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Computer-Aided Intelligent Product Design Process and Practice

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Abstract

Modern product design leverages computational software and intelligent systems to create high-performance and cost-effective products. In aerospace, materials must be continually made lighter and resistant to ensure structural integrity and safety. Traditional material selection processes rely heavily on expert knowledge and do not balance multiple performance criteria. This work develops an artificial intelligence-supported computer-aided model to forecast the accommodation of materials in aerospace structures and recommend the best solutions for the lightweight and high-strength parts. The approach to designing an aircraft landing gear strut assembly system involves using material data from the designed airship and applying an XGBoost classification model with Pareto optimisation, which ranks and predicts the most suitable materials for the aircraft. The best-performing materials are tested using finite element analysis using vibration/modal testing, and thermal testing to ensure structural integrity under operational conditions. Findings show the model achieved 98.1% accuracy in predicting aerospace-suitable materials based on key mechanical properties. Also, the selected material (Aluminium 7075-T6) exhibits a thermal conductivity of 130 W/m·K. These results confirm the framework's effectiveness in enabling data-driven, cost-efficient, and reliable material selection, thereby streamlining the structural design process and advancing intelligent product design practices in aerospace engineering.

Keywords: Computer-Aided Intelligent, Product Design, Aerospace Materials, Landing Gear Strut Assembly, Material Selection, Classification

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1. Introduction

Product design is an essential discipline in engineering and manufacturing that focuses on the conceptualisation, development, and realisation of functional and aesthetically optimised products [1]. Over the past several decades, product design has evolved from purely manual sketching and prototyping to a structured, iterative, and data-driven process, enabling designers to create high-performance solutions across industries [2]. Historically, the prevalence of systematic product design can be traced back over 50 years, beginning with industrial design practices in the 1960s and 1970s, which emphasised ergonomics, usability, and manufacturability [3]. Primarily brought by the introduction of computer-aided intelligent (CAI) technology, the conventional product design practice has been reinvented as computer-aided product design [4], in which the process of decision-making and prediction involves the use of artificial intelligence (AI) and machine learning (ML) technologies [5]. By leveraging AI, designers can analyse the material properties and design constraints to identify optimal configurations and anticipate structural, thermal, or operational issues before physical prototyping [6]. Over the last two decades, the integration of AI into product design has become increasingly prevalent, particularly in high-performance sectors like aerospace, where precision, lightweight structures, and reliability are paramount [7]. The result of this paradigm shift is that the alternatives in designs can be explored quickly, the rank of materials can be automatic, and predictable modelling of mechanical behaviour can be achieved, which saves time and dramatically reduces development costs [8]. As a result, the CAI product design is a synthesis of advanced engineering design and modern technologies, creating a powerful calculation atmosphere that has contributed to strong products that effectively respond to the requirements of dynamic environment industries.

The integration of CAI systems with AI techniques in product design has been recognised as a paradigm shift in aerospace engineering, of materials selection and structural optimisation [9]. This method of operation has become increasingly popular, becoming predominant in the aerospace industry since the turn of the millennium, with research and industrial usage proving risk to be more reliable, efficient, and innovative in structural design [10]. Conventionally, aerospace component development was highly protracted due to manual computations, experimental studies and resource-consumptive processes involving graphics curve trials coupled with resource-deprived efforts aimed at exhaustively studying the tremendous combination of materials and design parameters [11]. In the past twenty years, computational modelling, various tools, and AI-based technology have enabled designers to compare and assess thousands of material options, considering factors such as weight, strength, thermal conductivity, and fatigue stability [12]. Using ML frameworks based on optimisation algorithms allows CAI frameworks to identify materials that can reach high-performance levels of aerospace production with minimal development budget and duration [13]. This enables intelligent material selection and pre-emptive modelling of the mechanical behaviour, permitting engineers to create lightweight, strong constituents with enhanced safety, performance and durability, signifying a complete change to completely integrated intelligent product lateralisation in high-stakes aerospace systems utilisation [14].

1.1. Problem Statement

Several key concerns hinder the formation of aerospace components. This directly impacts the safety and performance of the structural design. The discovery of lightweight and strong materials is also a significant challenge, as reducing weight without compromising mechanical strength is a crucial factor in achieving fuel efficiency and strength [15]. Additionally, high heat resistance is a priority, especially in engine components and surfaces that are exposed to high temperatures. This would wear or deteriorate over time with conventional materials [16]. Poor endurance to fatigue and stress during repeated loading, vibration, and dynamic flight situations is also a challenge, which remains ongoing, with poor endurance rates leading to premature failure and increased maintenance expenses [17]. Moreover, with the advent of AI, it is challenging to predict suitable materials for use in the aerospace environment based on data-driven models, as material properties are complex and have limited datasets in their respective application areas [18]. To address these challenges, the proposed work aims to develop a computer-aided intelligent product design model that utilises AI to facilitate and suggest an optimised selection and analysis of materials, thereby producing lightweight, high-strength aerospace parts with enhanced functionality.

The key contributions of the suggested work are as follows:

- Demonstrates the CAI framework by leveraging mechanical materials to enable intelligent selection of lightweight materials for aerospace landing gear strut structural design.
- Integrates AI-based material suitability prediction using XGBoost with Pareto optimisation to predict the suitability of materials for aerospace structural use.
- Integrates AI-driven optimisation with structural simulation to provide a cost-effective, fast and reliable material selection and structural design process for aerospace components.
- Validates the framework by combining AI predictions and analysis methods to ensure practical applicability of top-performing materials suitable for real-world aerospace structural applications.

The paper will be structured as follows, with Section 2 containing a thorough review of the corresponding literature. The system methodology is described in Section 3. The analysis and discussion of the results are under Section 4. The study concludes in Section 5, presenting the main findings.

2. Literature Review

The initial studies in CAI product design typically had an empirical nature, focusing on the selection of materials. As the work conducted by Tan et al. [19] and Wang et al. [20] examined advanced algorithms and design practices to harness the potential of algorithmic modelling and visualisation techniques in transforming raw engineering data into interactive design tools, highlighting the importance of interdisciplinary techniques within engineering and design creativity. However, as time has progressed, AI has continued to be integrated at different stages of the product lifecycle (design, manufacturing, and service), providing a methodical and intelligent approach to the lifecycle. Within the framework of a study, the automated material selection strategy suggested by Pavlenko et al. [21] was correlated with probability-related schemes, including appropriate regression modelling articulated in the form of matrices, yielding analytical maxims for adequate material selection. Based on this, Wang et al. [22] and Chandrasekhar et al. [23] used neural networks and ML algorithms to develop various models to design products. Three-dimensional form information, surface and colour measurement, and emotional design integration recognition modelling were brought into their work. Further sophisticated research also equips fully connected neural networks, coupled to finite element solvers, where optimisation by the use of gradients and back-propagation is used to optimise material properties and structural geometry. Even though these methods were promising, constraints still remained in measuring exact, intricate requirements for an AI-based aerospace choice of material, as well as better material and structural assimilation structures.

With the introduction of AI, the product design has had a drastic transformation. The studies by Hao et al. [24] and Turetskyy et al. [25] provided frameworks that enabled engineers to address multi-objective trade-offs in product development. In their studies, they utilised deep neural networks and employed weighting schemes for competing design goals. The radial basis function was also introduced to facilitate the formulation of an objective weight assignment model, in which individual weights are assigned to each output, ensuring that each output corresponds to its own single decision criterion. Moreover, the battery production design employed a multi-output strategy, which relied on data-based models to estimate the final performance of the products based on intermediate features, thereby increasing efficiency in manufacturing optimisation. Building upon these developments, Gradi et al. [26] and Zhan and Li [27] addressed the selection of processes to be used when developing aerospace components, achieving higher grades validated by the presence of geometric complexity, metallurgical behaviour, mechanical properties and maturity of the supply chain. Their work dealt with the fatigue damage evaluation of aerospace alloys, which incorporates continuum damage mechanics theory and ML techniques. Over 500 experimental data sets were collected to breed predictive variants. Some of these approaches have performed better than others in achieving a certain level of accuracy, but the problem of accurately capturing the curves representing the nonlinear interactions between fatigue endurance and material ageing over time in aerospace applications remains, thus necessitating a more adaptive AI-based methodology.

Few studies have combined AI-driven innovations into the design of aerospace products, and researchers such as Ai et al. [28], Kraljevski et al. [29], and Du et al. [30] have made significant steps forward. Their studies utilised acoustic emission to detect the impacts that occurred during flight. They are providing a strategy for structural health monitoring. Also, random forest classifiers and AI Architectures were deployed in source localisation to form predictive models. The large-scale controlled impact tests on a full-scale thermoplastic aircraft elevator, conducted under laboratory conditions, yielded a substantial amount of data. These were trained on whole condition structures or for industrial use in aerospace engineering. Outside the context of impact monitoring, CAI techniques were also applied to the area of flexible cable design, utilising dynamic analogy modelling in conjunction with Cosserat theory and minimum potential energy principles to develop nonlinear optimisation models. Parallel work conducted by Kastratović et al. [31] and Grbović et al. [32] investigated the mechanical performance of composite materials applied to aircraft structures. Their approach attempted to integrate an experimental approach with numerical simulations to verify performance. Laminates were composites with an epoxy matrix and glass fibres, oriented at 0°, 45°, and 90°, manufactured according to aviation standards. Tensile and three-point bending tests provided essential insights into the material's strength and stiffness, while numerical analyses estimated the load-bearing capacities for light aircraft engine covers. These studies confirmed the use of composite materials in aerospace design, while also highlighting the importance of coupling AI-driven predictive modelling with traditional testing for improved material selection and structural optimisation.

Thus, although numerous studies have explored AI integration in product and material design, several challenges persist. It includes limited adaptability of models to nonlinear multi-objective conditions, inadequate fusion of data-driven intelligence with physical testing, and insufficient optimisation frameworks tailored for aerospace-grade materials. These gaps highlight the need for a unified, intelligent computer-aided design framework that integrates AI-based material prediction to ensure accurate aerospace component design.

3. Materials and Methods

The framework presents a CAI product design process tailored to the material choice and structural design features of aerospace applications, with the goal of prescribing lightweight, high-strength materials that can endure operating conditions beyond normal levels. This framework is driven by the imperative requirement within the aerospace sector to achieve both performance and safety selectively with materials by ensuring the material of interest is both mechanically strong and thermally stable, as well as fatigue-free. To achieve this, mechanical materials are used to construct an aircraft system design (landing gear strut assembly) framework. This designed data can be used as training data in an AI model, where the XGBoost algorithm, in combination with Pareto optimisation, can be used to train the AI-based classification model, resulting in a ranking classification output (Yes/No). The predictive model determines the viability of material use in aerospace, and the optimal ranking is correlated with the balancing of weight, strength, and thermal resistance.

The predictions made by the model are then analysed in the context of product design practice, forming the centre of an intelligent design decision-making process. Subsequently, the shortlisted materials are integrated during structural design using Finite Element Analysis (FEA), which includes vibration/modal analysis of an aircraft wing and turbine blade, as well as thermal analysis of engines and other heat- or temperature-sensitive parts. The process certifies their mechanical or thermal functional capability in aerospace-related conditions. At the end of the research laboratory, the AI-related predictive results and simulation results are merged to recommend the best material. This enables the faster and optimal selection of aerospace structural materials while also ensuring optimal performance and safety. The proposed workflow of the CAI methodology for materials selection and structural design in aerospace applications is shown in Figure 1.

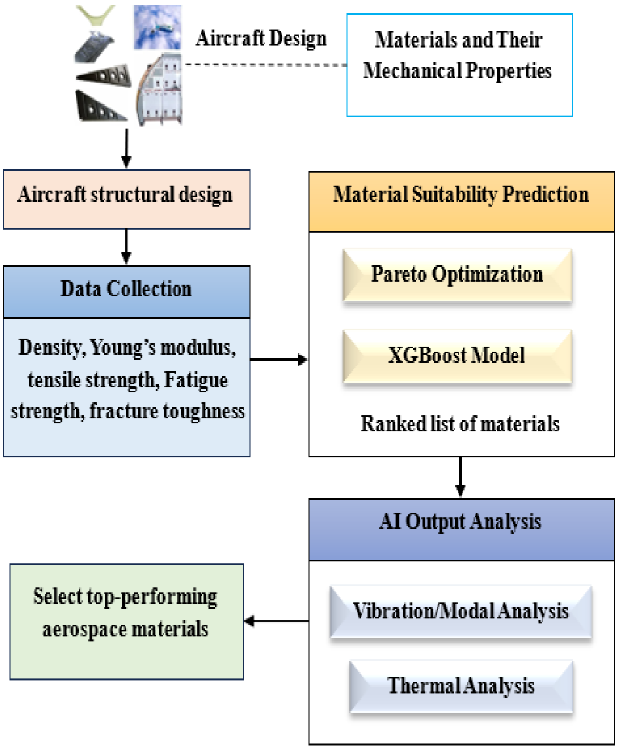

Figure 1. CAI-Driven Product Design Process Architecture in Aerospace Applications

3.1. Mechanical Properties

The mechanical characteristics of the landing gear strut assembly were studied to develop the aircraft system employing a combination of the geometric, material and load-specific data. The main structural component (hollow main strut) has a wall thickness of 3 mm and a cross-sectional area of 537.21 mm² and is made of Aluminium 7075-T6, having a yield strength of 503 MPa and a tensile strength of 572 MPa. The strut has a second moment of area of 218,780 mm⁴ and a polar moment of 437,559 mm⁴, which employs it to have a great resistance to bending and torsional forces. At a design axial force of 20 kN, the theoretical stress is 37.23 MPa. This is 13.5 times the design yield value and more than 21.5 times the design buckling value. The dynamic stability is guaranteed by the natural frequency of 173 Hz, whereas the minimal deflection of the system under operating loads is ensured by the stiffness of 64,196 kN/m. The overall mass of the strut is 0.91 kg, which, when paired with high thermal conductivity (130 W/m*K), proves that the strut is the right component to balance strength, fatigue strength, and thermal durability into the design.

Aircraft System Design

This is a structural modelling of a strut assembly of landing gears in an aircraft system. All of the components (main hollow strut, shock absorber, and axle) are characterised by geometry, mass, and material properties, allowing us to simulate stress, deflection, buckling, and fatigue at axial, lateral and impact loads accurately. Thermal analysis models the heat generation, transfer coefficients and expansion effects, whereas the modal analysis establishes the dynamic stability at a frequency of more than 170 Hz and the natural frequency. The combination of such data serves to assist AI-based optimisation and predictive modelling, which is the intelligent choice of materials and structural design of the engine in the aerospace industry. As shown in Figure 2, the total architecture of the designed aircraft system (landing gear strut assembly) is presented in the proposed CAI.

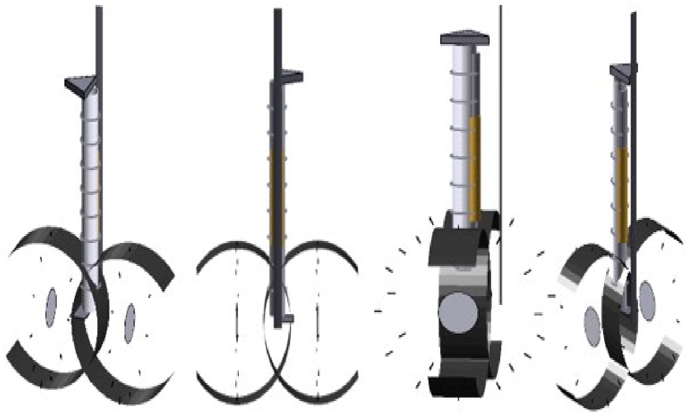

Figure 2. Design of Landing Gear Strut Assembly in Aerospace Applications

3.2. AI-Assisted Optimisation

Within the framework, AI-assisted optimisation is used to discover materials that best balance numerous conflicting performance needs in aerospace structural design (landing gear strut). To identify and formulate aerospace-specific material properties, the mechanical properties are first narrowed down to a subset of relevant material properties used as key features. To further improve the decision, a classification model is trained to provide the likelihood that a particular material will be considered structurally viable and classified as being used in aerospace (Yes/No). This also reduces density and enhances strength, fatigue resistance, and thermal stability. This prioritised list of candidate materials is appropriate to the aerospace performance specifications to validate and integrate structural design.

Feature Selection

Even aerospace designs are inherently multi-objective: structural designers strive to reduce the weight of their structures while simultaneously trying to maximise their strength, fatigue resistance, and thermal stability. These targets are contradictory by nature; for example, highly strong materials tend to be heavier, whereas materials with high thermal performance can undermine weight efficiency. To resolve this trade-off in a systematic way, the feature selection task is unexpectedly presented as a multi-objective optimisation problem and solved with Pareto optimisation.

Pareto Optimisation

The Pareto optimisation approach is an efficient method for multi-objective decision-making to achieve optimal performance. Sometimes, this may imply reducing density, but then increasing other objectives, such as stiffness, strength, fatigue resistance, and thermal stability. After this, the notion of a supremacy of solutions is introduced, wherein one solution is deemed superior to another, achieving the best results possible in all objectives, or at least in one of the objectives. According to this relation of dominance, the optimisation process is then continued to produce the Pareto front (along with all non-dominated solutions), representing the best possible trade-offs between objectives. These trade-offs can then be analysed by the user to derive the compromises involved in material behaviour, such as when deciding between ultra-orientation materials and moderate strength or heavier composites and better fatigue resistance. Ultimately, a decision-maker selects a solution (often informed by weighting factors or application-related constraints) from such a Pareto front, and that solution suitably addresses or satisfies the design problem in question.

Let the data set have x materials, each described by a vector of physical and mechanical properties, in the manner given by equation (1).

$$x = \{\rho, E, \sigma_t, \sigma_f, k, T_m\} \in \mathbb{R}^6 \tag{1}$$

Here, the ρ represent the density of the material, Young's modulus (E), tensile strength (σ_t), fatigue strength (σ_f), thermal conductivity (k), and melting point (T_m). Each feature corresponds to a property directly influencing the aerospace suitability of a material $\in \mathbb{R}^6$. The optimisation problem is then formalised as equation (2-3).

$$\min_{x \in X} F(x) = (f_1(x), f_2(x), f_3(x), f_4(x), f_5(x), f_6(x)) \tag{2}$$

Objectives defined as:

$\boldsymbol{f_1(x) = \rho(x)}$	(Minimize density for lightweight design)
$\boldsymbol{f_2(x) = -E(x)}$	(Maximize stiffness)
$\boldsymbol{f_3(x) = -\sigma_t(x)}$	(Maximize tensile strength)
$\boldsymbol{f_4(x) = -\sigma_f(x)}$	(Maximize fatigue resistance)
$\boldsymbol{f_5(x) = -k(x)}$	(Maximize thermal conductivity)
$\boldsymbol{f_6(x) = -T_m(x)}$	(Maximize melting point)

Here, minimisation is chosen as the unifying optimisation convention, and therefore maximisation objectives are represented with negative signs. In the context of Pareto optimisation, one solution x_1 is said to dominate another solution x_2 if and only if,

$$\forall i \in \{1,2,\ldots,6\}, f_i(x_1) \le f_i(x_2) \ \wedge \ \exists j \ \{1,2,\ldots,6\}: f_j(x_1) < f_j(x_2) \tag{3}$$

This hegemony condition assures that x_1 is as good as x_2 in every objective and is strictly stronger in at least one of them. The Pareto front ($\mathcal{P}$) is the set of all non-dominated solutions and is mathematically defined as in equation (4).

$$\mathcal{P} - \{x \in \mathcal{X} \mid \nexists y \in \mathcal{X}: F(y) \prec F(x)\} \tag{4}$$

Where $F(y) \prec F(x)$ means that y dominates x. It is the Pareto front of material properties across which no material can be optimised to better itself over another property.

A trade-off analysis is conducted on the Pareto front to balance the performance of realised materials, providing balanced performance based on aerospace requirements. An example is where one candidate can have low density with moderate strength, whereas the other may have high tensile and fatigue strength with a slightly higher density. To formalise this compromise, a scalarized decision function, $S(x)$, is introduced and can be represented in the form of equation (5).

$$S(x) = \sum_{i=1}^{6} w_i \cdot \hat{f}_i(x) \tag{5}$$

Where w_i is the weight of each objective applied depending on the top priority of the aerospace design (fatigue strength in turbine blades, thermal conductivity in engine parts), and $\hat{f}_i(x)$ is the normalised version of each objective equation so that the scale is not sensitive. Then, the most suitable material is selected as,

$$x - \arg\min_{x \in \mathcal{P}} S(x) \tag{6}$$

The flexible nature and design contextual sensitivity in the process ensure that the material chosen for the Pareto front is not only on the front owing to this selection equation (6) but also based on design-specific priorities in a manner that does not distort the design priority. Rather, it proposes a decision-based and optimisation-oriented model, which conveys cash evaluations based on all material properties against aerospace criteria with strict adherence. The results of this phase would be an optimised set of features and candidate materials that mostly balance weight, strength, fatigue life, and thermal performance in the model.

Algorithm 1. Pareto Optimisation for Aerospace Material Selection

Input: x ← Dataset containing n materials.
Output: $x*$ ← Final material selected from Pareto front based on scalarised decision

Begin
For each material x:
Normalise each feature $f_i(x)$ to ensure scale invariance
Define multi-objective function $F(x) = \{f_1(x), f_2(x) \ldots, f_6(x)\}$
End for
Initialise empty set P ← $\{\}$
For each pair of materials (x_1, x_2) in x:
If x_1 dominates x_2 across all objectives:
Mark x_2 as dominated
Else if x_2 dominates x_1:
Mark x_1 as dominated
Add all non-dominated materials (not marked) to set P
P now represents the Pareto-optimal front of solutions
For each material x in P:
Compute scalarised decision score: $S(x)$
End for
Select optimal material based on the weighting vector W
Return Pareto front P and selected the optimal material $x*$
End for
End Algorithm

Material Suitability Prediction

In determining the feasibility of a material to be directly integrated within an aerospace landing gear strut assembly design, a multi-objective modification of the XGBoost algorithm is adapted to address the incompatibility of requirements for building a lightweight structure, mechanical stability and thermal-resilience. It is an effective and scalable version of gradient boosting, usually applied to classification and regression. It composes a sequence of decision trees, with each additional tree seeking to correct the errors that the earlier ones minimise a differentiable loss function through gradient descent. There are a number of advanced features installed in this model to discourage overfitting; forlorn training is encouraged with the help of parallelisation of the tree, and sparseness is properly managed.

Input material data were preprocessed prior to model training. Numerical features were checked for missing values and handled using mean imputation. Although feature normalisation was applied during Pareto optimisation to ensure scale invariance across objectives, XGBoost does not require strict normalisation, so raw feature scales were retained for model training. No categorical variables were present in the dataset; hence, no encoding was necessary. This has enabled it to be among the most widely used ML algorithms as well as practical tools, particularly to learn complex patterns with high-dimensional data. As shown in Figure 3, the XGBoost capability classifier workflow architecture of the proposed system is illustrated.

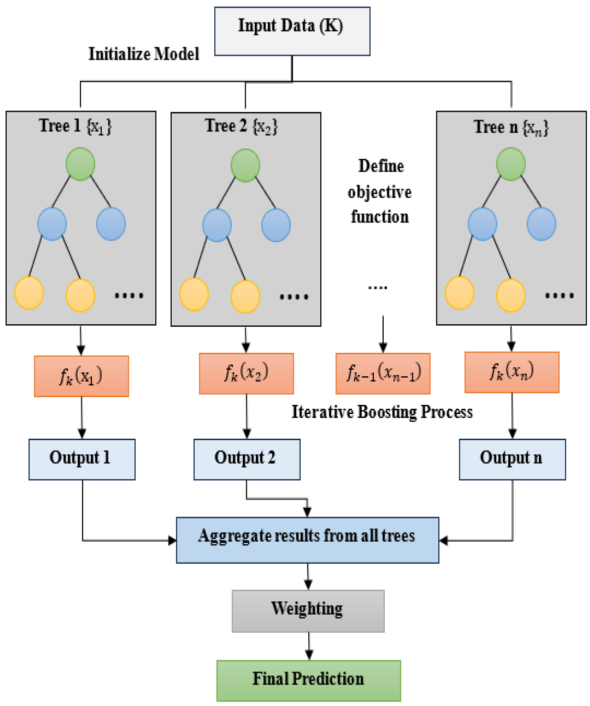

Figure 3. Architecture of the XGBoost Algorithm for Aerospace Material Suitability Classification

This work is extended to handle multiple objectives simultaneously by embedding Pareto-based optimisation principles within its loss formulation $\mathcal{L}(f)$. The optimisation problem is formulated as in equation (7).

$$\min_{x\in\mathcal{P}} \mathcal{L}(\mathrm{f}) = \sum_{i=1}^{N} \sum_{k=1}^{K} \omega_k \ell_k\big(y_i, f_k(\mathrm{x}_i)\big) + \Omega(f_k) \tag{7}$$

Where N denotes the number of materials in the data, K represents the number of objectives (lightweight, strength, fatigue resistance, and thermal stability), and $\ell_k(\cdot)$ is the loss function corresponding to the k-th objective. The weights ω_k balance the contribution of every objective and dynamically adapt according to the Pareto dominance and $\Omega(f_k)$ is the regularisation term which keeps the model complexity levels to avoid overfitting. The $f_k(\mathrm{x}_i)$ is used, depending on the predictive model of the $k-th$ objective, which will be used in predicting the feature vector of the $i-th$ material. The ground truth suitability value label of the individual materials can be denoted as $y_i \in \{0,1\}$ where 1 is any indication that the material could be used in an aerospace structural application, and 0 is any indication that the material cannot be used in an aerospace structural application.

For classification into aerospace-suitable or unsuitable classes, the probability (p) is computed using the logistic mapping.

$$p(y_i = 1 \mid \mathrm{x}_i) = \frac{1}{1+\exp\left(-\sum_{t=1}^{T} f_t(\mathrm{x}_i)\right)} \tag{8}$$

In this equation (8), $f_t(\mathrm{x}_i)$ represents the prediction of the t-th tree for material i and T is the total number of trees in the ensemble.

To explicitly capture the trade-offs among density, strength, fatigue life, and thermal stability, the gradient and Hessian statistics within XGBoost are redefined as a vector-valued formulation, shown in equations (9 & 10).

$$\nabla_i = \left(\frac{\partial \ell_1}{\partial f(\mathrm{x}_i)}, \frac{\partial \ell_2}{\partial f(\mathrm{x}_i)}, \dots, \frac{\partial \ell_K}{\partial f(\mathrm{x}_i)}\right) \tag{9}$$

$$\mathrm{H}_i = \left(\frac{\partial^2 \ell_k}{\partial f(\mathrm{x}_i)^2}\right)_{k=1}^{K} \tag{10}$$

Where ∇_i captures the slope of the loss functions with respect to the model prediction $f(\mathrm{x}_i)$. The function ℓ_K denotes the loss associated with the $k-th$ objective, while ∂ expresses how sensitive the error of the objective is k is to change in prediction. To complete this, the curvature of the error surface is represented in the Hessian H_i of the error function, with each of the terms being the second derivative loss of the objective number k to prediction, defining the break of the loss function.

Algorithm 2. Multi-Objective XGBoost for Aerospace Material Suitability Prediction

Input: Material data

Output: Suitability class label y_i

Initialise model ensemble $f = \{\}$

For each objective $k \in \{1 \dots K\}$:

Initialise loss component l

Assign adaptive weight ω_k

For $t = 1$ to T do:

For each material sample (x_i, y_i) in data do:

Compute Gradient and Hessian for all objectives

For each node j in the decision tree:

Compute Pareto dominance rank R_j based on objective improvements

Select optimal split feature $s*$

Grow subtrees recursively to minimise the aggregated Pareto loss $L(f)$

Add constructed tree to ensemble f

Update prediction $f(x_i) \leftarrow f(x_i) + \eta \cdot f_t(x_i)$

where η is the learning rate controlling step size

For each material i:

Compute probability p_i

Assign class:

If $p_i \geq \tau \rightarrow \hat{y}_i = 1$

Suitable for aerospace structure

Else $\rightarrow \hat{y}_i = 0$

Not suitable

Rank all materials

Output top-ranked Pareto-optimal materials as final recommendations

End for

End Algorithm

This allows decision trees to be constructed to optimise on several objectives at the same time, resulting in less dense splits that give maximum strength, fatigue life and thermal stability in a balanced manner. The end result of this process is a binary prediction on whether a material is suitable for an aerospace structure or not, and a list of the candidate materials assessed in rank depending on their composite performance score on the Pareto front. This ensures that the chosen materials have been optimised on all key design dimensions, making the framework both predictive and prescriptive in the aerospace material selection process.

Hyperparameter Tuning and Pareto-Front-Based Selection

To further enhance the robustness of the proposed multi-objective XGBoost classifier, a structured hyperparameter optimisation and Pareto-based selection strategy was introduced. The objective of this process was to balance multiple aerospace design criteria (weight minimisation, strength maximisation, fatigue resistance, and thermal stability) while maintaining high predictive accuracy.

(a) Hyperparameter Optimisation Framework
The tuning task employed a hybrid search algorithm, combining grid search with random search and k-fold cross-validation (CV) to enhance the robustness of the statistics. Different CV iterations calculated multi-objective scores instead of using a single scalar measure, making it possible to evaluate the performance of all important material objectives, which are recorded in Table 1.

Table 1. Hyperparameters and Search Space

Parameter	Range/Values Tested	Purpose
Learning rate	[0.01, 0.05, 0.1, 0.2, 0.3]	Controls the gradient descent step size
Max depth	[3, 5, 7, 10]	Limits tree complexity and mitigate overfitting
n estimators	[100, 200, 300, 400, 500]	Defines the number of boosting iterations
subsample	[0.6, 0.8, 1.0]	Specifies the fraction of training data per tree
Col sample by tree	[0.5, 0.7, 1.0]	Determines the fraction of features per tree
gamma	[0, 1, 3, 5]	Controls the minimum loss reduction required for a split

(b) Multi-Objective Cross-Validation Scoring
Each CV fold produced a composite performance score S_{cv} defined as in equation (11):

$$S_{cv} = \sum_{i=1}^{4} w_i . m_i \tag{11}$$

Where w_i denotes the Pareto-derived weight for each objective and m_i represents the normalised fold-level metric (accuracy, F1-score) associated with the respective design goal. This enables the evaluation of trade-offs among lightweight design, mechanical strength, fatigue endurance, and thermal resilience.

(c) Pareto-Front-Based Model Selection
Unlike traditional optimisation approaches that rely on a single scalar objective, the proposed scheme identifies the Pareto front of non-dominated hyperparameter sets, ensuring that no configuration performs strictly worse across all objectives. The final model configuration was selected from this front, promoting a balanced compromise among competing material performance criteria.

Final Optimised Configuration:

- Learning rate: 0.1
- Max depth: 7
- n estimators: 300
- subsample: 0.8
- col sample by tree: 0.7
- gamma: 1.0

This shows that the final hyperparameter configuration lies on the Pareto-optimal frontier, representing a balanced trade-off among the competing objectives of lightweight design, strength, fatigue resistance, and thermal stability. It indicates that the selected XGBoost model achieves near-optimal performance across all design dimensions without sacrificing one criterion to improve another. In essence, this configuration reflects the most efficient compromise point, where model complexity, generalisation, and multi-objective performance are simultaneously maximised—demonstrating the strength of Pareto-front-guided selection in aerospace material optimisation.

3.3. Design Process and Practice

Once the model generates predictions on the suitability of the materials, the product design process and its practices follow. The products are the classification results, presenting each material as either structurally suitable (Yes) or not (No) for use in aerospace purposes. A graphic representation of the ranked output is then performed with the objective of determining the best performing materials in terms of their forecasted trade-off between weight, strength, fatigue endurance and thermal resistance. Moreover, this is expanded into the design iteration process, wherein AI-generated knowledge is provided to the systems to refine and thus create a feedback loop between prediction and validation in the engineering process.

Product Design Process

It focuses on the logical explanation and use of an AI model to inform aerospace material selection. The results produced by this model upon determining the suitability of each material are organised into various hierarchies, which indicate that the available materials are most suitable for aerospace, such as lightweight, high strength, thermal management and resistance to fatigue. It is a process that constitutes the computational intelligence of CAI product design, where the raw material information is converted into actionable information. Unlike conventional methods of empirical testing or trial and error, AI findings can help designers identify statistically based material that fits aerospace features. At this step, it ensures that the decision-making process is not arbitrary but is instead supported by an evidence-based ranking system based on multi-objective optimisation.

Product Design Practice

In practice, the model results are incorporated into practice-based aerospace design processes which gives a strong statement on which materials need to be subject to additional analysis and simulation. Through AI analysis, it was discovered that the chosen alloys and materials are lightweight and provide thermal protection. The materials will automatically be shortlisted for inclusion in the structural designs, including the aircraft wings, fuselage frames, or turbine blades. The applied component is in the interpretation of predictions into engineering activities: AI suggestions are compared with modelling, safety requirements and manufacturing viability. This repeating synergistic feedback loop keeps the design process streamlined for aerospace real-world implementation. The practice itself is a component of this phase, thereby fortifying CAI by combining computational forecasts with the judgment of engineering conditions. Thus, ensures that the ultimate design choices are equally clever and viable.

The working regime of the product design process and practice stage in the CAI framework is indicated in the following courses of action.

- Collect predictions (Yes/No) of the AI model.
- Request a performance trade-off of ordered materials (strength, weight, fatigue, thermal).
- Discuss reasons as to why the best materials are at the top and record their characteristics.
- Best-fit components of the wings, fuselage, blades, or engines are removed to shortlist.
- FEA selection of materials to be simulated.
- Optimise the model and design loop for engineering validation.

This is stretched to design iteration, thus forming the cycle between computational conjecture and engineering confirmation. Therefore, the analysis step brings material recommendations and creates an organised decision-making practice that bridges reactions in data-supported predictions and realistic aerospace design demands.

3.4. Structural Design Integration

When the most ideal-performing materials are incorporated into the design process using FEA in structural design, it confirms their productiveness in operating conditions with aerospace characteristics. Vibration/modal analysis is the first step of the simulation. These ensure that the materials and structures remain intact after being subjected to oscillating aerodynamic loads during flight. The second stage is the thermal analysis, which is a model of the heat distribution and the thermal gradient to engine components and heat-sensitive structures. By subjecting the material to high thermal conditions similar to those experienced in jet propulsion, the thermal expansion, creep, and fatigue resistance are assessed. In this way, the framework can ensure the integration of structural and thermal robustness-proven materials into aerospace applications, thereby closing the gap between material selection and design engineering processes. Figure 4 implies the FEA schematic chart of aerospace material/structural integration procedures.

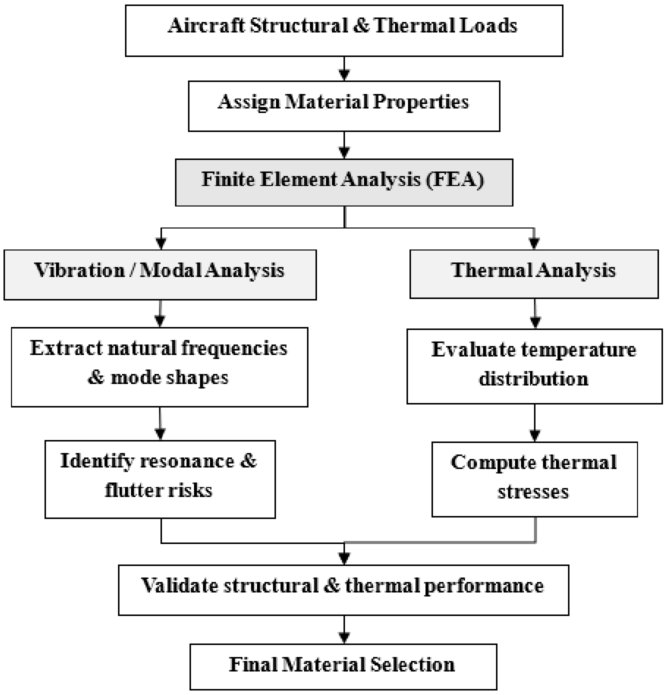

Figure 4. FEA System for Aerospace Structural Design Integration

Vibration/Modal Analysis

In the structural design integration stage, vibration and modal analysis play crucial roles in evaluating the dynamic stability of aerospace components, such as aircraft wings and turbine blades. Flutter is one of the most lethal failure mechanisms in the field of aerospace engineering when aeroelastic forces interact with structural modes of oscillation, causing oscillations to build up until a catastrophic event occurs. The importance of the vibration properties of candidate materials used in the structural components has to be strictly checked as a preventive measure against such disastrous behaviour. This is achieved through the equations of motion in structural dynamics, which mathematically formulate a system's response to external excitation. The generalised equation of the free vibration of a discretised aerospace structure takes the form in equations (11 and 12) below.

$$[M]\ddot{u}(t) + [C]\dot{u}(t) + [K]u(t) = F(t) \quad (12)$$

In which $[M]$ relates to the distribution of mass in the structure. $[C]$ relates to mechanisms of dissipating energy in the structure, $[K]$ relates to the nature of the material to maintain its configuration, and $u(t)$ relates to structural deformation at the time t. $\dot{u}(t)$ and $\ddot{u}(t)$ are the first and second derivatives of $u(t)$, which is the deformation, and $F(t)$ is the applied aerodynamic forcing. To perform modal analysis, traditionally, external forcing ($F(t) = 0$) and damping functions ($[C] = 0$) are ignored, and the equation is reduced to the classical eigenvalue problem.

$$([K] - \omega^2[M])\phi = 0 \quad (13)$$

In this case, ω is a vibration frequency of the circles and ϕ is a mode shape vector characterising the distribution of vibration. The solution to this eigenvalue problem is the natural frequencies ϕ_i and the mode shapes phi. These are the outcomes of aerospace design that determine the frequencies. When the external aerodynamic force is excited around the natural frequency of the structure, the amplitude of the vibration increases manyfold, and this causes the flutter or material fatigue.

The practical application of this involves assigning the candidate material properties (density, Young's modulus, and damping coefficients) to the mass and stiffness matrices. To illustrate, a low-density material that is stiff is placed such that its eigenvalues are higher, hence enhancing flutter resistance in aircraft wings. On the other hand, a material with insufficient stiffness could lead to a situation where natural frequencies appear within the operation range of aerodynamics and will therefore not be suitable in aerospace. The methodology, where the equations are incorporated into a simulation, allows the measurement and comparison of the vibration behaviour of any particular candidate material. In this way, the present case of this analysis, which is based on the eigenvalue formulation of structural dynamics, gives a testable way of shriving off the destructive resonance effects in aerospace design.

Thermal Analysis

Thermal analysis is also used in the structural design integration framework to determine the performance of aerospace components in terms of heat transfer and heat resistance, as well as in engine components and other heat-sensitive structures. In high-performance aerospace systems, materials are subjected to high temperatures and thermal gradients, which can lead to expansion, stress and even system failure if not properly considered. To model the thermal behaviour of materials in such situations, the station uses a framework that involves the governing heat conduction equation, which is a partial differential equation in general form, given by (13).

$$\rho c_p \frac{\partial T(\mathrm{x},t)}{\partial t} = \nabla \cdot (k\nabla T(\mathrm{x},t)) + Q(\mathrm{x},t) \quad (14)$$

In this case, ρ is the material density, c_p is the specific heat capacity, and $T(\mathrm{x},t)$ is the temperature field when the spatial location is x and the time is t. The k represents thermal conductivity, which is the rate of heat passage through the material, and $Q(x,t)$ is a volumetric heating generating term that indicates sources of internal heat within the engine, such as combustion. The heat diffusion during the process is represented by the operator ∇^2, where the operator $\nabla \cdot (k\nabla T)$ in the temperature field is operated in the form of the Laplacian operator.

In the case of steady-states, where the temperature is independent of time, the equation reduces to:

$$\nabla \cdot (k\nabla T(\mathrm{x})) + Q(\mathrm{x}) = 0 \quad (15)$$

The solution of this equation (14) represents the temperature distribution through one of the components, enabling an engineer to identify hotspots and areas where thermal stress exceeds that of the material. Evaluation of thermal expansion and stress may be made based on the relation as expressed in equation (15).

$$\sigma_{\text{thermal}} = E\alpha\Delta T \quad (16)$$

Where σ_{thermal} is the thermal stress, E is Young's modulus, α is the thermal interpretation of the resolution product module and ΔT is the thermal expansion of the component. This connection also holds true for high-strength materials that fail when thermal stresses exceed permissible values. The candidate materials proposed by AI are incorporated in thermal simulations, including the density, thermal conductivity, specific heat and thermal expansion characteristics.

Through the application of engine-representative heat fluxes and conditions, the framework assesses the response of each material to extreme thermal conditions and only materials that can withstand extreme temperatures without undergoing undue stress or other adverse criticism are taken into consideration as aerospace structure components. This idea enables the methodology to mathematically match material selection with thermal efficiency, resulting in a validated aerospace design.

Material Selection

The framework enables the provision of measurements to assess how well each candidate material performs under real-world aerospace operating conditions by comparing AI predictions with simulated mechanical and thermal responses. This analysis ensures that only materials that portray a perfect combination of structural stiffness, vibration resistance, thermal tolerance and fatigue endurance are kept. This strategy, therefore, has the benefit of avoiding risks of falling into the trap of picking up materials that would seem comfy in theory but that do not work in reality due to aerodynamic or thermal loads. The completed materials are then suggested to be incorporated structurally into aerospace structures, which include wings, fuselage structures, turbine blades and engine casings, constituting a secure and high-performance aerospace design. However, this process makes the framework a harmonious combination of neural algorithm-based choice and strict validation of a one-sided simulation, developing a rapid, low-investment, and intelligent technique of material choice in the aeroplane.

4. Experimental Evolution

This section is to create and test an AI-aided CAI system to choose the best and optimal materials and design structurally efficient aerospace components, a landing gear strut assembly. The experimental simulations are used to test the predictive accuracy of the proposed XGBoost-Pareto model and to test the mechanical and thermal performance of the chosen materials under typical aerospace loading conditions. All the implementation was performed in MATLAB on a system with the 12th Gen Intel(R) Core (TM) i5-12400 processor (2.50 GHz) and 8.00 GB RAM (7.75 GB active), which is efficient in the computation of multi-objective optimisation and finite element analysis. The main results of the AI-based selection process included cutting down the design iteration time and enhancing the accuracy of the decision-making process, which confirmed the high level of efficiency of the presented framework in the context of creating lightweight, high-strength and thermally resilient aerospace structures.

4.1. Material Screening

The material screening process which forms the basis of the aerospace structural design is introduced in this section, with emphasis the landing gear strut assembly. The findings confirm that carbon fibre and composite material have a better strength-to-weight ratio and thermal stability and therefore are suitable in areas of the strut structure that demand critical load-bearing and heat sensitivity.

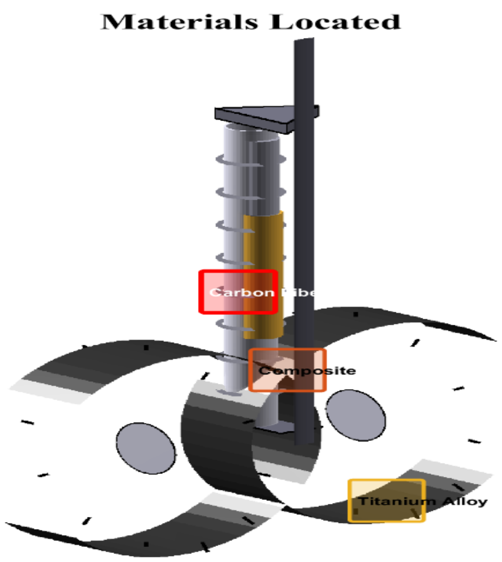

Figure 5. Optimised Material Allocation in Aerospace Landing Gear Assembly

The distribution of advanced materials in the planned landing gear strut assembly is displayed in Figure 5. This indicates every material used to perform the system in structure and thermal behaviour. This brings out the carbon fibre usage along the central shaft to give maximum strength-to-weight efficiency. Thus, the composite materials in the lower part produce high fatigue strength and the titanium alloy used at the base to provide maximum load carrying and thermal stability. This justifies the AI-based material selection process through mapping the best materials to their functional area in the assembly.

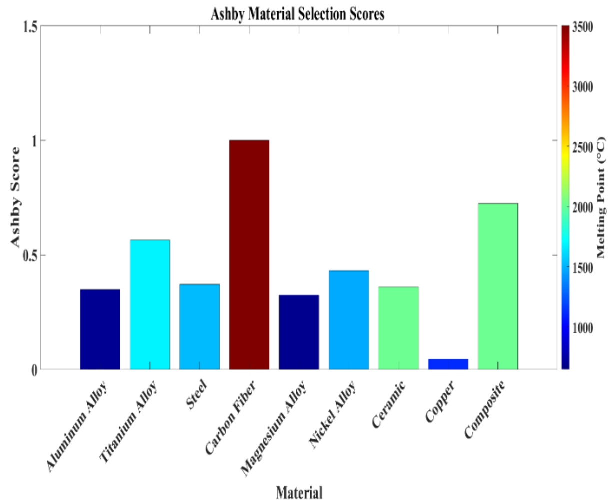

Figure 6. Ashby-Based Material Screening for Aerospace Structural Design

Figure 6 suggests that the analysis of candidate materials with the Ashby Score to design aerospace structures with special attention to the landing gear strut assembly. This represents the ranking of every material by a multi-objective performance measure to a product of density, strength and melting point. The Ashby Score (0-1) normalised factors of suitability with carbon fibre being at the highest score of 1.0 owing to the outstanding strength-to-weight ratio and thermal stability (melting point: 3500°C). Also, composite materials with a score of 0.724; titanium alloy and nickel alloy have scores of 0.565 and 0.431, respectively. This justifies the final choice of carbon fibre and composite as the best candidate for high performance.

Table 2. Material Screening Metrics for Aerospace Application

Material	Density (g/cm³)	Strength (MPa)	Melting Point (°C)	Score
Carbon Fiber	1.6	1200	3500	1.000
Composite	2.0	950	2000	0.724
Titanium Alloy	4.5	900	1660	0.565
Nickel Alloy	8.2	1000	1450	0.431
Steel	7.8	800	1500	0.371
Ceramic	3.9	250	2000	0.360
Aluminum Alloy	2.7	450	660	0.350
Magnesium Alloy	1.8	300	650	0.324

Copper	8.9	220	1085	0.046

Table 2 shows a screening of candidate materials based on key engineering properties used to calculate a single Ashby Score of aerospace structural design. This measures the suitability of the content in the landing gear strut assembly. The Ashby Score is a list of materials with the highest to the lowest performance based on a multi-objective optimisation model. This tabulated information supports the process of the selection conducted by AI and proves the fact that the carbon fibre and composite materials can be used in order to be integrated in high-stress zones and in heat-sensitive areas of the aerospace landing gear construction.

4.2. Performance of AI Model

The effectiveness of the AI model shows that the XGBoost algorithm, with the help of the Pareto optimisation, is able to successfully classify material and determine whether the material is fit or not to be used in the aerospace structures. This proves the model was accurate, which validated its suitability in multi-objective selection of materials used in the aerospace industry.

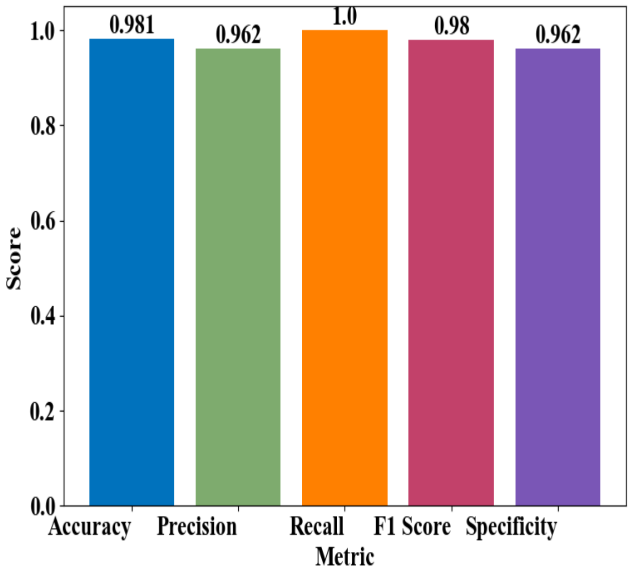

Figure 7. Validation Metrics of AI-Powered Aerospace Material Classifier

Figure 7 shows the performance indicators of the proposed AI-based material classification model of XGBoost and Pareto optimisation to forecast aerospace suitability of potential material. The important assessment parameters are accuracy (0.981), precision (0.962), recall (1.000), F1 score (0.980) and specificity (0.962). This indicates that the model is dependable to perform the task of multi-objective classification. This confirms the model is able to detect all the appropriate aerospace materials with no false negatives, whereas the appropriate balance between precision and specificity gives the minimal misclassification. Therefore, it strengthens its practicability in the aerospace design processes.

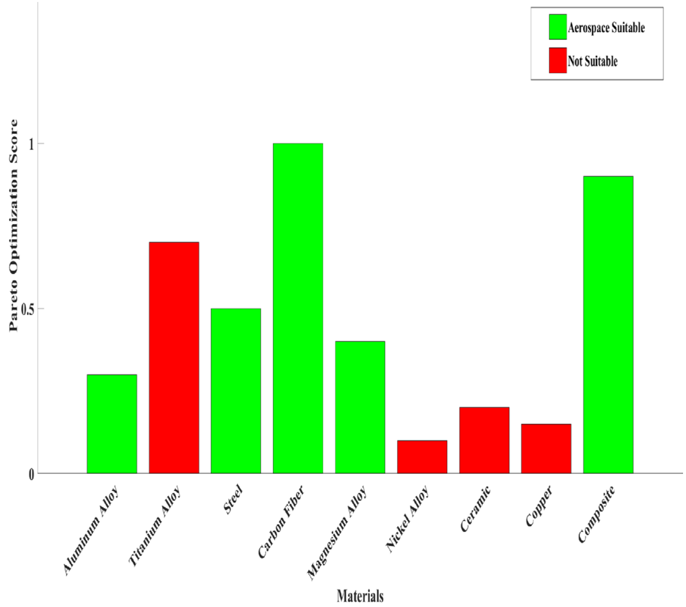

Figure 8. AI-Based Aerospace Material Suitability Classification Using Pareto Scores

Figure 8 shows AI-based classification of candidate materials using their Pareto optimisation scores to be used in aerospace structural engineering as either Aerospace Suitable or Not Suitable. The Pareto scores were developed based on the multi-objective optimisation of density, strength, melting point and carbon fibre with the highest Pareto score (1.48), followed by composite (1.32) and magnesium alloy (1.21). Such materials as ceramic and copper were defined as inappropriate because of low strength and thermal constraints. This justifies the predictive nature of the AI model and graphically justifies the choice of high-performance materials to be incorporated into the landing gear strut assembly to have maximum strength/weight ratio and thermal stability.

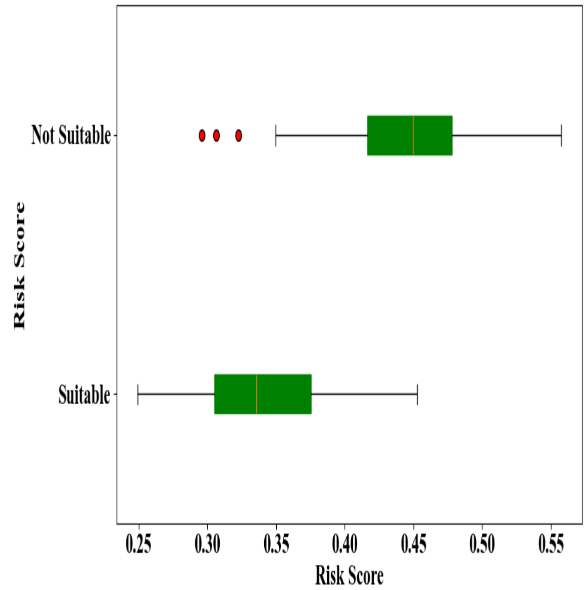

Figure 9. Risk Score Distribution for Aerospace Material Suitability

According to the AI model, Figure 9 shows the distribution scores of risks between materials that are identified as "suitable" and "not suitable" materials to use in aerospace structures. This illustrates the interquartile range (IQR), the median and outliers of both categories, which provides the variability of the classification process. Materials that can be selected have a narrower range of risk scores (0.42-0.52) and no significant outliers, which means that all design objectives are performed steadily and reliably. On the contrary, the Not Suitable group exhibits greater dispersion (0.28-0.48), and three outliers are on low ends, indicating greater uncertainty and lower predictive power. This tests the AI classifier and proves the materials chosen to be integrated in the landing gear strut assembly.

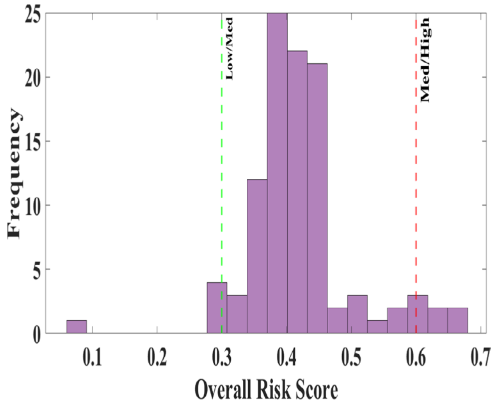

Figure 10. Risk Score Distribution for Aerospace Material Classification

Figure 10 shows the distribution of the total risk scores by the considered material data to the AI-based model to identify the materials as either good or bad in aerospace structural applications. This visualises the frequency of risk scores between 0.1 and 0.7, with the majority of the scores falling between 0.3 and 0.5. Two threshold indicators of 0.3 (low/medium risk) and 0.5 (medium/high risk). It assists in grouping the population into doable groups. The contents whose values are below 0.3 should be regarded as highly reliable, whereas above the 0.5 threshold, they should be excluded due to the materials have high uncertainty. The distribution proves that most aerospace-suitable materials, including carbon fibre and composites, have low to medium risk scores, supporting the predictive reliability of the model and screening accuracy.

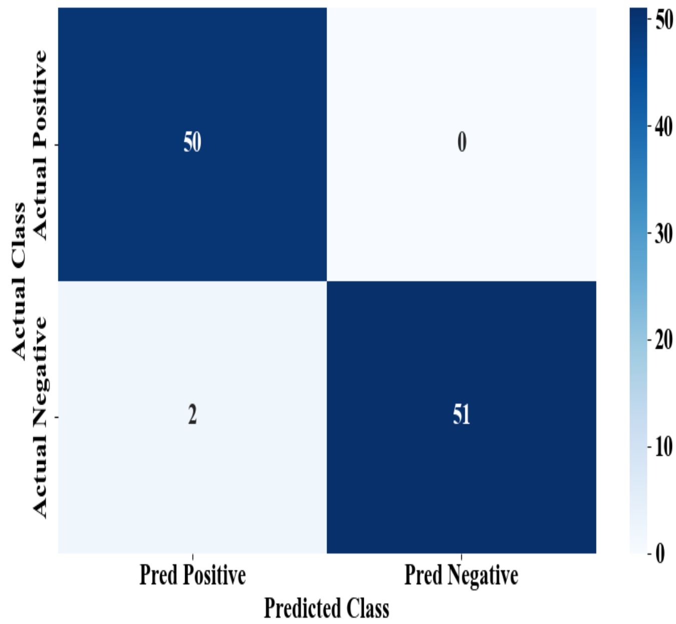

Figure 11. Confusion Matrix Validation of AI-Based Aerospace Material Classifier

The confusion matrix which the performance of the suggested AI model was assessed is illustrated in Figure 11. It is the ratio of the predicted outcomes and actual outcomes, of which 50 of the true positives and 51 of the true negatives prove the true prediction and 2 of the false positives and 0 of the false negatives. This helps in justifying the effectiveness of the XGBoost classifier combined with Pareto optimisation to make the appropriate choice of materials as well as regretting the misclassification. In such a way, verifying that the model provides a reliable method of the intelligent material screening of the aerospace structural design by the identification of the aerospace-appropriate materials is confirmed.

4.3. Vibration / Modal Analysis

This analysed to determine the dynamic behaviour of aerospace components under oscillatory loads in FEA to determine natural frequencies, mode shapes and possible resonance risks. This suitable materials and construction designs are stable in terms of mechanics in the flight and landing activities.

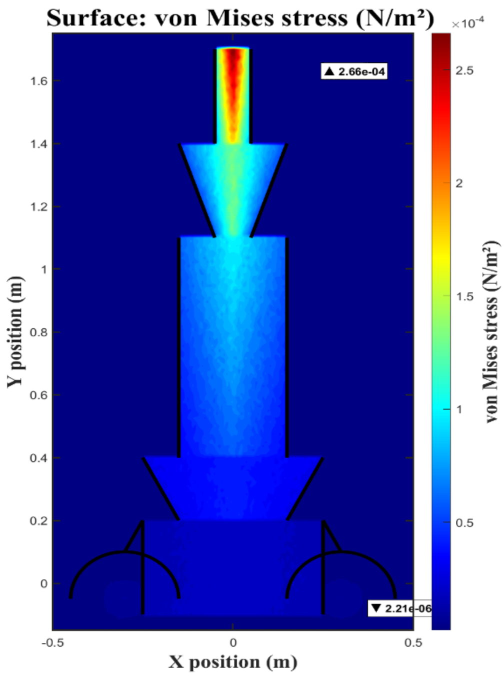

Figure 12. von Mises Stress Distribution Component

According to Figure 12, the von Mises stress distribution in a geometrically complex aerospace structural component subjected to mechanical loading is visualised. This is to determine the concentration of stresses and to check the structural integrity of the design are high operational loads with the landing gear strut assembly. The simulation shows that the highest stress values of 2.66 x 10^{-4} N/m² are found in the top central area, whereas the lowest values of stresses of about 2.21 x 10^{-6} N/m² are reported in the corners of the base, and there is minimal risk of failure and ensuring compliance with aerospace safety standards.

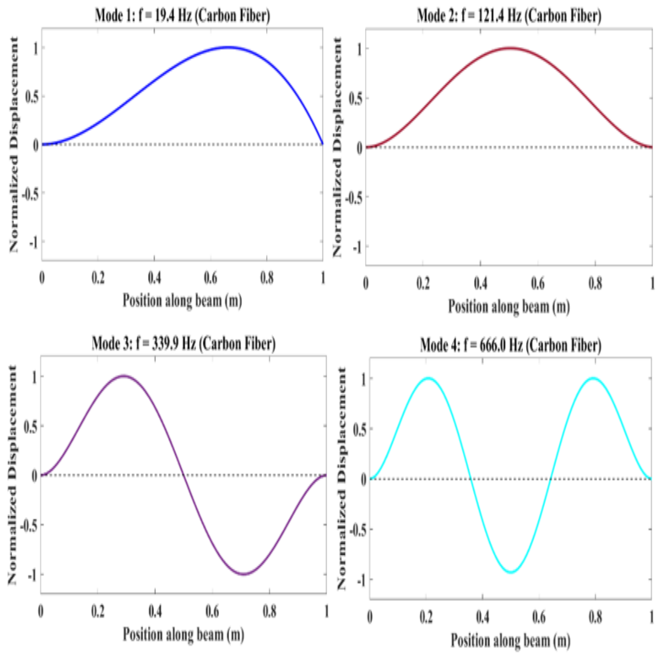

Figure 13. Vibrational Mode Analysis of Carbon Fiber Beam

Figure 13 represents the vibration behaviour of a carbon fibre beam with four different modal frequencies, which is represented as normalised displacement profiles. The dynamic response and structural stability of aerospace-grade materials under an oscillatory loading is analysed, which is particular interest when considering the landing gear strut assembly. The plots showed mode-specified frequencies: Mode 1 (19.4 Hz), Mode 2 (121.4 Hz), Mode 3 (339.9 Hz) and Mode 4 (666.0 Hz), with the complexity of the wave and the displacement nodes increasing respectively, and support the use of carbon fibre in aerospace vibration components by confirming that carbon fibre has high modal stiffness and low deformation over a large frequency range.

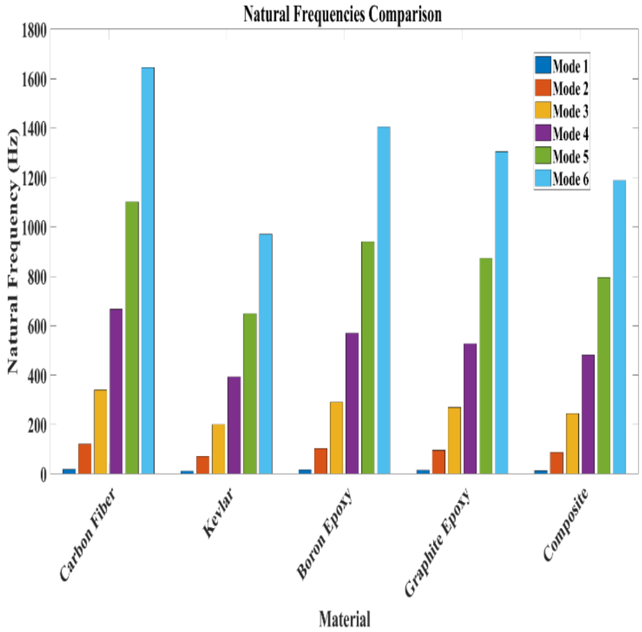

Figure 14. Multi-Modal Frequency of Aerospace Materials

Figure 14 shows the relative natural frequencies of five aerospace candidate materials in six vibrational modes. This offers a dynamic performance standard of structural application. It analyses the stiffness and resonance behaviour of every material under modal excitation of components (landing gear struts and fuselage supports). These findings demonstrate that carbon fibre and composite would always have the highest natural frequencies and even Mode 6 in the range of up to 1750 Hz. This is confirmative of its better vibration resistance and structural stability and justifies its choice in vibration-critical aerospace structures.

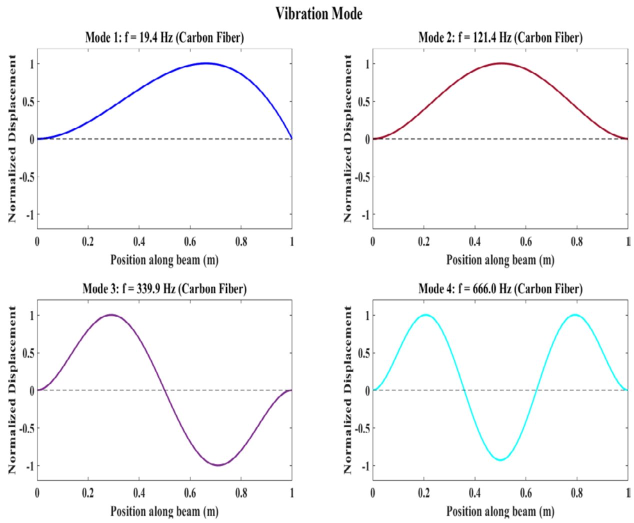

Figure 15. Mode Shape Visualization of Carbon Fiber Beam Under Vibrational Excitation

Figure 15 represents the vibrational mode shapes of a carbon fibre beam in four different frequencies showing the beam is displaced along its entire length under dynamic excitation. This study models the behaviour and structural stability of aerospace use, especially in components such as landing gear struts that are subject to cyclic loading. The plots show that the carbon fibre has a high modal stiffness and low deformation frequency across a vast range of frequencies, namely, Mode 1 at 19.4 Hz, Mode 2 at 121.4 Hz, Mode 3 at 339.9 Hz, and Mode 4 at 666.0 Hz, which confirms that carbon fibre is a good material in vibration-sensitive aerospace structures where the material does not violate the operation reliability.

4.4. Thermal Analysis

This section provides the validation of AI-selected aerospace materials by using FEA based on the behaviour of the landing gear strut assembly under oscillatory loads and thermal gradient. This analysis will be useful to guarantee that the materials used have a highly natural frequency and have low deformation due to aerodynamic excitation in structural integration with flight-critical structures.

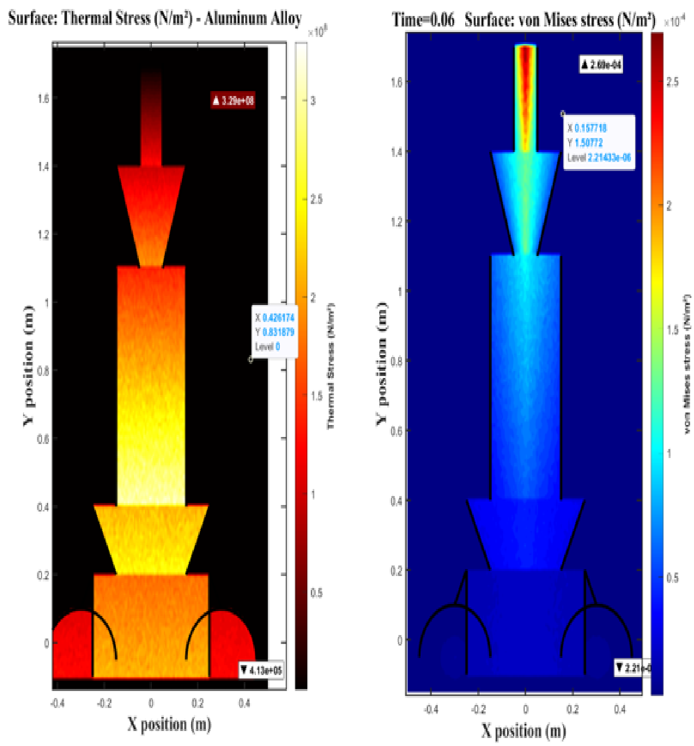

Figure 16. Thermal and Modal Stress Validation of Landing Gear Strut Assembly

According to Figure 16, the vibration endurance and thermal stress performance of aircraft components are examined: in particular, the landing gear strut assembly under the conditions of FEA is used to justify the AI-chosen aluminium alloy within the operating conditions. The left panel shows the thermal stress distribution with a maximum of 3.32 x 108 N/m², which proves the ability of the material to withstand the heat. The right-hand stimulus indicates von Mises stress of 2.00 x 104 N/m² in the dynamic loading of 0.06 seconds and the localised stress concentrations at the upper structural interface. This proves the fact that the chosen material will be deployed safely in aerospace environments.

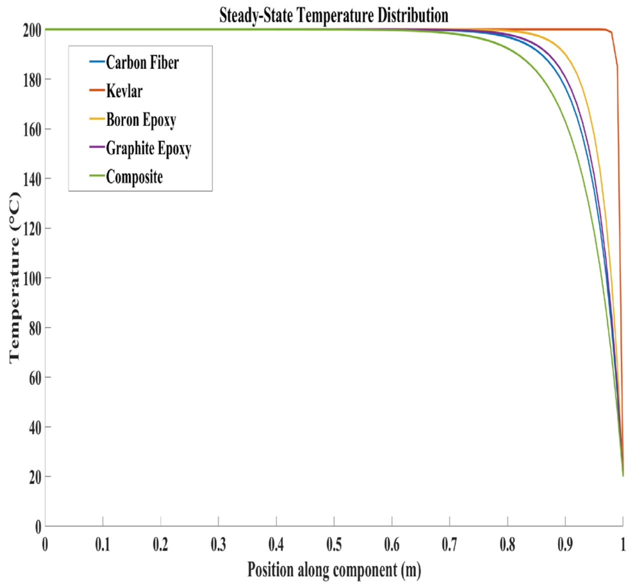

Figure 17. Steady-State Thermal Gradient Analysis

Figure 17 shows the constant temperature profile on an aerospace component that is 1 metre long and made of a combination of candidate materials. This measures the thermal conductivity and heat retention attributes of each material under uniform thermal loading conditions to choose the components that are subjected to engine heat or aerodynamic friction. The graph indicates that carbon fibre has the highest thermal stability over 180°C at the majority of the component length and dropped towards the end. Closely behind are composite and graphite epoxy, which show good heat retention and low thermal gradient in aerospace structures to withstand high thermal loads and less expansion as heat loads.

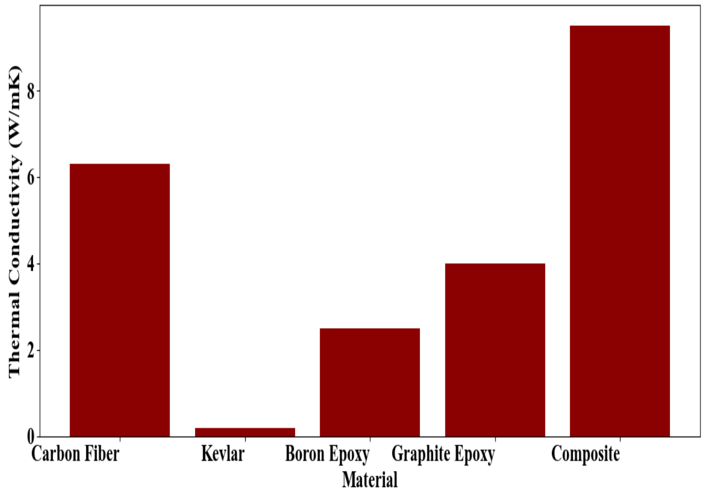

Figure 18. Thermal Conductivity Comparison

Figure 18 shows the relative thermal conductivity of five aerospace candidate materials to conduct heat according to the operating conditions. It determines the materials for heat-sensitive aerospace items like engine housings and turbine blades to curb structural damage. The findings indicate that the thermal conductivity of composite is the highest with 9 W/mK, followed by carbon fibre, which has a thermal conductivity of 7 W/mK; Kevlar has the lowest thermal conductivity of 0.5 W/mK. This implies that it cannot conduct heat easily, confirms the choice of composite and carbon fibre materials in aerospace applications that have high thermal conditions and structural integrity at high temperatures.

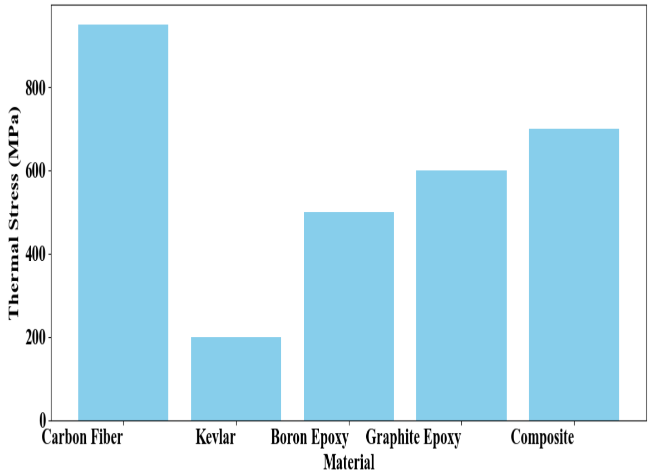

Figure 19. Thermal Stress Resistance

Figure 19 represents the relative thermal stress resistance of advanced materials under aerospace simulated thermal loading conditions. The findings indicate that carbon fibre has the greatest thermal stress capacity of about 900 MPa, then composite and graphite epoxy have 700 and 600 MPa. This measures the performance of every material to endure the mechanical pressure by high temperatures during the choice of components used to make engine housings, turbine blades and structural areas that require high heat.

4.5. Discussion

This study has shown that combining AI with CAD practices can be effective in dealing with the complicated task of aerospace materials selection. The validity of the results is enhanced by the incorporation of real mechanical properties of an aircraft landing gear strut assembly with the validation added by simulation. The predictive capability of the model and compatibility with the practical aerospace performance requirements are justified by the high values of the safety factors, modal frequencies and thermal conductivities of the chosen materials. The results are relevant to the overall intelligent product design and aerospace engineering field since they present a scaled, data-driven alternative to the conventional processes of expert-based material selection. The research design will combine FEA and AI-based prediction so that the outputs of the model will be practically feasible. This mixed methodology fills the divide between computational prediction and physical feasibility, a major necessity in aerospace problems where safety and reliability are of utmost importance.

Comparing it with past research, as presented in Table 3, which used neural networks to design products, the present model is a step forward in the field as it involves the use of multi-objective optimisation as the direct part of the learning process. In addition, as opposed to the previous works, this work presents a scalarised decision function that enables the provision of dynamic weighting of the design priorities, which is more flexible and responsive to context. The recent addition of Pareto-based loss functions to XGBoost allows multiple material properties to be optimised simultaneously without affecting model interpretability or model performance.

Table 3. Comparative Analysis of AI-Based Aerospace Material Selection Studies

Study	AI Method	Optimisation	Validation	Contribution of This Study
[33]	Random Forest	Manual weighting	Empirical	Adds Pareto + FEA + real aerospace use case
[34]	ML for alloys	Grid search	Alloy prediction	Adds structural simulation + multi-objective ranking
[35]	ML + Pareto	Discovery-focused	Materials screening	Applies Pareto to structural design, not just discovery
[36]	High-dimensional	Pareto algorithm	Aerospace design	Embeds Pareto logic into XGBoost classifier

Overall, this study introduces a strong and flexible CAI model that can not only speed up the process of material selection but also make it more accurate and reliable. The new level of intelligent aerospace design is determined by the new combination of AI-based classification and simulation-based validation.

5. Conclusion

The present study successfully designed and tested a landing gear strut under the CAI product design paradigm with the AI multi-objective optimisation to improve aerospace material selection and construction. The framework is based on the integration of the Pareto optimisation mechanism into the XGBoost classification model, through which the materials with the best performance measures were ranked in a systematic manner. These findings validate the material as suitable in the aerospace industry, and the classification model has a predictive accuracy of 98.1% to select the best applicant by using multi-objective measures of performance. As well, the analysis demonstrated that the landing gear strut assembly utilised Aluminium 7075-T6, which had a yield strength of 503 MPa, a tensile strength of 572 MPa and a modal frequency of 173 Hz with a safety factor of 13.5 against yield and more than 21.5 against buckling. The combination of AI-aided prediction with FEA ensures that the chosen materials are theoretically best suited to the conditions they are subjected to in operational settings. In this way, design times were reduced, development costs were lowered, and reliability was improved in high-stakes aerospace applications, allowing informed decisions to be made in a variety of trade-offs in aerospace material choice and providing new performance-driven standards of innovative engineering. However, this work is flawed in the fact that it relies on pre-existing material setups that might be ineffective in capturing emerging aerospace composites. Moreover, the availability of real-world fatigue and thermal degradation data might limit the model's performance.

5.1. Future Work

Future enhancements to the CAI framework will include real-time sensor feedback and adaptive learning, enabling in-flight material performance monitoring that is dynamically re-evaluated under operational conditions. Also, the combination of generative design algorithms and AI-guided material selection will be discussed to suggest geometry-material pairs to maximise weight, strength, and manufacturability of next-generation aerospace parts. This will facilitate a shift from static to adaptive material selection, enabling aerospace systems to respond to real-time operational pressures and environmental conditions.

Data Availability

The datasets generated and/or analysed during the current study are available from the corresponding author upon reasonable request.

Author Contribution

Xiang Zhang: Conceptualization, Methodology, Data Curation, Writing – Original Draft, and Supervision.
Ying Zhou: Software, Validation, Visualization, and Formal Analysis.
Jingjing Shi: Investigation, Resources, and Writing – Review & Editing.

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