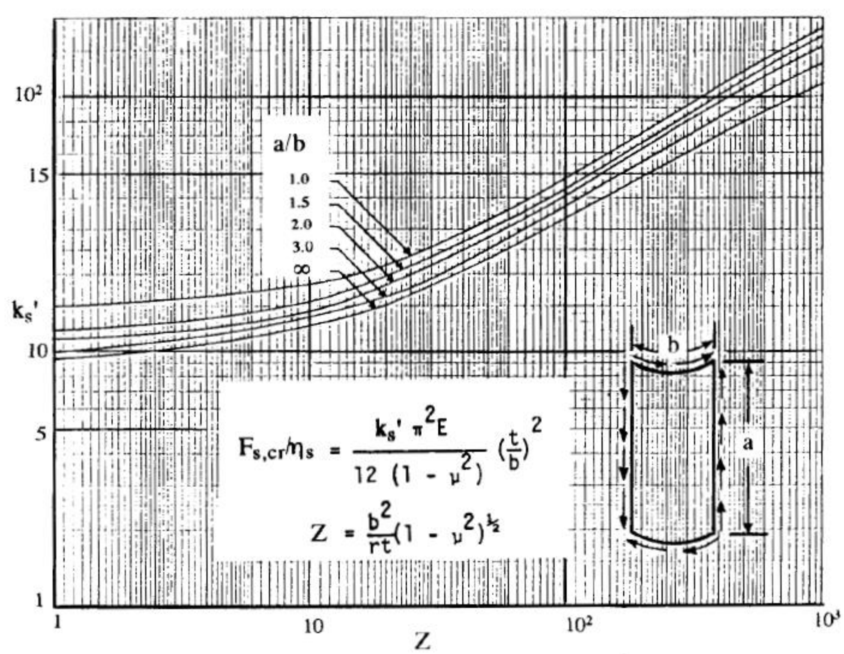



Fig 3-19:Long Curved Plate Coefficient K.: (Shear) - Four Edges are Clamped

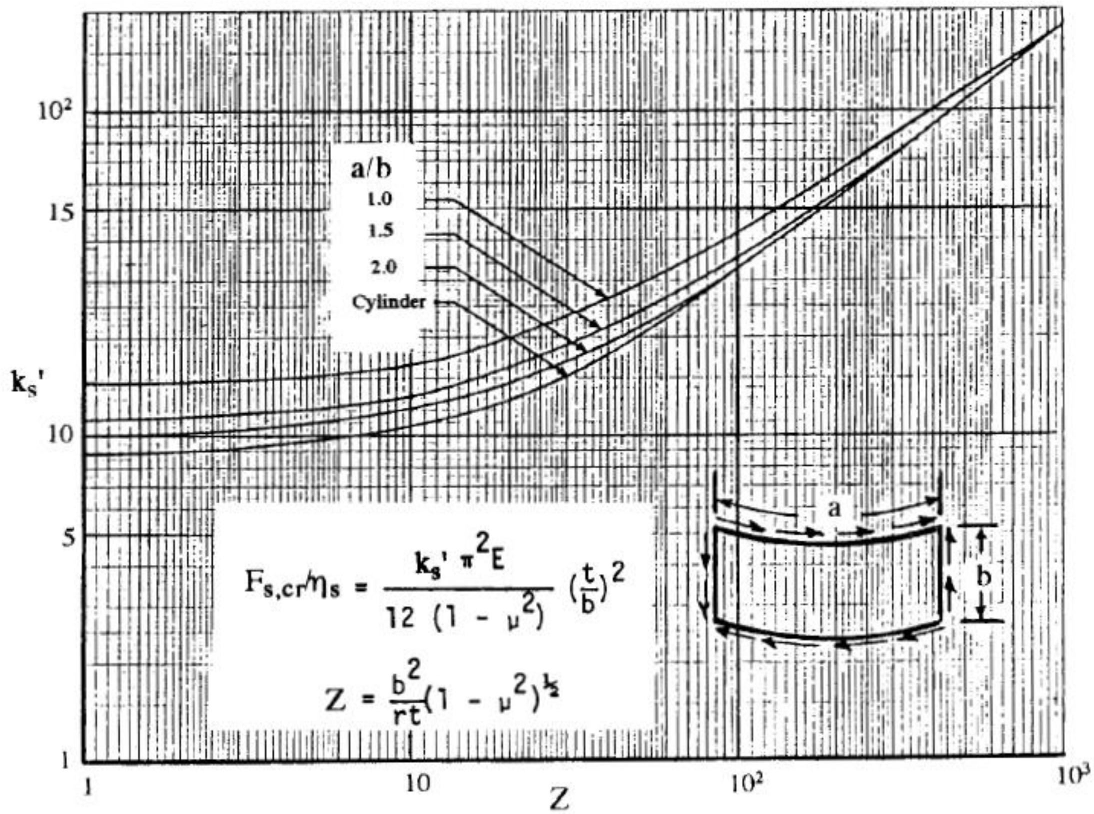



Fig 3-20:Wide Curved Plate Coefficient k,' (Shear)- Four Edges are Clamped

Find out Panel aspect ratio:

$$\frac{a}{b} = \frac{d}{h}$$

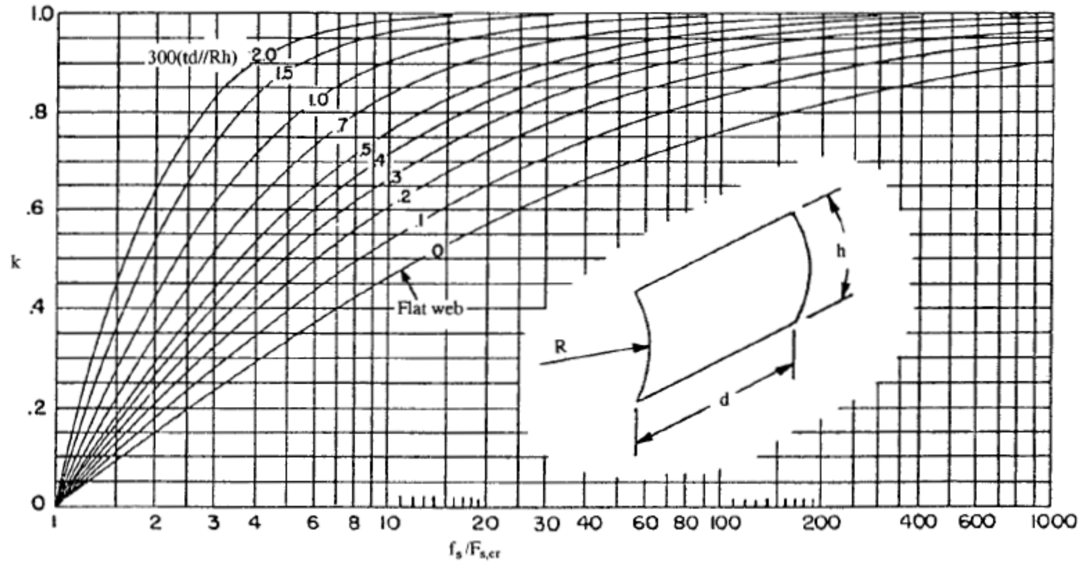
Determine the reduced skin shear buckling stress $F'_{s,cr}$ due to axial compression stress $f_c$

$$A = \frac{F_{c,cr}}{F_{s,cr}}$$

$$B = \frac{f_c}{f_s}$$

$$F'_{s,cr} = F_{s,cr} R_c$$

The diagonal tension factor (k) for curved skin can be found from the figure below:




(If h > d, replace $\frac{td}{Rh}$ by $\frac{th}{Rd}$; if $\frac{d}{h}$ or $\frac{h}{d} > 2$, use 2)

Fig 3-21:Diagonal Tension Factor, k

$$\frac{f_s}{F'_{s.cr}}$$

Find the allowable shear stress $(F_{s,all})$

Assume the angle of diagonal tension $\alpha = 45°$ (to be checked later) with $k$ from Figure given below obtain:

$$\frac{A_{st}}{ht}$$
$$\frac{A_{fr}}{dt}$$

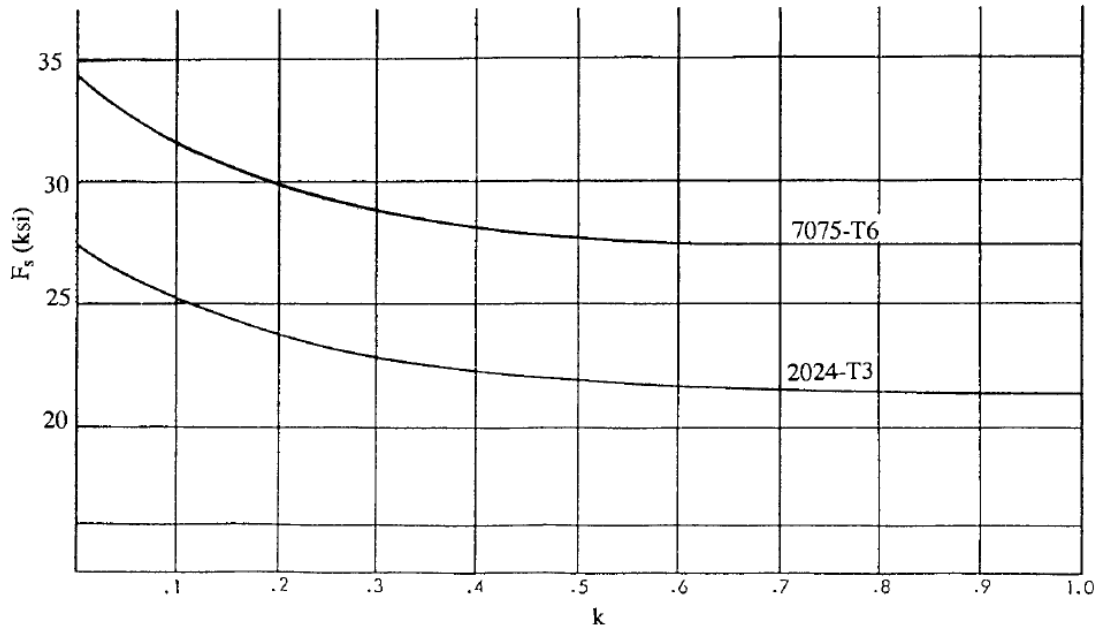



Fig 3-22:Allowable Maximum Web Stress

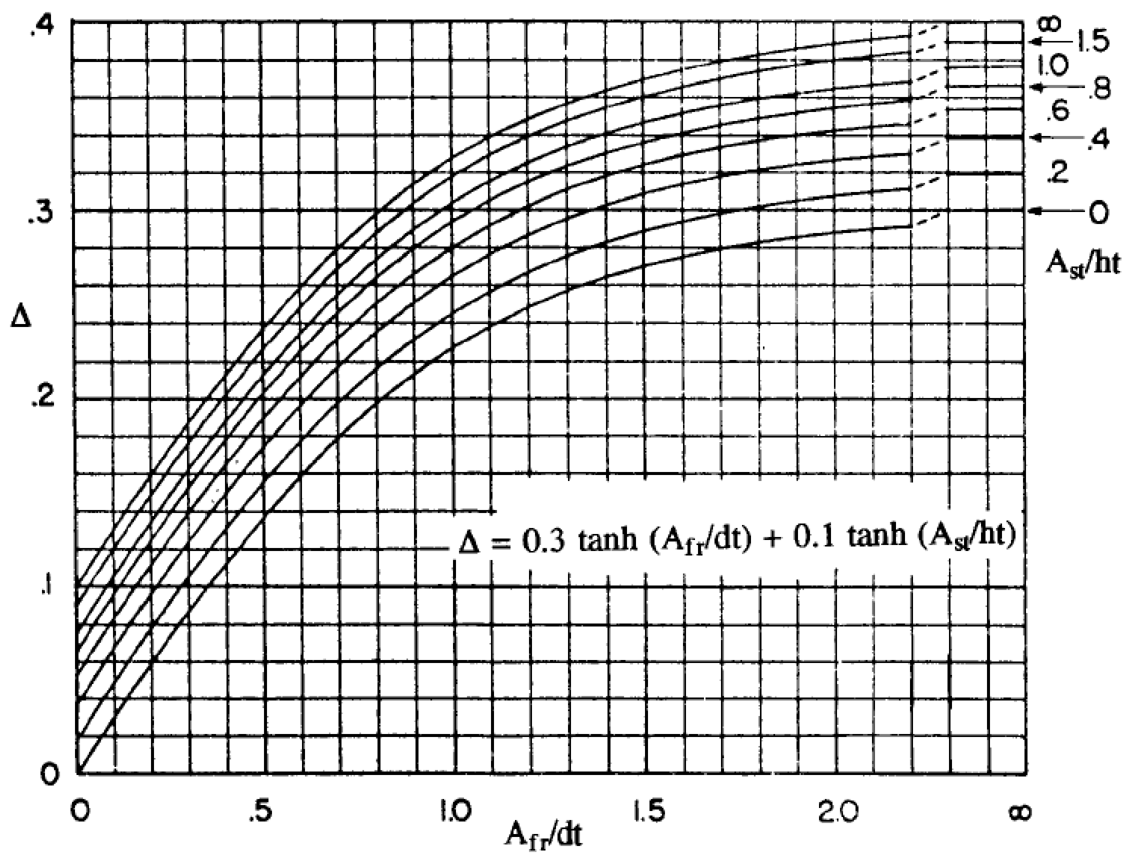



Fig 3-23:Correction for Allowable Ultimate Shear Stress in Curved Skin

Correction factor is determined using:

$$\Delta = 0.3 * \tanh(\mathrm{Afr} / \mathrm{dt}) + 0.1 * \tanh(\mathrm{Ast} / \mathrm{ht})$$

$$\mathrm{F_{s,all}} = \mathrm{F}_s(0.65 + \Delta)$$

Then we calculate:

$$\mathrm{MS} = \frac{\mathrm{F_{s,all}}}{\mathrm{f_s}}$$

To get Stringer and frame stress assume an angle of diagonal tension,

$\alpha = 45°$, Average stringer stress from Equation:

$$\mathrm{f}_{st} = \frac{-kf_s\cot\ \alpha}{\frac{\mathrm{A_{st}}}{\mathrm{ht}} + 0.5(1-k)(\mathrm{R_c})}$$

Average frame stress ( $\mathrm{f_{fr}}$ ) from Equation (this is a shear-tie frame):

$$f_{fr} = \frac{-kf_s\tan\ \alpha}{\frac{A_{fr}}{ht} + 0.5(1-k)}$$

Now to calculate Diagonal tension angle ( $\alpha$ ), we calculate stringer and frame strains:

$$\varepsilon_{\mathrm{sk}} = \left(\frac{f_{\mathrm{s}}}{E_{\mathrm{sk}}}\right)\left[\frac{2\mathrm{k}}{\sin\ 2\alpha} + \sin\ 2\alpha(1-k)(1+\mu)\right]$$

From Equation

$$\varepsilon_{st} = \frac{f_{st}}{E_{\mathrm{st}}}$$

And From

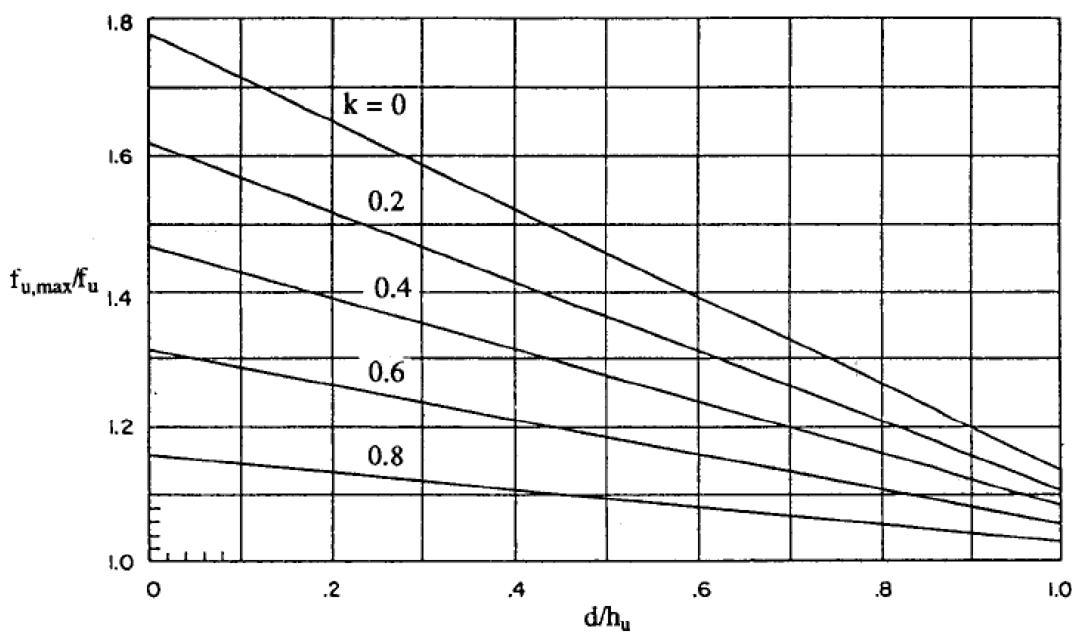
$$\varepsilon_{fr} = \frac{f_{fr}}{E_{fr}}$$

The $\alpha$ values are defined in the equation below (for $d > h$ ) as below:

$$\tan^2 \alpha = \frac{\varepsilon_{sk} - \varepsilon_{sl}}{\varepsilon_{sk} - \varepsilon_{fr} + \frac{1}{24}\left(\frac{h}{R}\right)^2}$$

If The angle of diagonal tension reasonably agrees with the assumed $\alpha = 45°$; the calculation is complete, if not the process is to be repeated.

Now we calculate the Stringer stress By entering k, $\frac{h}{d}$ into the curves in Figure below:




**Note:** For use on curved webs:
For ring, read abscissa as $\frac{d}{h}$; for stringer, read abscissa as $\frac{h}{d}$.

Fig 3-24:Ratio of Maximum to Average Stiffener Stress

Let $\left(\frac{f_{u,\max}}{f_u}\right) f_u = \left(\frac{f_{st,\max}}{f_{st}}\right) f_{st}$ and use Equation below to obtain the maximum stringer stress ( $f_{st,max}$ ):

$$\left(\frac{f_{st,\max}}{f_{st}}\right) f_{st}$$

No Secondary bending moment ($M_{st}$) on stringers between frames is obtained from:

$$M_{st} = \frac{kf_s htd^2 \tan\ \alpha}{24R}$$

The stringer bending stress (compression on the stringer outstanding flange which does not attach to the skin) at frames:

$$f_{st} = \frac{M_{st}(b' - Y')}{I_x}$$

The stringer bending stress (compression on skin) between frames (at center span):

$$f_{st} = \frac{M_{st} Y'}{I_x}$$

After this Stringer forced crippling stress is calculated using:

$$F_{cc} = \frac{\sum\ b_n t_n\ F_{ccn}}{\sum\ b_n t_n}$$

The lip section is checked using the figure:

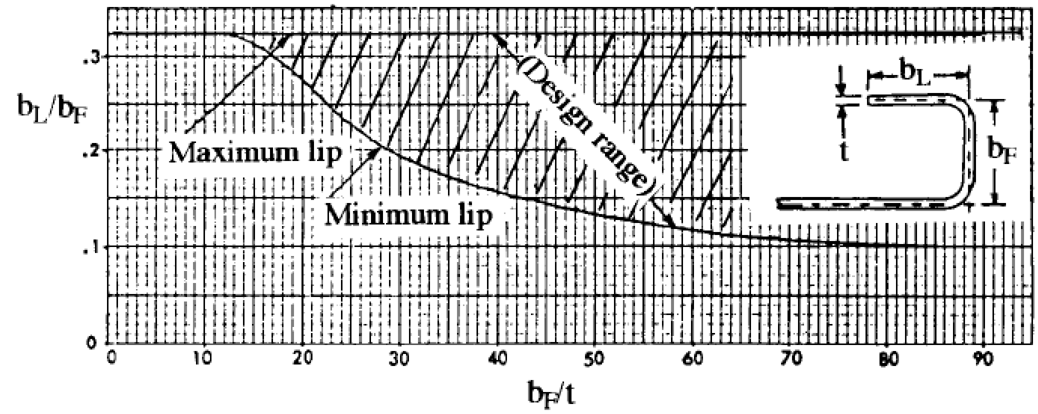



Fig 3-25:Lip Criteria for Formed Sections

Now the crippling stress is calculated using the $\frac{t_{st}}{t_w}$ ratio anf comparing value from the figure given below:

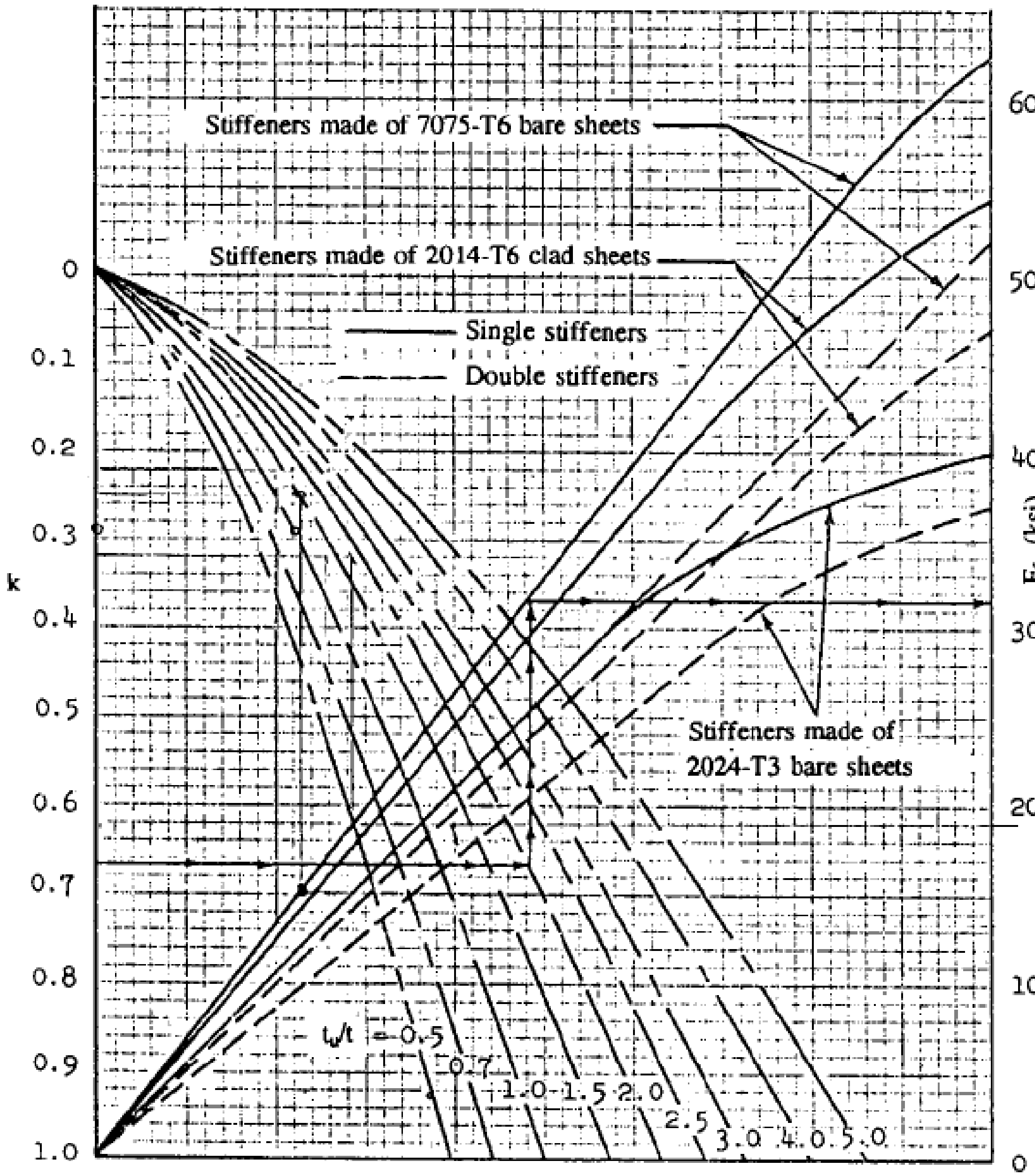



Fig 3-26: Allowable Forced Crippling Stress of Stiffeners

Now obtain Allowable compression stress (Fc,) of the stringer from the material properties and comparison.

Use the interaction equation:

$$MS = \frac{1}{\frac{f_c + f_{sb}}{F_{cc}} + \frac{f_{st,max}}{F_{l,st}}} - 1$$

For stringer column failure:

$$MS = \frac{1}{\frac{f_c + f'_{sb} + f_{st}}{F'_{cc}}} - 1$$

Now, between frames (mid-span of the stringer)

$$MS = \frac{1}{\frac{f_c + f_{sb} + f_{st}}{F_c}} - 1$$

MS (margin of safety) should be close to 0, if MS=0 , the FOS (Factor of safety) is maintained.

Similar pattern is followed by calculating frame stresses, with the loads and properties of frames.

Such is the schematic diagram for curved stiffened panel:

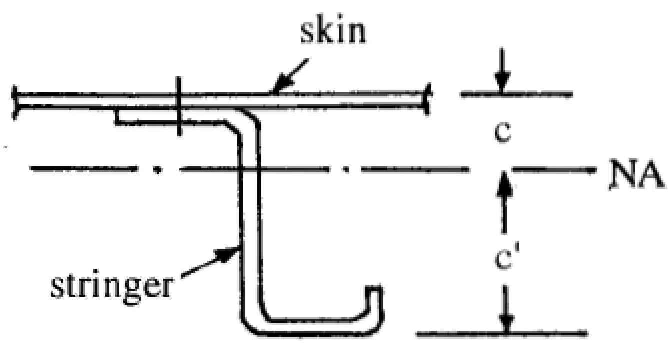



Fig 3-27:Curved Panel Geometry

## 3.4 CODE DEVELOPMENT FOR THE DESIGN PROCESS

The complete design process was automated by developing the codes of the process and calculations in the python language, PyCharm was the interface used. The codes are attached in the appendix at the end of the thesis.

## 3.5 TOOLS, MATERIALS, AND DATASETS

### Programming Environment

Language: **Python**

Libraries:

1. NumPy, Pandas – Data manipulation
2. Scikit-learn – Machine learning algorithms
3. Matplotlib/Seaborn – Visualization
4. SciPy – Structural calculation (buckling, interpolation)
5. JSON, Datetime, OS – Data formatting, export

### Datasets Used

**Flat Panel Dataset (sp.csv)**

Generated using a structured sampling of:

1. Skin, stringer, and frame thicknesses
2. Load inputs (axial load, pressure)

3. Material combinations

4. Output parameters include margins of safety, buckling stress, section geometry and properties.

**Curved Panel Dataset (curvedData.csv)**

Generated using extended formulations:

1. Includes curvature-dependent geometric effects

2. Uses shell-theory-based stress analysis

3. Same format as flat panel data but includes radius of curvature or equivalent arc parameters.

Each dataset contains **hundreds to thousands of rows**, each representing a unique structural configuration. Data was generated using a combination of analytical scripts and **Latin Hypercube Sampling (LHS)** for better coverage of the input space.

## 3.6 DESIGN PROCESS AND DATA GENERATION (FLAT AND CURVED PANELS)

The design pipeline includes multiple custom Python scripts that simulate realistic panel behavior using the following structure:

**(a) Helper Functions (Used in Both Cases)**

generate_thickness_values () – defines acceptable ranges for skin, stringer, and frame thickness.

generate_material_combinations () – defines valid combinations of alloy, form (sheet, extrusion), and heat treatment (temper).

is_valid_material_thickness_combination () – filters impractical or non-manufacturable combinations.

run_single_analysis(params) – core design function that performs all calculations:

1. Buckling stress (Euler, empirical)
2. Crippling loads
3. Section modulus and area
4. Margins of safety (MS)
5. Material check and validation

**(b) Panel-Specific Design Logic**

**Flat Panels**:

Geometry is assumed to be rectangular.

Loads: uniformly distributed surface pressure + axial load.

Buckling calculations use:

Flat panel buckling equations (e.g., $\sigma\_cr = k * \pi^2 * E / (12(1-\nu^2)) * (t/b)^2$)

Effective width methods for stringer spacing

Valid results stored with margin-of-safety filters.

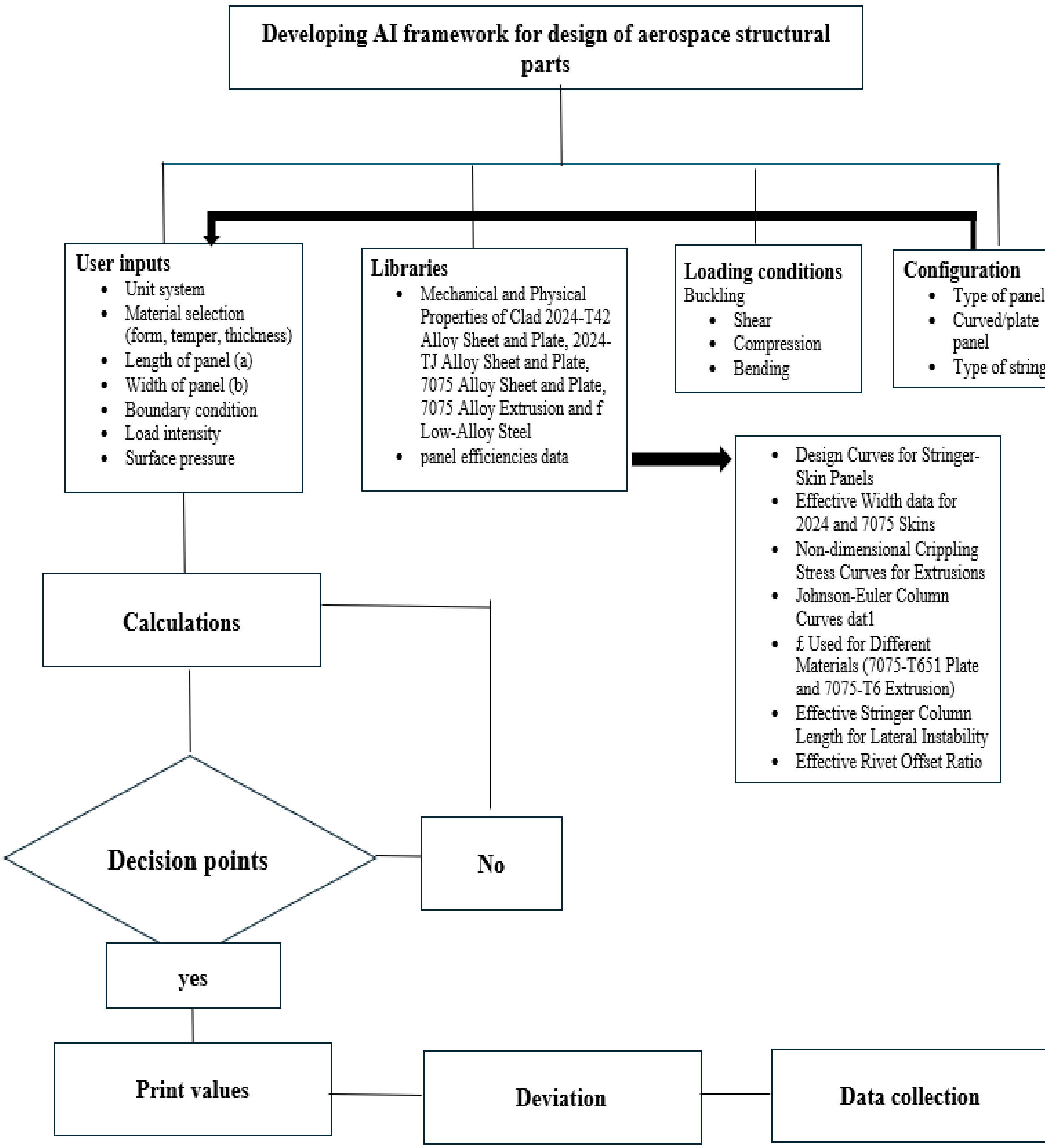



Fig 3-28:Basic Code flowchart

## Code Flow:

```
START
  |
  v
1. Imports & Globals (set excel_filename, kc_data,
   material_specifications, panel_efficiency_data, etc.)
  |
  v
2. Define Helper Functions (get_value_from_data_row, parse_thickness,
   parse_force_input, parse_surface_pressure, parse_load_intensity,
   get_panel_dimensions, select_material/temper/form,
   extract_material_properties, force_set_material_properties,
   select_boundary_condition, linear_interpolation, extract_kc,
   calculate_fcr_or_fcy, select_stringer_type, panel_interpolation
   routines, section-property routines, etc.)
  |
  +-----------------------------+
  v                             v
thickness_array_handler() -->| main(skip_excel_save=False)
  ^                             ^
  |                             |
  |                          Work through:
  |                         a) get_stringer_properties
  |                         b) parse_thickness (skin)
  |                         c) select_material/temper/
  |                            form / extract_material
  |                         d) get_panel_dimensions
  |                         e) parse_load_intensity
  |                         f) parse_surface_pressure
  |                         g) select_boundary_condition
  |                         h) calculate_fcr_or_fcy
  |                         i) select_stringer_type
  |                         j) compute_stringer_dimensions
  |                         k) find_solution_for_exact_NL
  |                         l) calculate_thickness
  |                         m) calculate be/t, be, ta, b, …
  |                         n) calculate neutral axis 2
  |                         o) check_against_design_guidelines
  |                         p) beam-column & down-bending
  |                         q) optimize_panel_design twice
  |                         r) compute fastener & rivet geom.
  |                         s) calculate_number_of_stringers
  |                         t) IF skip_excel_save==False:
  |                              log_row_to_excel(data_row)
  |                         u) return data_row
  |
  +--> After each call to main(skip_excel_save=True) inside thickness_array_handler:
       • Append metadata (iteration number, indices, thicknesses)
       • all_data_rows.append(data_row)

9. After all loops: Write all_data_rows to Excel (log_row_to_excel)
   Restore original functions & input(), print "PROCESSING COMPLETE"
  |
  v
END
```

Fig 3-29:Flat panel code flow

**Curved Panels**:

Geometry includes curvature (e.g., arc or cylindrical segment).

Additional parameters:

Radius of curvature

Arc length

Radial stress

Curved panel buckling formulations are applied:

Shell theory–based σ_cr_cyl = C * E * t / R * sqrt (1 - ν²)

Tangential and radial stiffness integration

Analysis includes curvature-induced stiffness benefits or penalties.

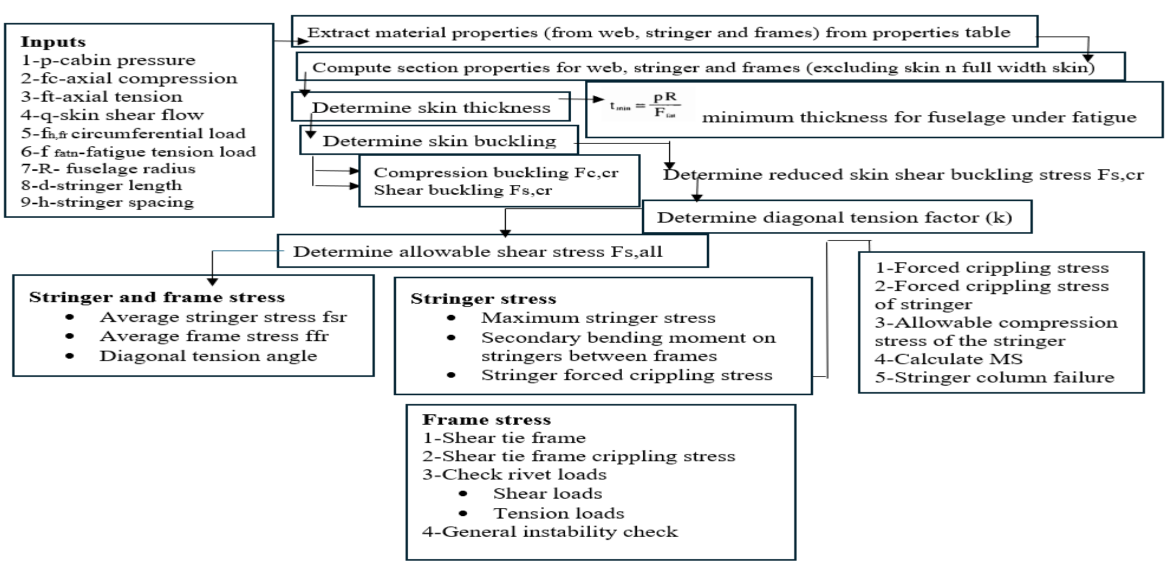



Fig 3-30:Curved panel Code

**Code flow**

```
START

  |
  ▼

1) IMPORTS & GLOBAL DATA SETUP
   - math, numpy, scipy.interpolate, matplotlib,
     itertools, pandas, datetime, json,
     scipy.optimize.curve_fit, etc.
   - Load or define any "lookup" tables (material
     properties, buckling curves, etc.) as Python
     dictionaries or DataFrames.

  |
  ▼

2) HELPER FUNCTION DEFINITIONS

• is_valid_material_thickness_combination(params)
    - Verifies if (material, form, temper, thickness)
      satisfy practical bounds (e.g., gauge, ratios).

• create_failure_record(params, reason, partial_results)
    - Builds a dict with "valid: False" plus metadata,
      capturing why an analysis failed.

• generate_thickness_values()
    - Returns a list/array of feasible thickness tuples
      (skin, stringer, frame).

• generate_material_combinations()
    - Returns a list of all possible (material, form,
      temper) combinations for web, stringer, frame.

• run_single_analysis(params, vary_geometry=False)
    - Performs one complete panel analysis:
      ◦ Input unpacking (thicknesses, materials,
        geometry)
      ◦ Check is_valid_material_thickness_combination
      ◦ Compute geometry-dependent buckling stresses,
        crippling stresses, margins of safety, etc.
      ◦ If any step fails → create_failure_record()
      ◦ If successful → return a "results" dict with
        all computed outputs ("valid: True", stresses,
        MS values, section properties, etc.)

• Optionally:
  - generate_geom_variations(base_params)
    • Creates small perturbations on a base (skin,
      stringer, frame) set to explore geometry space.

• (Other utility routines used inside run_single_analysis):
  - normalize_margin_of_safety(MS)
  - compute_section_properties(...)
  - check_buckling_and_crippling(...)
  - curve_fit_wrappers (for fitting empirical curves)
  - etc.
```

```
3) GENERATE_TRAINING_DATA(n_samples, output_file,
      vary_geometry, include_failures)

  3.1) PRINT "Generating X samples…"

  3.2) thickness_values = generate_thickness_values()
       material_combos  = generate_material_combinations()
   PRINT counts for debugging.

  3.3) INITIALIZE:
       results = []       # will hold all sample dicts
       successful = 0      # count of valid samples
       failed = 0          # count of failed samples
       attempts = 0        # total tries so far
       lhs_index = 0       # index through LHS samples

   lhs_samples = LatinHypercubeSampling(…)  # yields
                  # a list of "param dicts" with
                  # (skin_thickness, stringer_thickness,
                  #  frame_thickness, plus random pick
                  #  of material combination).

  3.4) WHILE successful < n_samples:
       attempts += 1

       3.4.1) IF lhs_index < len(lhs_samples):
                params = lhs_samples[lhs_index]
                lhs_index += 1
              ELSE:
                BREAK   # No more LHS points available

       3.4.2) UNPACK params:
               skin_t   = params["skin_thickness"]
               stringer_t = params["stringer_thickness"]
               frame_t = params["frame_thickness"]
               material_info = params["materials"]

       3.4.3) IF NOT
               is_valid_material_thickness_combination
               (skin_t, stringer_t, frame_t):
             failed += 1
             IF include_failures:
               rec = create_failure_record(params,
                   reason="Invalid thickness combo")
               results.append(rec)
             CONTINUE  # skip to next iteration
```

```
3.4.4) IF vary_geometry is True:
     geom_list = generate_geom_variations(params)
   ELSE:
     geom_list = [params]
```

```
3.4.5) FOR each "param_set" in geom_list:

     3.4.5.1) TRY:
          result_dict = run_single_analysis(param_set)
          - Compute all stresses, section props, MS
            buckling checks, etc. If ANY internal
            step raises an exception or yields invalid,
            it will be caught below.

     3.4.5.2) EXCEPT Exception as e:
          failed += 1
          IF include_failures:
            rec = create_failure_record(param_set,
                reason=str(e),
                partial_results=None)
            results.append(rec)
          CONTINUE to next param_set

     3.4.5.3) IF result_dict["valid"] == False:
          failed += 1
          IF include_failures:
            results.append(result_dict)
          CONTINUE to next param_set

     3.4.5.4) ELSE (valid result):
          successful += 1
          results.append(result_dict)
          IF successful >= n_samples:
            BREAK out of BOTH loops
```

```
3.4.6) IF successful >= n_samples:
     BREAK out of WHILE loop
```

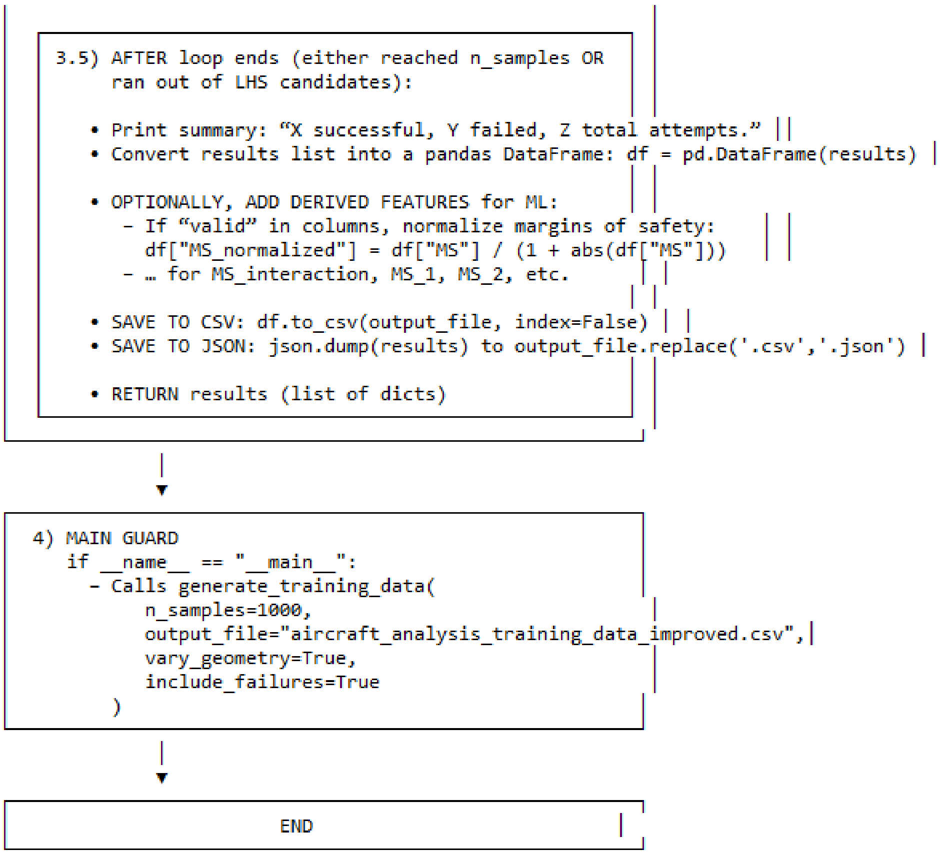



Fig 3-31:Curved Panel code flow

## 3.7 AI MODEL TRAINING AND PREDICTION

Each output is predicted using **individual Random Forest Regressor models**, due to the differing nature of each target variable.

1. **Learns from patterns in real data:**

   The AI (Random Forest Regressor) analyzes how input parameters (lengths, pressure, load) relate to structural outputs in your historical dataset.

2. **Builds decision trees:**

   The Random Forest creates many decision trees during training. Each tree learns different rules or "if-then" splits to predict an output (e.g., thickness, stress, material type).

3. **Combines three predictions:**

   Instead of relying on one decision tree, it takes the average (or majority vote) across all trees for a more accurate and stable prediction.

4. **Adapts per output column:**

   For each engineering output (e.g., margin of safety, weight, material), the model customizes its learning, finding the best combination of the four input values to match that specific target.

5. **Make intelligent predictions:**

   When a user gives new input values, the AI quickly evaluates them against the patterns it has learned and predicts all target design parameters simultaneously — as if it's thinking through a learned engineering logic.

6. **Decodes technical terms:**

   If a prediction involves a label (like a material name), the model decodes it back to human-readable form, so the user gets understandable results.

7. **Responds instantly:**

After completing all predictions, the AI formats the output neatly into a structured response (JSON) and sends it back to the user interface — just like a smart assistant delivering calculated answers.

**Training Process:**

1. Clean dataset (remove nulls, invalids)
2. Encoding categorical values (LabelEncoder)
3. Split data into training/testing
4. Train one RFR model per output column
5. Evaluate performance via:
    - $R^2$ score
    - Mean Squared Error

**Prediction & Inference:**

1. User provides values for a, b, Axial loading intensity and transverse loading intensity.
2. The trained models return predictions for all outputs.
3. If any value is categorical (e.g., material), it's decoded back.

4. Results compiled into structured JSON.

## 3.8 APDL CODE GENERATION AND INTEGRATION

A major innovation of this framework is the **automatic generation of APDL (ANSYS Parametric Design Language) code**, allowing **direct geometry creation** without manual intervention.

**Flat Panels:**

The AI-predicted geometry (length, width, thickness) and material properties are converted into:

1. Key points
2. Areas
3. Material definitions
4. Element assignments

Script is written as .txt file compatible with ANSYS APDL.

No meshing or analysis performed is only geometry modeling.

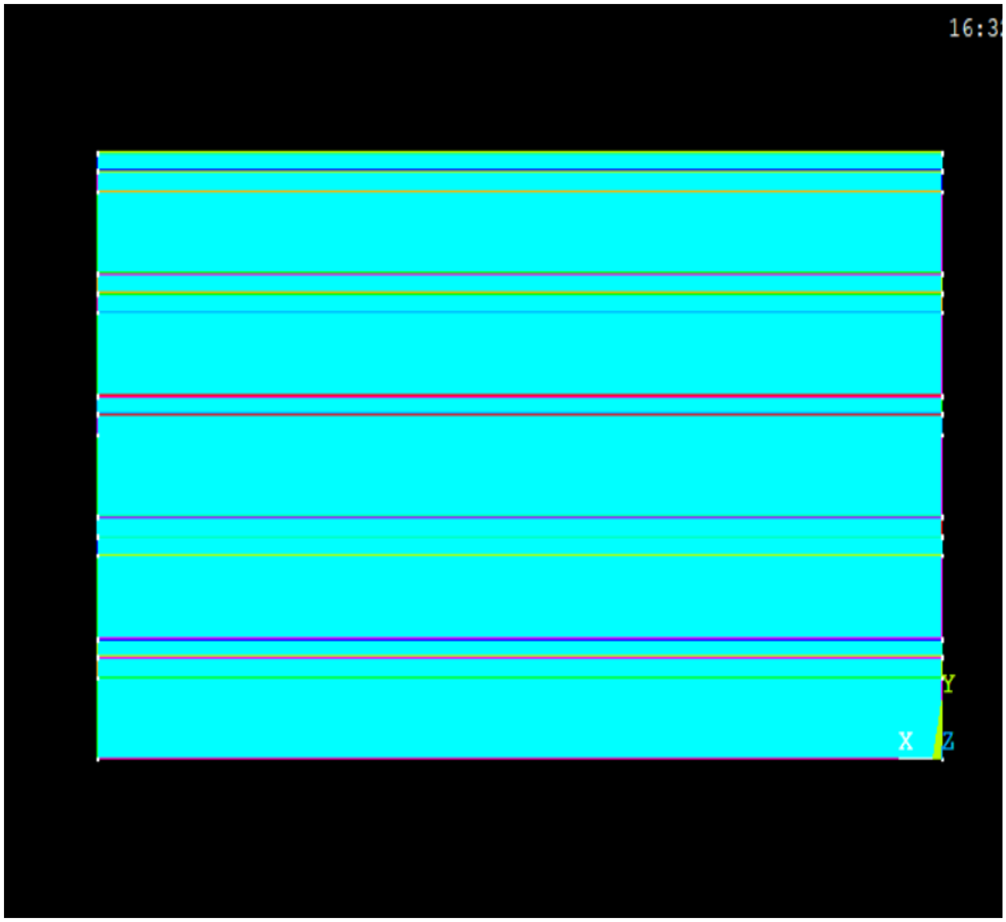



Fig 3-32:Flat panel APDL geometry

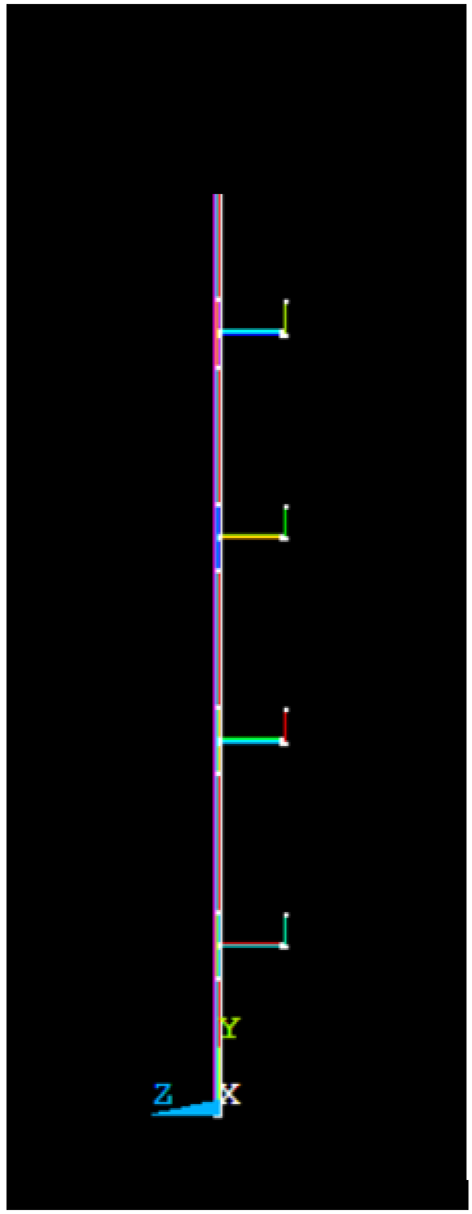



Fig 3-33:Flat panel APDL geometry (side view)

**Curved Panels:**

Includes:

1. Radius of curvature
2. Arc angle calculation
3. Key point adjustment to create curved shell
4. Stringers

Geometry is modeled using circular arcs, sweeping operations, and appropriate shell elements.

Allows visualization of the predicted structure inside ANSYS Mechanical APDL.

The APDL scripts are saved and can be run directly to **generate the panel geometry in seconds**, replacing traditional CAD drawing steps.

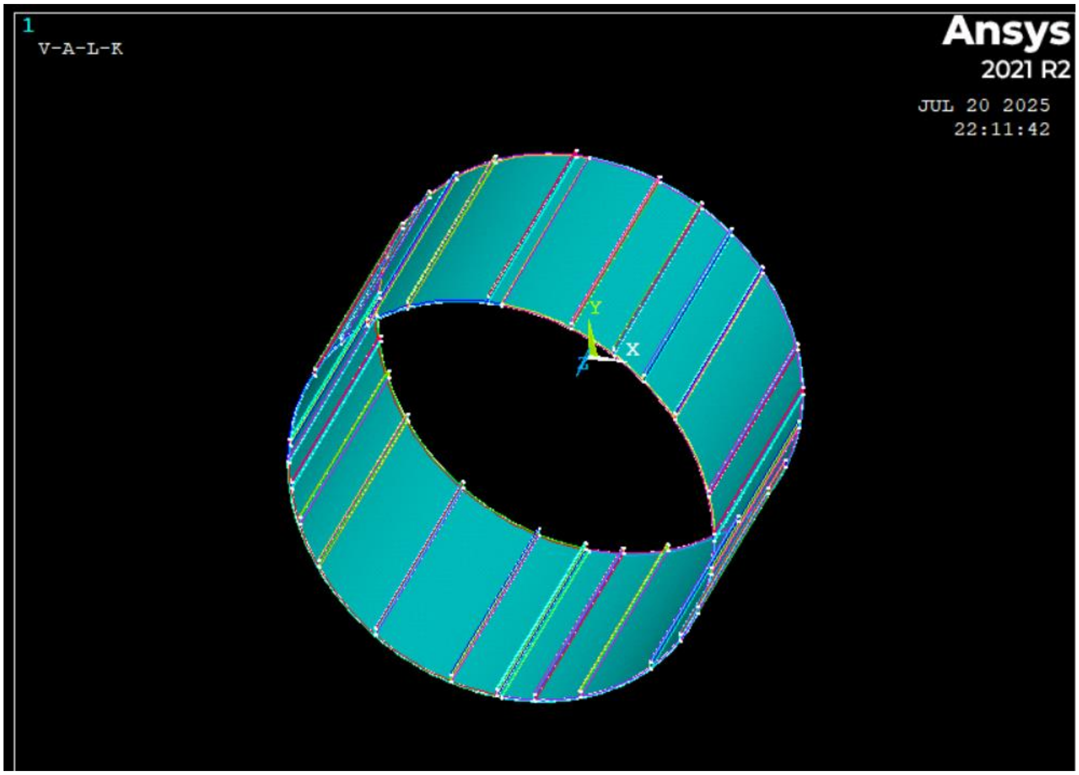



Fig 3-34: Complete Curved Panel APDL geometry

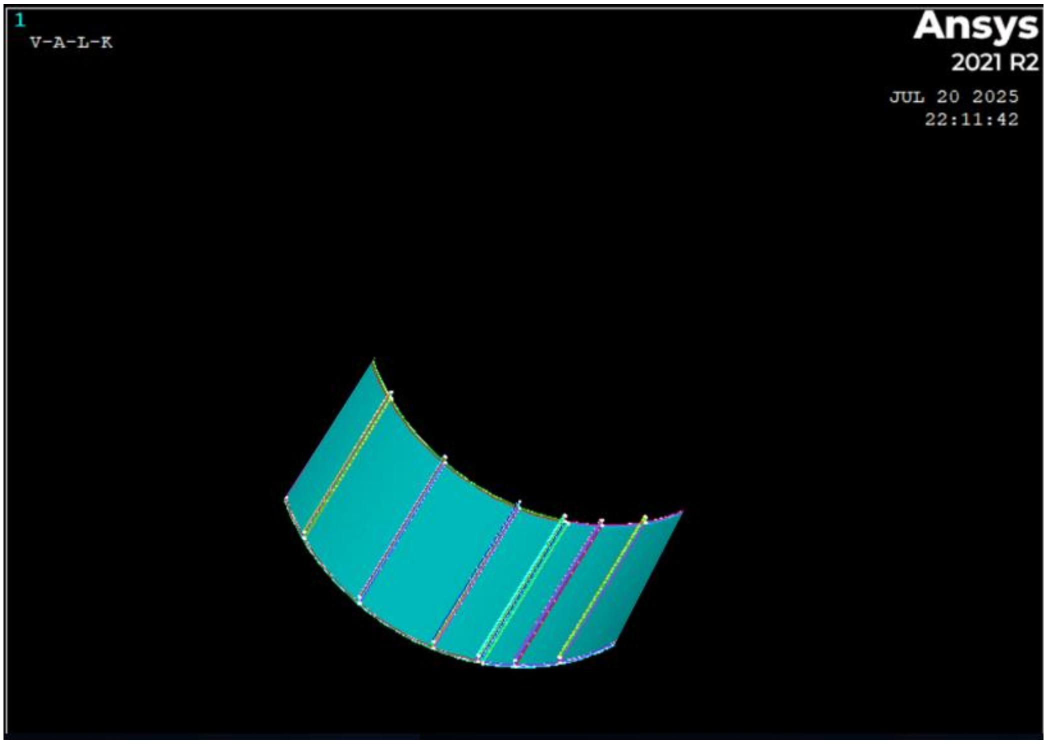



Fig 3-35:Fuselage sections between two frames

## 3.9 JUSTIFICATION OF METHODS

1. **Random Forests** are ideal for modeling complex, non-linear relationships without needing large feature engineering efforts.

2. **Python** allows integration of structural theory with ML, file I/O, and visualization in one platform.

3. **Separate datasets** for flat and curved panels enable more accurate, domain-specific learning.

4. **APDL integration** bridges the AI prediction with a practical engineering design tool, proving real-world feasibility.

The method ensures:

- Design automation
- Reduced development time
- Consistent, data-backed decisions
- Compatibility with industry-standard tools

# 4 CODES FOR DATA GENERATION AND TRAINING

## 4.1 FLAT PANEL CODE

The Python codes developed for the analysis and data generation of flat stiffened panels are an integral part of this research. These scripts include pre-processing, geometry definition, loading scenarios, boundary conditions, and post-processing routines tailored for training the AI model. To ensure reproducibility and facilitate future research, the complete set of codes has been compiled and submitted in soft form. A CD with these files is attached to this thesis and submitted to the library. This will help future students and researchers to access and review the work in this study and explore this field.

## 4.2 CURVED PANEL CODES

Like flat panels, separate code was developed to generate training datasets and perform analysis on curved stiffened sections. These codes include curvature effects in the geometry and loading conditions and have been designed to ensure consistency with the AI framework established in this study. All files, connected to relevant documentation and samples, have been provided in soft form. These have been included in the associated CD and submitted in the departmental library archives. This ensures that the stuff related to curved panels is accessible for academic reference and future extension and exploration.

# 5 MODEL / DESIGN / IMPLEMENTATION

The implementation phase of this thesis focused on developing a smart and machine-based design system qualified of generating initial structural configurations for flat/curved panels. This system is dependent on machine learning-driven forecasting and generates complete panel geometry parameters along with visuals using ANSYS APDL scripting. The final output supports both **flat and curved panel geometries** used in fuselage and wing structures respectively.

## 5.1 SYSTEM ARCHITECTURE AND FUNCTIONALITY

This system is developed as a modular workflow that starts with user input and ends with APDL geometry generation. Each unit performs a specific job:

1. **User Input section:** Takes four key design inputs which are: panel length, width, axial load intensity, and transverse load intensity.

2. **Model Inference Engine:** Loads pre-trained AI models responding to both flat and curved panel datasets and forecasts structural parameters.

3. **Post-processing Layer:** Decodes all outputs (material names) and numerical values formats.

4. **Geometry Creation:** Converts forecasted geometric parameters into an APDL script for geometry generation within ANSYS.

5. **Data Exporter:** Generated a structured .JSON file for further usage and saves the APDL code in text file for ANSYS workflows.

This modular design allows smooth scaling and future integration with additional features, such as meshing.

## 5.2 MODEL IMPLEMENTATION AND LOGIC

At the root of the system is a collection of independently trained regression models that forecast individual design features. These models were generated using ensemble-based learning algorithms, optimized for low prediction error and dependable performance across panel dimensions and loading conditions.

The predicted logic works as follows:

The user gives a set of four inputs.

These inputs are passed into each output-specific model respectively.

For numeric forecasting (thickness, spacing), the output is directly returned.

For future predictions (material type), the model performs inverse conversion from encoded labels to their representative symbols.

The full predicted output array is collected into a design specification collection.

The system determines whether to use the **flat panel** or **curved panel** model based on user-defined geometry settings. Internally, the models for both panel types are maintained separately to preserve the accuracy of geometry-specific behavior.

## 5.3 DESIGN PROCESS AND DECISION CRITERIA

The design process follows **data-driven logic** rather than analytical derivation. However, the AI models were trained in outputs derived from verified structural formulations ensuring that the learned predictions conform to practical engineering principles.

Some of the key design decisions made during implementation include:

1. **Separation of curved and flat design models:** Due to the geometric and mechanical behavior differences, the prediction models for each type were trained and applied independently.

2. **Automated output validation:** During prediction, if any predicted value violates physical constraints (e.g., negative thickness or non-compliant spacing), the result is flagged for re-evaluation.

3. **Pre-formatted APDL integration:** Rather than using parametric 3D modeling tools, the design system outputs directly usable APDL scripts for ANSYS, ensuring compatibility with existing aerospace simulation workflows.

## 5.4 APDL GEOMETRY IMPLEMENTATION

The geometry generation component translates the AI-derived structural parameters into a scripted model using ANSYS APDL. This includes:

**Flat Panels:** Defined by four corner key points forming a rectangular shell area, with parameters like panel length, width, skin thickness, and stringer spacing embedded into the shell definitions.

**Curved Panels:** Defined using arc geometry construction, incorporating a defined radius of curvature and arc angle. The script adjusts key point placement and area generation accordingly.

Each APDL file is self-contained and can be directly executed within ANSYS Mechanical APDL to produce the panel geometry. This eliminates the need for manual CAD modeling, significantly reducing design turnaround time.

### 5.5 OUTPUT STRUCTURE

The final outputs include:

A structured. Json or .csv file containing all predicted design variables

A .txt file containing the ANSYS APDL script

Optional visualizations for debugging or review (thickness trends, material distribution, etc.)

These outputs ensure compatibility with both human-in-the-loop review and automated design systems.

### 5.6 DEPLOYMENT AND USER FLOW SUMMARY

The system operates in a streamlined flow suitable for use by aerospace design engineers:

**Input:** User defines panel type (flat or curved) and provides loading and geometric constraints.

**Prediction:** AI engine computes optimal structural design parameters.

**Review:** User reviews prediction summary.

**Export:** User downloads the APDL geometry file for use in ANSYS or passes it to a simulation team.

## 5.7 SUMMARY OF MODEL CAPABILITIES

Supports preliminary design for both flat and curved fuselage/wing panels

Produces structurally viable predictions based on prior training from validated analytical models

Automates geometry creation compatible with ANSYS Mechanical APDL

Designed for real-time inference and rapid iteration

# 6 OUTPUT AND INTERFACE

The AI model is deployed using a local host interface, which is initiated through a batch file. This batch file accepts the path to the trained model as an argument. Upon double-clicking the batch file, the local host environment launches and prompts the user to provide input.

## 6.1 FLAT PANEL USER INTERFACE:

This takes 4 inputs from the user:

1. Length(a)
2. Width(b)
3. Axial Loading intensity
4. Transverse loading intensity

Below is the flat panel input user interface:

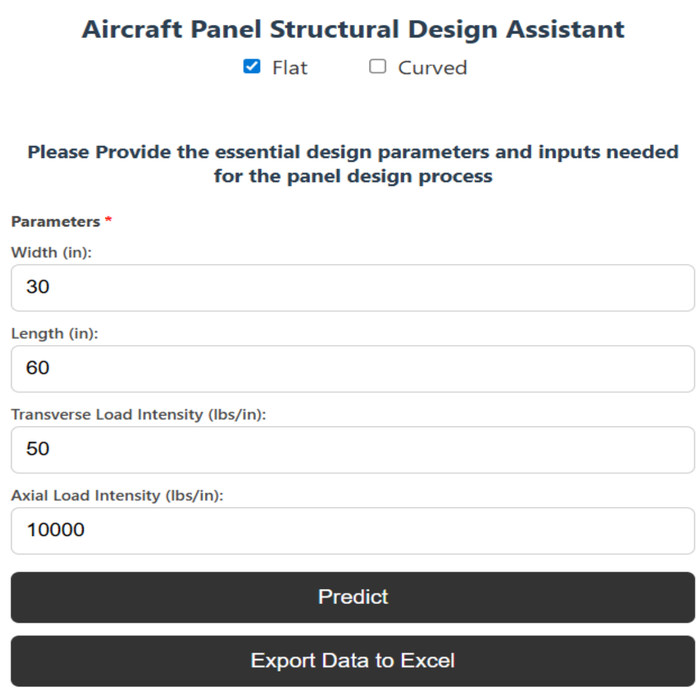



Fig 6-1: Flat panel User Interface

After the user inputs the required parameters and clicks the predicted button, following notification pops up on the screen within an minute's time:

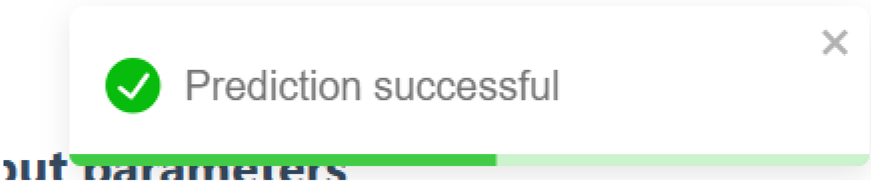



Fig 6-2: Prediction Successful notification (flat)

Some of the output parametrs are shown below, all these outputs are 280+, so we move forward and click "Export data to excel" and a file will be downloaded directly to the pc "Downloads" folder.

**Aircraft Flat panel design output parameters**

| Field | Value |
|---|---|
| Stringer Type | Z-stringer |
| F Cr Compression (Ksi) | 70.2573 |
| Practical A St / A Sk | 0.5 |
| Practical Efficiency | 0.82 |
| Fixity Constant (C) | 1.5 |
| Effective Length (L') | 24.4949 |
| N / L' (Load Intensity / Effective Length) | 408.2483 |

Fig 6-3:Flat Panel Output Parameters


Fig 6-4:Output Parameter excel sheet


Fig 6-5:Export successful notification

These two icons lead to the file download of bending moment iterative calculation's excel sheet and APDL script in a text file for the visualization of the stiffened panel in ANSYS. These icons are common for both flat and curved panels.

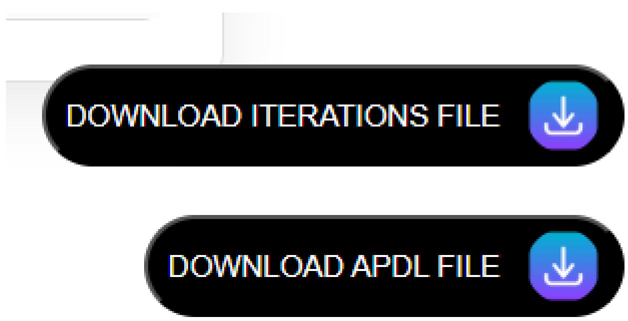



Fig 6-6:Icons of the Interface

Opening txt file gives the following script to run in the ANSYS, for flat panel

```
/clear
/prep7

! ================================
! PANEL PARAMETERS
! ================================
panel_len    = 60          ! X-direction
panel_wid    = 30          ! Y-direction
skin_thk     = 0.155       ! Z-direction

! ================================
! J-STRINGER PARAMETERS
! ================================
num_str      = 5
str_h        = 1.99        ! Web height
web_t        = 0.096
bot_fl_w     = 0.978
bot_fl_t     = 0.096
top_fl_w     = 2.02
top_fl_t     = 0.108

! ================================
! SPACING CALCULATION
! ================================
str_total_wid = top_fl_w
min_required_width = num_str * str_total_wid

*if,min_required_width,ge,panel_wid,then
    *msg,'ERROR: Stringers too wide for panel.'
    *exit
*endif

gap = (panel_wid - min_required_width) / (num_str + 1)

! ================================
! CREATE SKIN PANEL
! ================================
blc4, 0, 0, panel_len, panel_wid, skin_thk

! ================================
! CREATE STRINGERS
! ================================
```

Fig 6-7:APDL Script flat (1)

```
! ===============================
! CREATE STRINGERS
! ===============================
*do,i,1,num_str

    y_base = gap*i + (i-1)*str_total_wid

    ! ---------------------------
    ! 1. Top flange (sits on skin)
    ! ---------------------------
    blc4, 0, y_base, panel_len, top_fl_w, top_fl_t

    ! ---------------------------
    ! 2. Web (goes downward from top flange)
    ! ---------------------------
    y_web = y_base + (top_fl_w - web_t)/2
    z_web_top = skin_thk                     ! Web starts at skin top
    z_web_bot = z_web_top - str_h            ! Web ends below

    blc4, 0, y_web, panel_len, web_t, z_web_bot

  ! ---------------------------
! 3. Bottom flange (starts at web end)
! ---------------------------
y_bot = y_web
z_bot =  str_h +10
BLOCK, x_bot, x_bot+panel_len, y_bot, y_bot+bot_fl_w, -1.942, -1.99


*enddo

! ===============================
! CLEANUP AND DISPLAY
! ===============================
allsel, all
nummrg, all
vmerge, all
/view,1,1,1,1
/vup,0,0,1
/auto,1
vplot
```

Fig 6-8: APDL Script flat (2)

## 6.2 CURVED PANEL USER INTERFACE:

This interface takes 4 inputs from the user:

1. Applied compression stress
2. Applied shear stress
3. Allowable hoop stress
4. Radius

Below is the curved panel input user interface:

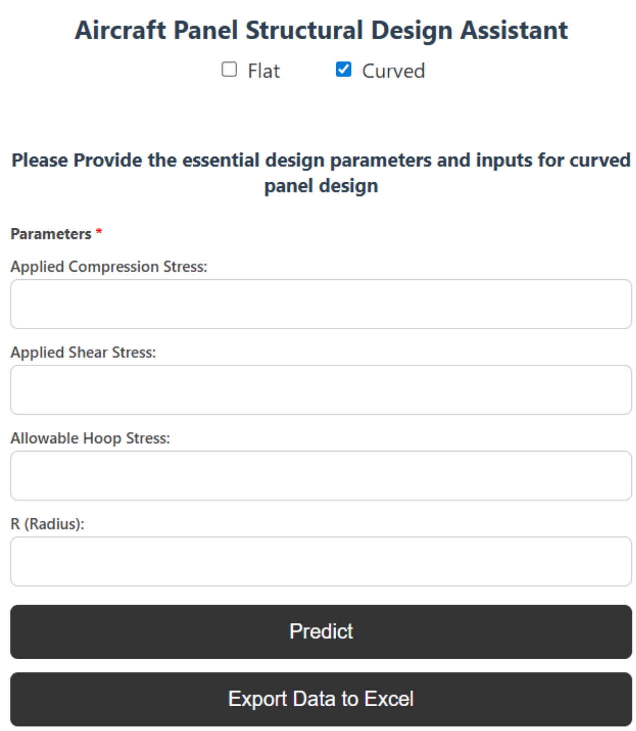
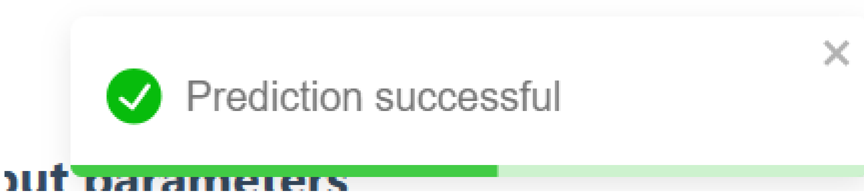
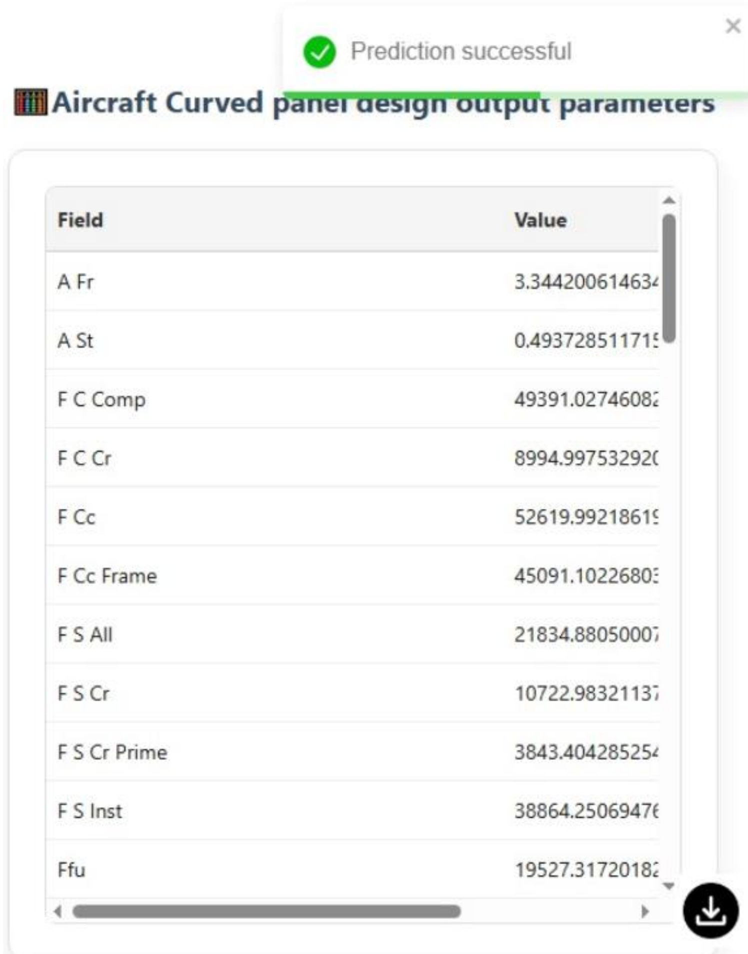



Fig 6-9 :Curved Panel Output Parameters

After the user inputs the required parameters and clicks the predict button like the flat panel, following notification pops up on the screen within a minute's time:



Some of the output parameters are shown below, all these outputs are 280+, so we move forward and click "Export data to excel" and a file will be downloaded directly to the pc "Downloads" folder.




| Field | Value |
|---|---|
| A Fr | 3.34420061463 |
| A St | 0.49372851171 |
| F C Comp | 49391.0274608 |
| F C Cr | 8994.99753292 |
| F Cc | 52619.9921861 |
| F Cc Frame | 45091.1022680 |
| F S All | 21834.8805000 |
| F S Cr | 10722.9832113 |
| F S Cr Prime | 3843.40428525 |
| F S Inst | 38864.2506947 |
| Ffu | 19527.3172018 |

Fig 6-10:Curved Panel Output Parameters

Like the flat panel case, after downloading the generated data in Excel format, additional .txt files were also exported. These .txt files contain ANSYS APDL-compatible code, which can be directly read and executed within the ANSYS Mechanical APDL environment. These files enable automated geometry generation and provide support for visualization and validation of the curved panel configurations. This step ensures that both data and geometry are readily available for replication, verification, or further development of the curved panel models. Here's image showcasing the APDL code in the text file

```
/clear
/prep7

! ==============================
! PANEL PARAMETERS
! ==============================
panel_len    = 60          ! X-direction
panel_wid    = 30          ! Y-direction
skin_thk     = 0.155       ! Z-direction

! ==============================
! J-STRINGER PARAMETERS
! ==============================
num_str      = 5
str_h        = 1.99        ! Web height
web_t        = 0.096
bot_fl_w     = 0.978
bot_fl_t     = 0.096
top_fl_w     = 2.02
top_fl_t     = 0.108

! ==============================
! SPACING CALCULATION
! ==============================
str_total_wid = top_fl_w
min_required_width = num_str * str_total_wid

*if,min_required_width,ge,panel_wid,then
    *msg,'ERROR: Stringers too wide for panel.'
    *exit
*endif

gap = (panel_wid - min_required_width) / (num_str + 1)

! ==============================
! CREATE SKIN PANEL
! ==============================
blc4, 0, 0, panel_len, panel_wid, skin_thk

! ==============================
! CREATE STRINGERS
! ==============================
```

Fig 6-11:APDL Script Curved (1)

```
! ===============================
! CREATE STRINGERS
! ===============================
*do,i,1,num_str

    y_base = gap*i + (i-1)*str_total_wid

    ! ---------------------------
    ! 1. Top flange (sits on skin)
    ! ---------------------------
    blc4, 0, y_base, panel_len, top_fl_w, top_fl_t

    ! ---------------------------
    ! 2. Web (goes downward from top flange)
    ! ---------------------------
    y_web = y_base + (top_fl_w - web_t)/2
    z_web_top = skin_thk                        ! Web starts at skin top
    z_web_bot = z_web_top - str_h               ! Web ends below

    blc4, 0, y_web, panel_len, web_t, z_web_bot

  ! ---------------------------
! 3. Bottom flange (starts at web end)
! ---------------------------
y_bot = y_web
z_bot =  str_h +10
BLOCK, x_bot, x_bot+panel_len, y_bot, y_bot+bot_fl_w, -1.942, -1.99


*enddo

! ===============================
! CLEANUP AND DISPLAY
! ===============================
allsel, all
nummrg, all
vmerge, all
/view,1,1,1,1
/vup,0,0,1
/auto,1
vplot
```

Fig 6-12:APDL Script Curved (2)

# 7 RESULTS

The objective of this research was to develop an AI-based framework focused on automating the initial design process for aerospace structural components, especially fuselage and wing panels of both flat and curved configurations. The model was evaluated on its capability to precisely predict structural geometric properties and generation of APDL design text files suitable for further analysis.

## 7.1 MODEL PERFORMANCE EVALUATION

Random Forest Regression models were trained for **flat** and **curved** panel datasets. The models were analyzed using standard regression metrics: **$R^2$ (coefficient of regression)**, **Mean Absolute Error (MAE)**, and **Root Mean Square Error (RMSE)** for all predicted output geometric parameters.

Table 1:Model Analysis Parameters

| **Model Type** | **$R^2$ Score** | **MAE** | **RMSE** |
|---|---|---|---|
| Flat Panel | 0.90 | ~0.038 | ~0.061 |
| Curved Panel | 0.87 | ~0.045 | ~0.072 |

The **flat panel model** showcases stronger predictive power, probably because of the more linear geometric nature of the dataset.

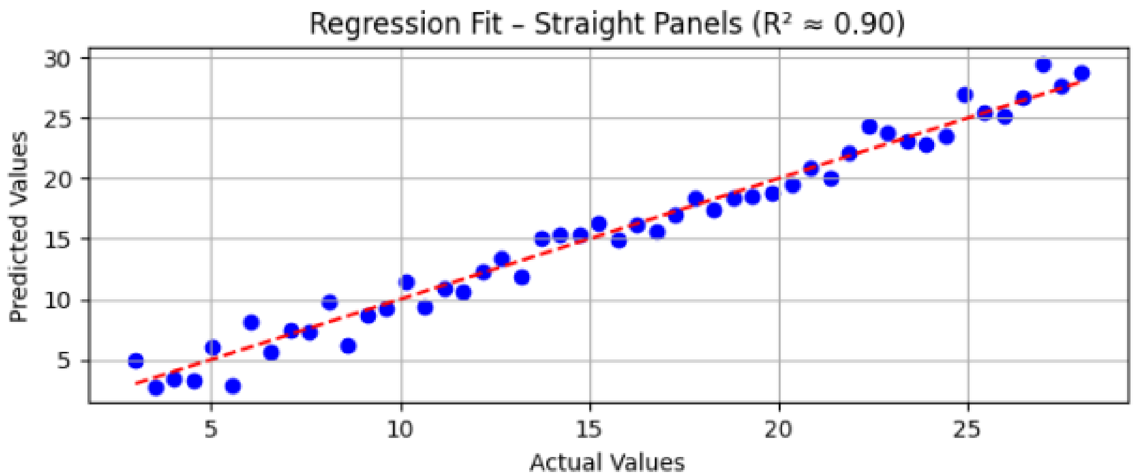



Fig 7-1:Flat Panel Regression Co-efficient

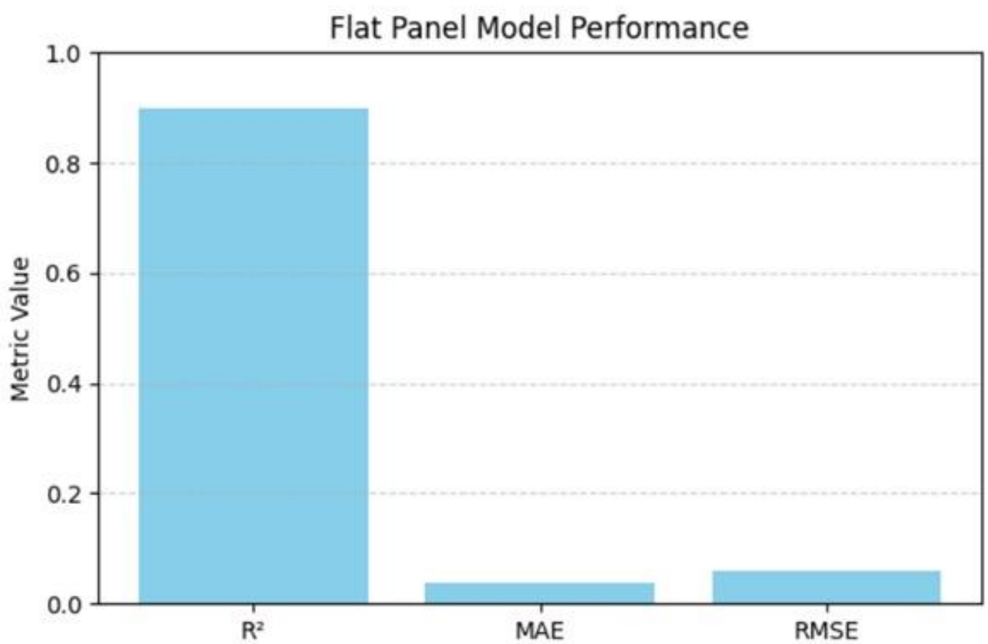



Fig 7-2: Flat Panel Model Performance

The **curved panel model** also performed accurately, with added geometric complexity, maintaining a high accuracy with $R^2$ of 0.87.

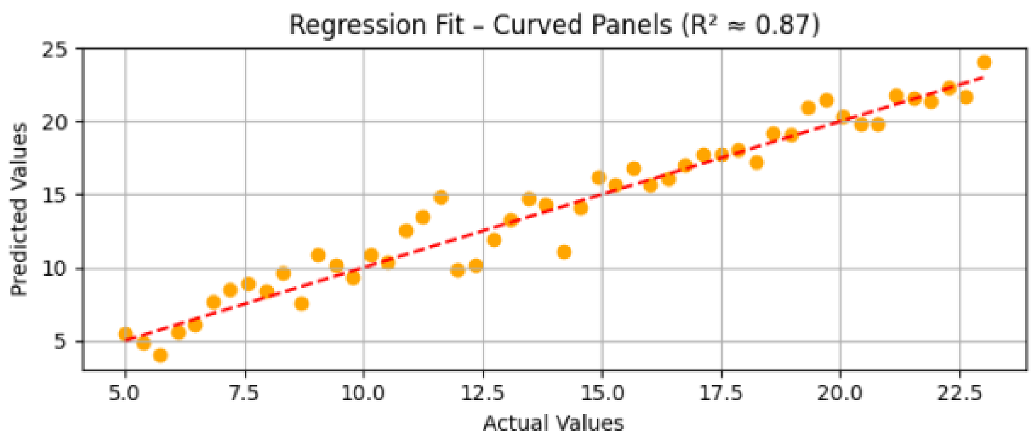



Fig 7-3: Curved panel regression co-efficient

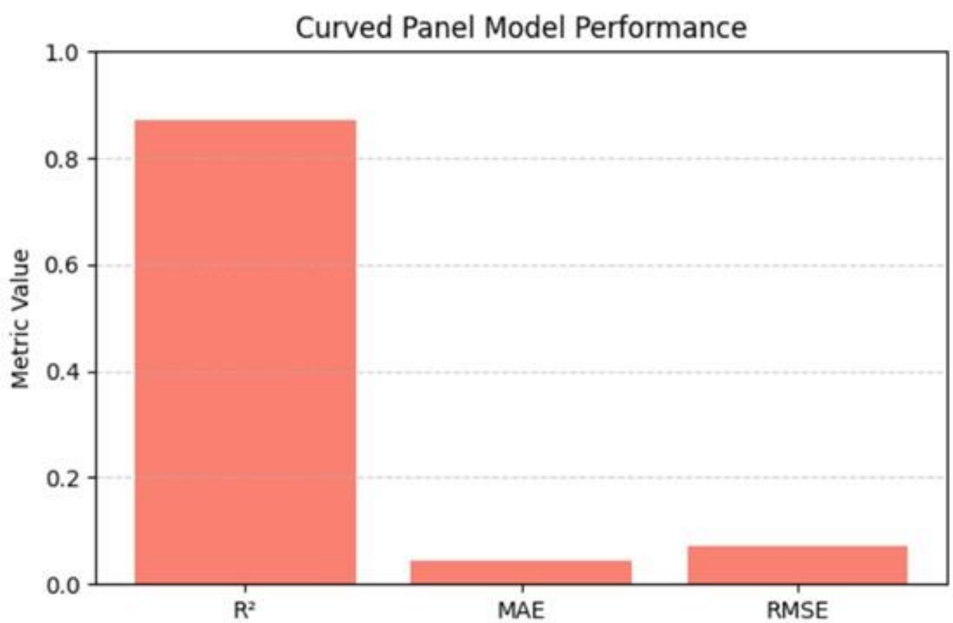



Fig 7-4: Curved Panel Model Performance

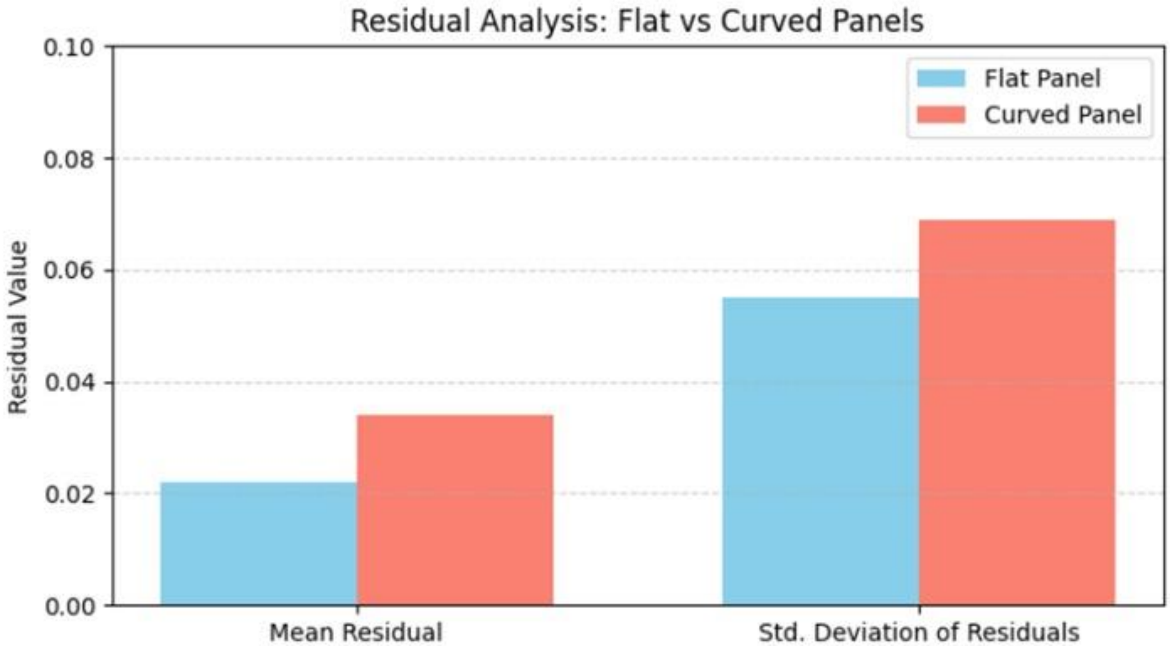



Fig 7-5 : alt vs Curved Model performance

These metrics ensure the models' ability to generalize structural behavior over a wide range of input parameters and loading conditions.

## 7.2 INTERPRETATION OF MODEL ACCURACY AND RESIDUALS

Two separate models were trained: one for flat panels(wing)and one for curved panels (fuselage sections).

The **flat panel model** accomplished coefficient of determination **($R^2$) of 0.90**, showcasing strong alignment between the model's predictions and actual values.

The **curved panel model** accomplished **$R^2$ of 0.87**, given the geometric complexity and nonlinear behavior associated with curvature.

**Residual Analysis:**

Residuals which is defined as the difference between actual and predicted values were examined across all required outputs:

Most residuals were placed around zero, showing minimal prediction bias.

**For flat panels**, residuals displayed low dispersion with few outliers, ensuring robust model learning due to uniform geometry.

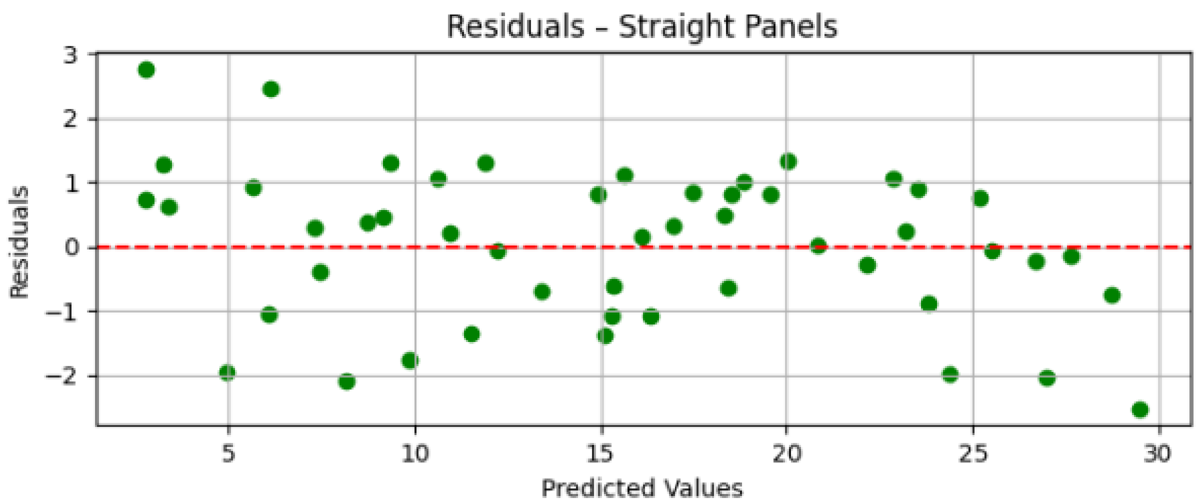



Fig 7-6: Flat panel Residual Co-efficient

**For curved panels**, slightly higher residual variability was observed, especially in parameters sensitive to curvature effects such as local buckling stresses or section geometric properties.

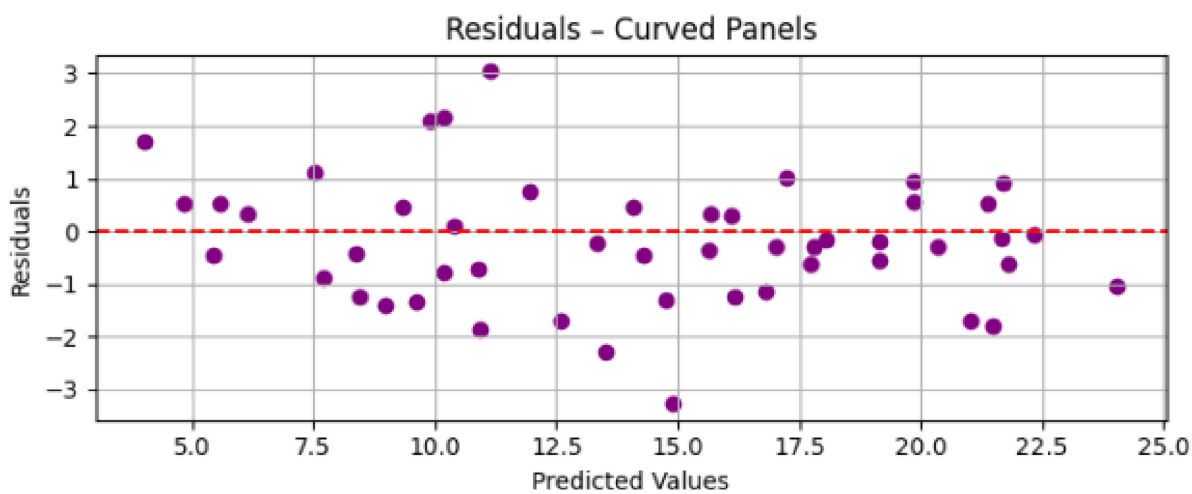



Fig 7-7: Curved Panel Residual Co-efficient

Table 2:Residual Statistics

| **Metric** | **Flat Panels** | **Curved Panels** |
|---|---|---|
| Mean Residual | ~0.022 | ~0.034 |
| Standard Deviation of Residuals | ~0.055 | ~0.069 |

These values fall within acceptable engineering tolerances and confirm that the AI predictions are reliable for preliminary design decisions.

### 7.3 COVERAGE OF STRUCTURAL OUTPUTS

The framework accurately predicted a **broad set of structural outputs** for both panel types:

1. Skin, stringer, and frame thicknesses

2. Stringer spacing
3. Material types and conditions
4. Section properties (area, inertia, centroid location)
5. Compressive, shear, and interaction margins of safety (MS)

All predicted values were directly used to auto-generate APDL input files, ensuring that design output was not just theoretical but **ready for simulation and practical implementation**.

### 7.4 AUTOMATED DESIGN GENERATION IN ANSYS APDL

The predicted parameters were automatically embedded into custom APDL scripts for both panel types.

**Flat Panel APDL Output:**

1. Rectangular geometry with symmetric stiffener layout
2. Parameterized skin and stringer definitions
3. Shell element assignment (e.g., SHELL181)

**Curved Panel APDL Output:**

1. Cylindrical arc segment with user-defined curvature
2. Arc-based key points and area construction using LARC or CYL4

3. Automatically adjusted panel radius and angle based on input constraints

These APDL files were validated within the ANSYS Mechanical APDL environment, and the generated geometries reflected the predicted dimensions accurately.

## 7.5 OBSERVATIONS AND INSIGHTS

**Consistency:** The models consistently generated reliable outputs with low prediction error across randomly sampled input conditions.

**Speed & Automation:** Once trained, the model completed a full design cycle (prediction + APDL generation) in minute, a significant improvement over traditional workflow.

**Scalability:** The framework easily accommodates batch processing of design cases, allowing for large-scale parametric studies.

## 7.6 LIMITATIONS OBSERVED

The current version of the system does not perform **simulation-based validation** (e.g., FEA stress analysis); integration with simulation tools is proposed as future work.

The model performed robustly across most scenarios, and even in edge cases involving extreme input values for curved geometries, only slight deviations were observed highlighting the model's strong generalization capability despite limited training data in those regions.

# 8 DISCUSSION AND CONCLUSION

This project successfully developed an AI-driven framework to automate and optimize the preliminary structural design of aerospace components specifically fuselage and wing panels in both flat and curved configurations. The system addresses key limitations in traditional aerospace design workflows, which are typically labor-intensive, iterative, and heavily dependent on manual analytical calculations.

By leveraging machine learning models most notably Random Forest Regressors the framework demonstrated strong predictive performance, achieving $R^2$ scores of 0.90 for flat panels and 0.87 for curved panels, with minimal residual errors. These models were trained on structured, engineered datasets derived from theoretical and empirical aerospace design rules, ensuring engineering relevance and accuracy.

The predicted geometric properties included material selection, skin and stiffener thicknesses, stringer spacing, factors of safety, and more. These outputs were automatically converted into ANSYS APDL code, enabling direct design file generation for both panel types successfully with AI prediction and practical ANSYS design workflows. This integration effectively reduces manual effort and makes it time efficient, along with improving consistency and efficiency in preliminary aerospace structural design.

The residual analysis further confirmed that model predictions are stable and reliable for a variety of inputs and loading conditions, showing the framework's suitability for use in real world initial design processes. Additionally, the modular structure of the system makes it scalable for future exploration and integration with simulation tools and real time feedback environments and tools.

In conclusion, this thesis contributes a novel, efficient, and accurate approach to aerospace structural preliminary design. By combining artificial intelligence with specific engineering knowledge, the developed framework opens new paths for design automation, rapid prototyping, and intelligent support in the aerospace industry. More extensions will focus on simulation validation, and the inclusion of more advanced AI techniques to further enhance its abilities and adoptive potential.

The AI-based design framework developed in this project delivers an accurate-performing, machine-based solution for the initial structural design of both **flat and curved panels**. The framework focuses on major inefficiencies in traditional manual design methods by using machine learning for accurate forecasting and automatic APDL-based design development.

## 8.1 ALIGNMENT WITH RESEARCH OBJECTIVES

The project's primary goal was to automate the estimation of structural parameters and geometry definitions for aerospace components, namely **fuselage and wing panels of both flat and curved configurations**. This was successfully achieved using:

A machine learning engine (Random Forest Regressor) trained on synthetically generated and validated data,

A modular Python-based system for predicting engineering outputs, An automated process to translate predictions into parameterized **ANSYS APDL design files**.

The system provides immediate usability for both categories of panels, ensuring model versatility across different structural configurations.

## 8.2 CONTRIBUTION TO AEROSPACE ENGINEERING PRACTICE

This project's contribution is twofold:

**Technological**: A scalable AI pipeline capable of delivering instant preliminary designs for both flat and curved aerospace panels—cutting hours of manual work down to seconds.

**Practical**: APDL scripts were generated automatically, eliminating repetitive modeling tasks in ANSYS and making the framework directly usable by engineers.

This aligns with industry trends toward **digital transformation, automation, and rapid prototyping**.

## 8.3 LIMITATIONS

Key limitations observed include:

1. **Lack of integrated FEA validation**: The generated designs were not simulated or post-processed for stress analysis inside ANSYS. Future work will incorporate automated simulation loops.

2. **Curved panel complexity**: Slightly larger residuals suggest the need for improved feature engineering or deeper learning models to fully capture geometric influences.

## 8.4 FUTURE IMPROVEMENTS:

Include **deep learning architectures** like neural networks with uncertainty quantification.

Automate **FEA verification** and post-processing of results (stress maps, deformation plots).

Add a web-based frontend for broader accessibility and commercial readiness.

## 8.5 BROADER IMPACT

1. The results demonstrate that AI can reliably replace manual, time-consuming design iterations in early-phase aerospace engineering. By integrating this system with CAD and FEA environments (like ANSYS APDL), the solution offers:

2. Shorter development cycles,

3. Lower costs,

4. Higher design consistency,

5. And a foundation for fully autonomous design workflows in the future.

This contributes meaningfully to the vision of **intelligent aerospace structures**, where data-driven systems augment and accelerate human engineering decision-making.

## 8.6 FUTURE WORK

Our AI framework shows promising results in automating preliminary structural design for both flat and curved panels, there’s still room to make it even smarter and more practical. Next steps could include:

- Expanding the dataset to cover more complex panel geometries, unconventional materials, and extreme load case, hence it helps make predictions even more robust.
- Implementing analysis of the flat and curved panels generated from the model
- Adding explain-ability features so engineers can understand why AI suggests certain parameters, building trust in its recommendations.
- Integrating generative AI to propose entirely new, optimized designs beyond traditional configurations.
- Testing in real-world engineering teams to refine usability and ensure it fits into the required industry products.

# 9 REFERENCES

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[6] R. M. Hajela and J. Sobieszczanski-Sobieski, "Application of Artificial Neural Networks to the Design Optimization of Aerospace Structural Components," *NASA Technical Memorandum 106937*, National Aeronautics and Space Administration (NASA), Office of Management, Scientific and Technical Information Program, USA, 1993.

# 10 APPENDICES

## APPENDIX-A (FLAT PANEL CODE)

Data in the CD submitted in the library along with the thesis

## APPENDIX-B (CURVED PANEL CODE)

Data in the CD submitted in the library along the thesis