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Introducing a Regression Model for Environmental Assessment in Aircraft Production

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Abstract
Life Cycle Assessment (LCA) has become essential for comprehensive environmental analysis, particularly as air transport continues to grow and the demand to mitigate its environmental impact intensifies. A core challenge in conducting LCA studies lies in the extensive input data required—especially during the Life Cycle Inventory (LCI) phase, which serves as the backbone of the entire assessment. The LCI's data-intensive nature often makes the process time-consuming and resource-demanding. This paper presents a high-level LCA methodology aimed at enabling faster assessments with reduced data requirements, focusing on identifying the key parameters that most significantly influence environmental outcomes. The proposed approach begins with a cradle-to-gate LCA, with the focus on the production phase of baseline aircraft. It includes regional models (ATR42, ATR72, and E190-E2), narrow-body types (A220, A320neo, and A321neo), and wide-body aircraft (B787, A330, and B777). This requires the creation of extensive LCIs, including manufacturing processes and aircraft materials and components. Regression models are then built using the results of the LCA impact categories, which include climate change and resource use, as the dependent variables. Aircraft parameters (e.g., aircraft or engine weight) are then used as the independent variables. Three regression approaches are evaluated: linear, quadratic, and cubic. This approach enables efficient and reliable LCA calculations and is aimed at LCA practitioners and stakeholders in academia and industry. It introduces a set of equations to quickly assess environmental impacts of aircraft based on in-depth LCA calculations. Such LCA results may be used to prioritise action and support informed Design for Environment (DfE).

1. Introduction

Traditionally, the success of product development in aviation has been measured by technical performance and profitability. However, growing concerns about environmental sustainability have shifted attention toward integrating design strategies such Design for Environment (DfE), design for circular economy, and low-impact manufacturing approaches.[45] In this context, Life Cycle Assessment (LCA) has emerged as a vital tool for evaluating the environmental performance of complex systems like aircraft, offering a structured framework to assess impacts throughout a product's life cycle.
Despite its strengths, the practical application of LCA in aviation remains limited. A key barrier is the data- and time-intensive nature of the Life Cycle Inventory (LCI) phase, which can hinder the use of LCA during early stages of design where it would be most impactful.[50] Aircraft-specific data requirements, complex system boundaries, allocation procedures, and functional units further complicate its deployment.[34] Although interest in LCA within the aeronautical sector is growing, especially in relation to alternative fuels, few studies have applied LCA as early as in the aircraft design process.[56] To address these challenges, this study proposes a high-level LCA methodology designed to reduce the effort required for data collection and modelling, while still delivering reliable environmental assessments. The approach builds upon detailed LCAs of representative aircraft types—regional, narrow-body, and wide-body — and uses regression-based modelling to predict environmental outcomes from key parameters.
The remainder of this paper is structured as follows: Section 2 outlines the fundamentals of LCA, reviews current methodological approaches, and discusses their applicability to aviation. Section 3 describes the research methodology, including both the detailed LCA and the development of the high-level model. Section 4 presents the results of the analyses, comparing detailed and high-level outcomes. Finally, Section 5 concludes the paper with key findings and

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discusses future directions, including the integration of this LCA approach into early-stage aircraft design. By reducing the data efforts typically associated with aviation LCAs, this work contributes a practical approach aimed at enabling quicker environmental evaluations across the sector.[24]

2. Life Cycle Assessment

2.1 Fundamentals

LCA is a systematic methodology used to evaluate the environmental impacts of a product, process or service throughout its entire life cycle. This includes all life cycle stages from the extraction of raw materials to the disposal of the final product.[29,30] This comprehensive approach is particularly valuable in the aviation industry, where environmental concerns are growing and stakeholders begin to seek solutions to mitigate the sector's environmental footprint. It is comprised of four key steps: 1. Goal and scope definition, 2. LCI, 3. Life Cycle Impact Assessment (LCIA), and 4. Interpretation.

To carry out an LCA study properly, it's essential to define a clear study purpose from the outset, as this informs scope and boundary conditions. The goal should outline the intended application, motivation for the study, and target audience. The scope should be described in sufficient detail to ensure the level of analysis aligns with the study's objectives. It covers the product system to be analysed, functional unit, system boundaries, selected impact categories, required data, and any limitations.[13] The functional unit establishes a consistent reference for quantifying inputs and outputs in an LCA, ensuring meaningful comparisons between systems. The system boundary defines the start and end points of the life cycle analysis. It defines the scope of the life cycle analysis by specifying which processes, activities, and stages are included—from resource extraction to End-of-Life (EoL) treatment.[29,30]

The LCI step is usually the most time-consuming phase of an LCA. Guided by the goal and scope definition, the analysis primarily involves collecting and compiling data on elementary flows from all processes, drawing from a range of sources. It encompasses information such as energy and raw material consumption, emissions to air and water, solid waste generation, and other outputs throughout the life cycle.[12,29] LCIs consist of two systems: foreground and background. Foreground data refer to the processes directly under the control or influence of the study's practitioners—typically site-specific or project-specific activities. Background data are generic and typically obtained from third-party databases and are often highly aggregated.[20] Practitioners usually collect primary data for key processes and use databases such as ecoinvent to model supporting activities.[57] Due to the data-intensive nature of LCA, the accuracy and reliability of this information are crucial for ensuring credible and meaningful results.[8]

The LCIA phase evaluates the potential environmental impacts associated with the inputs and outputs identified in LCI. This is achieved by linking inventory data to specific impact categories—such as climate change, resource depletion, acidification, eutrophication, and human toxicity—using scientifically established characterisation models and LCIA methodologies.[17] The result is a set of impact scores that quantify how the product system contributes to various environmental issues. These scores help to interpret the environmental relevance of each flow and provide a basis for comparing alternatives or identifying environmental hot-spots within the system.[22] The interpretation phase is the final stage of the LCA process, where results from the LCI and LCIA steps are summarised and evaluated considering the assumptions made throughout the study. This step leads to conclusions, recommendations, and decisions that align with the study's defined goal and scope.[23]

2.2 LCA approaches

The following section delves into different LCA approaches: full LCA, Streamlined LCA (SLCA), and Parametric LCA (PLCA). A full LCA is a highly scientifically rigorous methodology and involves a thorough and detailed analysis of all stages of a product's life cycle, including raw material acquisition, manufacturing, transportation, use, and EoL management.[26,49] This approach aims to quantify all relevant environmental impacts, such as greenhouse gas emissions, resource depletion, water usage, and air pollution, providing a holistic understanding of the product's environmental performance.[27] While full LCAs offer the most comprehensive environmental assessment, they can be time-consuming and resource-intensive, requiring extensive data collection and detailed modelling.[1]

In order to overcome challenges from performing a full LCA, such as resource and data requirements, SLCA can be deployed as a simplified alternative, focusing on the most significant environmental aspects and life cycle stages of a product, process, or service—usually alongside screening techniques and simplifying assumptions to reduce data collection and analysis effort.[39,47] The aim is to provide a quick and cost-effective assessment and main areas of application are product development and procurement.[49] Two streamlining approaches are identified within the SLCA: firstly, at the LCI level, the utilisation of surrogate data facilitates the simplification of data collection and modelling;

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secondly, at the LCIA level, the communication of results is streamlined through the reduction of impact categories.[24] However, given its simplified approach, SLCA often overlooks environmental burdens or life cycle stages, potentially leading to incomplete or biased analyses.
Finally, the complexity and duration of LCA can be reduced through a parametric approach, which offers advantages over both full and streamlined LCAs. Parametrisation in LCA can be applied in various forms, including the modularisation of processes, the use of fixed life cycle structures with adjustable parameters for specific stages, and the implementation of either rigid or flexible scenario-based models.[35] It has been applied across different sectors, including architecture and the built environment,[25] additive manufacturing,[59] energy systems,[44] hydrogen production,[7] and early-stage aircraft and component design. Table 1 provides an overview of the advantages, disadvantages, and applicability to aviation of full LCAs, SLCAs, and PLCAs, along with the analysed studies.

Table 1: Overview of LCA approaches and their applicability to aviation.

Category	**Full LCA**	**SLCA**	**PLCA**
Advantages	✓ Comprehensive assessment of environmental impacts across all life cycle stages; ✓ Identification of hotspots and improvements; ✓ Credible and transparent results for decision-making.	✓ Rapid and cost-effective assessment of environmental impacts; ✓ Focus on key environmental aspects and life cycle stages; ✓ Useful for identifying major improvement opportunities and prioritising actions.	✓ Flexible and adaptable to different scenarios and design options; ✓ Useful for early-stage design and development; ✓ Allows for more flexible implementation of improvements during product development phase.
Disadvantages	✗ Resource-intensive and time-consuming; ✗ Requires extensive data collection and analysis; ✗ May be challenging to apply to complex systems with limited data availability.	✗ May overlook certain environmental impacts or life cycle stages; ✗ Potential for incomplete or biased assessment; ✗ Limited ability to identify subtle or secondary impacts.	✗ Accuracy depends on the quality of models and assumptions; ✗ May oversimplify complex relationships and processes; ✗ Requires expertise in modelling and simulation.
In aviation	✓ Evaluating the environmental footprint of entire aircraft; ✓ Comparing different aircraft designs or technologies; ✓ Identifying opportunities to reduce environmental footprint and improve resource efficiency.	✓ Screening environmental impacts of aviation products or processes; ✓ Identifying major areas for improvement; ✓ Supporting preliminary decision-making in design and operations.	✓ Exploring the environmental implications of different aircraft designs or technologies; ✓ Evaluating the impact of changes in operating conditions or maintenance practices; ✓ Supporting technology development.
Publications	Lopes (2010),[38] Jordão (2013),[33] Howe (2013),[28] Lewis (2013),[36] Cox (2018),[11] Fabre (2022),[18] Rahn (2022)[46]	Dallara (2013),[14] Parolin (2021),[43] Whittle (2024)[58]	Dallara (2013),[14] Johanning (2014),[32] Schäfer (2018),[51] Parolin (2021),[43] Vivalda (2024),[56] Anagnostopoulou (2025)[4]

2.3 Literature review

In line with the focus of this paper, a review of current literature on streamlined and parametric LCA approaches for aircraft will be conducted. For a more detailed analysis of full LCAs within the aviation sector, refer to Rahn (2022).[46] To understand how LCA is adapted for early design, the following section reviews key streamlined and parametric approaches in aviation that balance effort and decision-making utility.

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Dallara (2013)[14] introduces qUWick, a streamlined LCA tool for rapid environmental assessment of aircraft during early design. It models four life cycle phases—materials production, manufacturing, service, and end-of-service—using design inputs to calculate environmental impacts across key categories. To manage data limitations and the complexity of global supply chains, the tool uses a combination of public datasets and proprietary data. Parolin (2021)[43] develops an ecodesign tool that integrates SLCA into the conceptual aircraft design phase. Using design parameters and ecoinvent as background database the tool assesses cradle-to-grave environmental impacts and associated uncertainties. Applied to a freighter aircraft and a composite airframe scenario, results confirm the dominance of the operation phase and highlight the value of uncertainty visualization in early design decisions. Whittle (2024)[58] proposes an SLCA framework designed to reduce data and resource demands while maintaining decision-making relevance. The approach applies standardised LCA methods iteratively and incorporates continuous stakeholder engagement. Applied to an aviation case study involving sustainable aviation fuels and digitalised training regimes, the framework enables rapid assessment of environmental impacts—such as Global Warming Potential (GWP) and water consumption—without requiring granular data. Results highlight the importance of a sustainable supply chain and demonstrate the framework's suitability for early-stage evaluation of decarbonisation strategies in aviation.
A number of studies apply PLCA in the context of aircraft design. Johanning (2013)[31] integrates parametric LCA into the conceptual aircraft design phase, using simplified calculations to assess environmental impacts across manufacturing, operation, and EoL stages, with application to an Airbus A320. Manufacturing impacts, treated as one-time events, are distributed across the total passenger-kilometers of the fleet, making their influence smaller than that of recurring flight emissions. In a subsequent publication,[32] the authors extend this approach by analysing the trade-off between minimising environmental impacts and reducing Direct Operating Costs.[6,52] Schäfer (2018)[51] introduces a Life Cycle Sustainability Assessment framework for quantitative aircraft design assessment, integrating the three dimensions of sustainability (economic, environmental, and social) over the aircraft entire life cycle, from development, production, operation, maintenance, and EoL. The author presents a case study assessing a reference aircraft regarding sustainability indicators such as climate impact, noise and air pollution, among others. The aircraft is redesigned and variation in parameters such as Mach number as well as initial design parameters (e.g., wing loading and thrust-to-weight) are performed. Vivalda (2024)[56] presents a parametric LCA method for assessing the environmental impact of aircraft during the preliminary design stage. The approach covers four life cycle phases—production, operation, maintenance, and disposal—with particular emphasis on phases beyond fuel consumption. The method uses parametric equations based on early design data, such as mass breakdown and technology level. Validation against detailed reference studies shows deviations within ±10%. Anagnostopoulou (2025)[4] presents a multi-criteria sustainability assessment for aircraft components, combining LCA, life cycle costing, and performance metrics within a structured Multi-Criteria Decision-Making (MCDM) framework. Ten criteria across environmental, cost, and performance categories are evaluated using SimaPro and various MCDM methods.

3. Methods

Given the vehicle's various and complex characteristics, different baseline aircraft are used as basis for the detailed assessment, ranging from regional (ATR42, ATR72, and E190-E2), narrow-body (A220, A320neo, and A321neo), and wide-body (B787, A330, and B777). The propulsion system is differentiated between turboprop (TP) and turbofan (TF) engines. Usually, aircraft with different characteristics (e.g., fuselage diameter or number of aisles) are designed to serve different market segments, with the most suitable aircraft being chosen for each application. Regional airlines typically operate aircraft such as regional jets and TP with a capacity of 19 to 130 seats on short- to medium-haul routes.[10] Narrow-body aircraft are single-aisle, short-haul aircraft that typically carry 100–200 passengers, while wide-body aircraft are double-aisle, medium- to long-haul aircraft that can carry 200–450 passengers.[55]
The proposed approach begins with a detailed LCA of aircraft from different classes. The aircraft concepts are developed within the DLR project DEPA 2070.[15] The second step is a faster environmental impact assessment method, the so-called high-level LCA, obtained via regression models that best represent the relationship between the given set of data points. The process illustrated in Figure 1 follows the ISO 14040/14044[29,30] structure and is divided into four main steps. In step 1, the scope is defined as a cradle-to-gate LCA of aircraft production, categorised by aircraft class: regional, narrow-body, and wide-body. Aircraft components are grouped into structures, systems, furnishings and operator items, and the power unit. Step 2 involves compiling the LCI with both background and foreground data. The background data encompass energy use, resource inputs, transportation, and raw material extraction, along with the associated waste and emissions. Foreground data focus on aviation-specific elements, including alloys, manufacturing processes, and component production. The LCI is distinguished between TF and TP aircraft and aircraft category. Given that our study is a cradle-to-gate LCA, life cycle phases such as maintenance, flight operations, and EoL are out of scope.
Step 3 carries out the LCIA by evaluating midpoint impact categories such as climate change or resource depletion.

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In this stage, the results from the detailed LCA are then evaluated and form the basis for the high-level assessment. The selected LCIA method is EF 3.1, recommended by the European Commission due to its robustness and reliability for quantifying environmental performance.[17] Regression models are developed using these impact results as dependent variables, with key Top-Level Aircraft Requirements —such as Operating Empty Weight (OEW) and engine weight—serving as independent design parameters. Finally, step 4 involves the interpretation of results, integrating findings from the previous steps to support the environmental assessment.

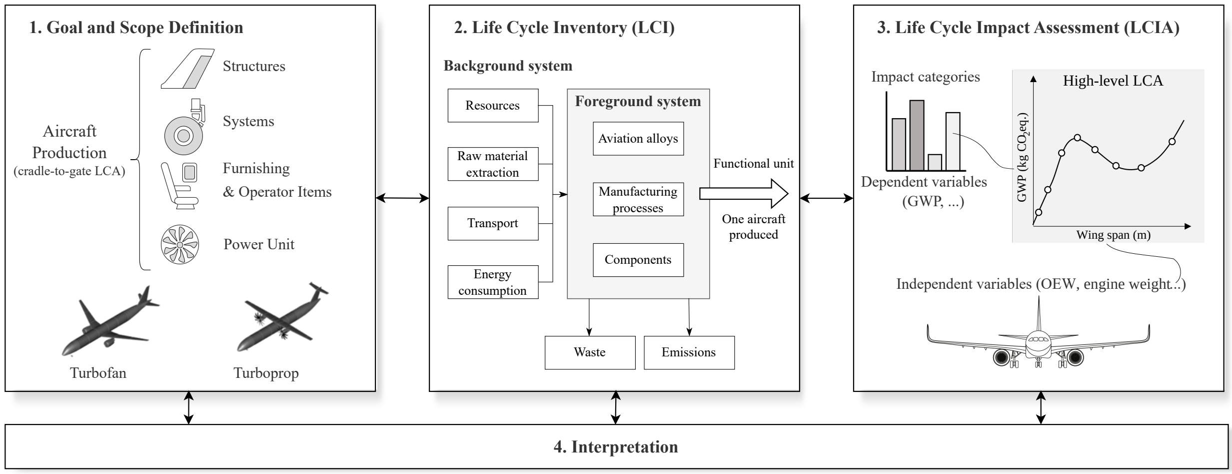

Figure 1: Overview of the LCA framework applied to aircraft production.

A thorough understanding of the complexity involved in aircraft design and manufacturing is crucial for conducting a detailed assessment. To accurately evaluate the environmental impact of each production stage, a comprehensive, component-level inventory is necessary. LCIs specific to individual aircraft models are developed, comprising databases that encompass both the production phase—including structures, engines, components, and systems —and aviation-grade materials from various sources.[2,5,19,21,48] These include aluminium, steel, titanium, nickel, and composite materials (e.g., Carbon Fibre Reinforced Polymer (CFRP), Glass Fibre Reinforced Polymer (GFRP), and Aramid Fibre Reinforced Polymer (AFRP)) along with their associated raw material extraction and manufacturing processes.[16,42,54] A more in-depth component breakdown (e.g., wing skin, aileron, fuselage stringers, etc.) is available in previous research by Rahn (2022).[46]
Foreground data are based on the component-level breakdown presented in Equation 1, while background data are sourced from the ecoinvent 3.9.1 database,[57] which provides standardised inventories for base materials, utilities, and resource consumption. The following equations provide a breakdown of the contributions to the overall LCA of aircraft production. Equation 1 defines the total production-related LCA ($\mathrm{LCA}_{\mathrm{Production}}$) as the sum of the impacts from furnishing, operator items, the power unit, structure, and systems.

$$\mathrm{LCA}_{\mathrm{Production}} = \mathrm{LCA}_{\mathrm{Furnishing}} + \mathrm{LCA}_{\mathrm{Operator\ Items}} + \mathrm{LCA}_{\mathrm{Power\ Unit}} + \mathrm{LCA}_{\mathrm{Structure}} + \mathrm{LCA}_{\mathrm{Systems}} \tag{1}$$

Equations 2 and 3 present the LCA for two engine configurations: TP ($LCA_{Power\ Unit,\ TP}$) and TF ($LCA_{Power\ Unit,\ TF}$). Both include the combustor, engine systems, gearbox, High Pressure Turbine (HPT), Low Pressure Turbine (LPT), Low Pressure Compressor (LPC), High Pressure Compressor (HPC), and nacelle. The TP also includes the air inlet and propeller, while the TF accounts for the fan. LCIs are based on extensive prior research on aircraft engines and refined using mass and material data from TF and TP engines, specifically the V2500 and PW100 models. To determine the LCA's material composition and weight distribution, the authors applied a reverse engineering approach,[40,41] estimating component masses using alloy types and dimensions. Engine parts and materials were assessed along with their manufacturing energy consumption.

$$\begin{aligned}\mathrm{LCA}_{\mathrm{Power\ Unit,\ TP}} = {} & \mathrm{LCA}_{\mathrm{Combustor}} + \mathrm{LCA}_{\mathrm{Engine\ Systems}} + \mathrm{LCA}_{\mathrm{Gearbox}} + \mathrm{LCA}_{\mathrm{HPC}} + \mathrm{LCA}_{\mathrm{HPT}} + \mathrm{LCA}_{\mathrm{LPC}} \\ & + \mathrm{LCA}_{\mathrm{LPT}} + \mathrm{LCA}_{\mathrm{Nacelle}} + \mathrm{LCA}_{\mathrm{Air\ Inlet}} + \mathrm{LCA}_{\mathrm{Propeller}}\end{aligned} \tag{2}$$

$$\begin{aligned}\mathrm{LCA}_{\mathrm{Power\ Unit,\ TF}} = {} & \mathrm{LCA}_{\mathrm{Combustor}} + \mathrm{LCA}_{\mathrm{Engine\ Systems}} + \mathrm{LCA}_{\mathrm{Gearbox}} + \mathrm{LCA}_{\mathrm{HPC}} + \mathrm{LCA}_{\mathrm{HPT}} + \mathrm{LCA}_{\mathrm{LPC}} \\ & + \mathrm{LCA}_{\mathrm{LPT}} + \mathrm{LCA}_{\mathrm{Nacelle}} + \mathrm{LCA}_{\mathrm{Fan}}\end{aligned} \tag{3}$$

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Equation 4 describes the LCA results associated to structural components ($LCA_{Structure}$), comprising the fuselage, Horizontal Tail Plane (HTP), Vertical Tail Plane (VTP), pylons, and wings.

$$\mathrm{LCA}_{\mathrm{Structure}} = \mathrm{LCA}_{\mathrm{Fuselage}} + \mathrm{LCA}_{\mathrm{Pylon}} + \mathrm{LCA}_{\mathrm{HTP}} + \mathrm{LCA}_{\mathrm{VTP}} + \mathrm{LCA}_{\mathrm{Wing}} \tag{4}$$

Lastly, Equation 5 expands the systems-related LCA ($LCA_{Systems}$) to include the Auxiliary Power Unit (APU), air conditioning, autoflight system, communication, deicing, electrical system, fire protection, flight controls, hydraulic system, instrument panel, landing gear, and navigation. This formulation applies to all TF aircraft. To save weight and reduce costs, the ATR 42/72 does not have an APU. Instead, it uses an electronic propeller brake that is activated on the right-hand engine (hotel mode).[53] To reduce weight and operating costs, the ATR 42/72 is designed without an APU.[53] As none of the regional TP aircraft analysed are equipped with an APU, this system is excluded from the calculations for both the ATR42 and ATR72.

$$\begin{aligned}\mathrm{LCA}_{\mathrm{Systems}} = {} & \mathrm{LCA}_{APU} + \mathrm{LCA}_{\mathrm{Air\ Conditioning}} + \mathrm{LCA}_{\mathrm{Autoflight\ System}} + \mathrm{LCA}_{\mathrm{Communication}} + \mathrm{LCA}_{\mathrm{Deicing}} \\ & + \mathrm{LCA}_{\mathrm{Electrical\ System}} + \mathrm{LCA}_{\mathrm{Fire\ Protection}} + \mathrm{LCA}_{\mathrm{Flight\ Controls}} + \mathrm{LCA}_{\mathrm{Hydraulic\ System}} \\ & + \mathrm{LCA}_{\mathrm{Instrument\ Panel}} + \mathrm{LCA}_{\mathrm{Landing\ Gear}} + \mathrm{LCA}_{\mathrm{Navigation}}\end{aligned} \tag{5}$$

Following the detailed LCA, our methodology advances to a high-level LCA, in which key aircraft design parameters influencing each impact category are identified. The outcomes of the detailed LCA for all aircraft serve as dependent variables, with regression models constructed to quantify the relationships between selected parameters (e.g., OEW or engine weight) and environmental impact metrics (e.g., GWP).

4. Results and discussion

This section includes the outcomes of both the detailed and high-level life cycle assessments, aiming to evaluate the extent to which the simplified model captures the essential environmental impacts identified in the full LCA. While our analysis delves into GWP, the complete results, including all impact categories, can be found in the Appendix A of this paper.

4.1 Detailed LCA results

GWP results, expressed in tonnes CO_2-equivalent, are presented in Figure 2. It shows the environmental burdens associated with the production phase of various commercial aircraft, categorised by furnishing, operator items, power unit, structure, and systems. The data reveal a clear trend of increasing total GWP with aircraft size and complexity. Regional turboprops such as the ATR42 and ATR72 exhibit the lowest impacts (300 tCO_2eq and 400 tCO_2eq, respectively), while wide-body jets like the B787, A330, and B777 show significantly higher values, with the B777 reaching a peak of 5,300 tCO_2eq. The structure consistently represents the largest share of impacts across all aircraft types, with an especially significant effect in wide-body models. For example, structural components alone account for more than 3,000 tCO_2eq in both the B787 and B777. The complete LCA results for all impact categories can be found in Appendix A.

Among the materials evaluated for structural components, CFRP demonstrates the highest global warming potential, reaching approximately 88.7 $kgCO_2$-eq per functional unit, according to EF 3.1 characterisation factors (Table 2). This substantial environmental burden arises from the intensive energy requirements associated with both the production of carbon fibres and the subsequent manufacturing processes. In comparison, materials such as Al2024 and GFRP show significantly lower impacts, at approximately 26.6 kg and 14.2 $kgCO_2$-eq, respectively, while AFRP exhibits a similar value of around 14.6 $kgCO_2$-eq. Despite its relatively high LCA footprint, the use of CFRP remains justified in aviation applications due to the performance gains it enables in terms of structural weight reduction and overall aircraft efficiency.

Table 2: GWP results per kg of material, based on EF 3.1 characterisation factors.[17]

Metric	CFRP	GFRP	AFRP	Al2024
GWP ($kgCO_2$-eq/kg)	88.7	14.2	14.6	26.6

To evaluate the trustworthiness of the full LCA results, an uncertainty analysis is performed. First, the pedigree matrix[9] is employed to quantify uncertainties in the input data for the LCIs. This method evaluates each input parameter across

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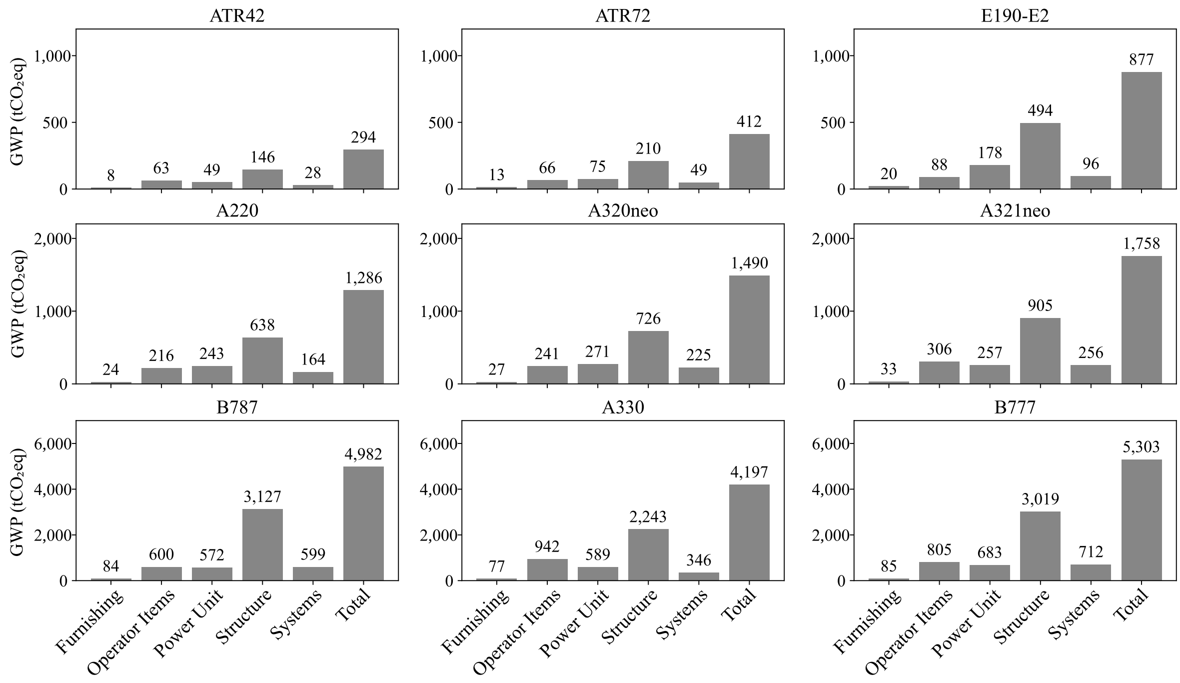

Figure 2: GWP results per aircraft, comprised of furnishing, operator items, power unit, structure, and systems.

five categories: reliability, completeness, temporal correlation, geographical correlation, and technological correlation. For each category, a score is assigned that is then transformed to a lognormal probability distribution. Finally, these input uncertainties are propagated via Monte Carlo Simulation (MCS) to assess their impact on the LCA results. This random sampling method is the most widely used within LCA studies that address uncertainties.[37]

Figure 3 shows the MCS results for the three aircraft categories - regional, narrow-, and wide-body. The cross (×) indicates the deterministic total results from Figure 2, while box plots and overlaid histograms provide insight into the distribution of MCS results. All distributions are asymmetrical and exhibit positive skewness, i.e., the tail of the distribution is longer towards higher GWP results. This behaviour results from the lognormal probability distributions in the input parameters, which exhibit the same behaviour. It is also notable that the deterministic results for all aircraft are lower than both the median and the mean of the MCS results. This suggests that the deterministic results tend to underestimate the GWP impacts that are realistically to be expected.

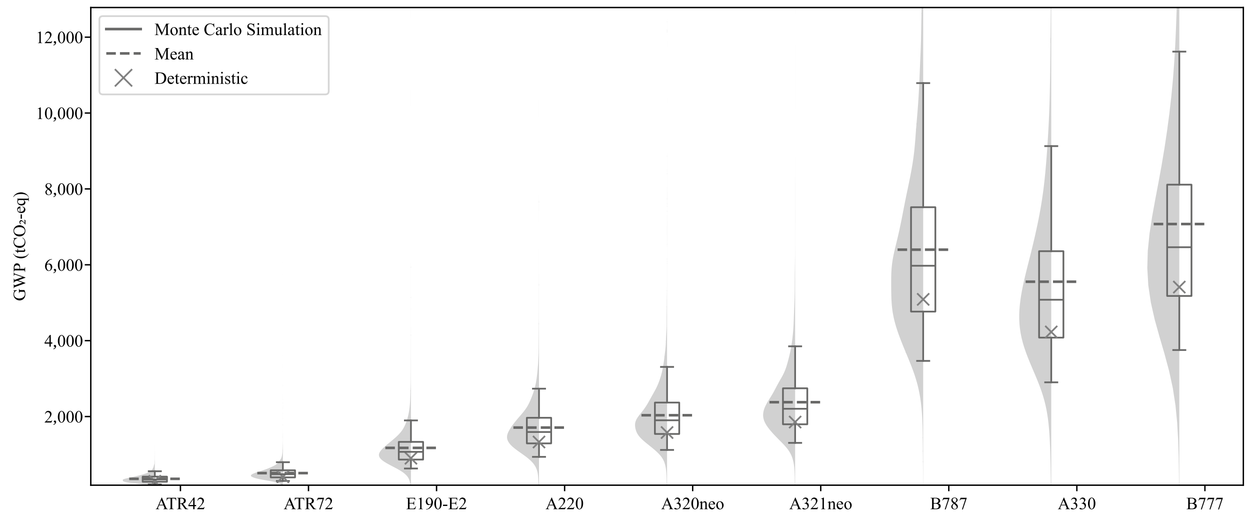

Figure 3: Uncertainty propagation results for overall aircraft production. The box plot shows the 5th and 95th percentiles as whiskers, as well as the 25th, 50th (median), and 75th percentiles as the box. The mean is indicated by a dashed line and the deterministic value is represented by the cross (x).

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4.2 High-level LCA results

In this section, we investigate different polynomial regression approaches — linear, quadratic, and cubic — and compare their performance using metrics such as R-squared (R^2) and Mean Absolute Percentage Error (MAPE). In such models, y is the predicted (or fitted) value of the dependent variable, x is the independent variable, β_0 is the intercept, β_1 is the coefficient of the linear term, β_2 is the coefficient of the quadratic term (used in the quadratic and cubic models), and β_3 is the coefficient of the cubic term (used only in the cubic model). Main features are presented in Table 3.

Table 3: Regression model formulas with classification, valid domain, and coefficient conditions for monotonic increase over $x \in [0, +\infty)$.

Model	Formula	Classification	Valid Range	Monotonic Increase Conditions
Linear	$y = \beta_0 + \beta_1 x$	Linear, monotonic	$x \in [0, +\infty)$	$\beta_1 > 0$
Quadratic	$y = \beta_0 + \beta_1 x + \beta_2 x^2$	Convex or concave	$x \in [0, +\infty)$	$\beta_1 > 0,\ \beta_2 \geq 0$
Cubic	$y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3$	Possible inflection point	$x \in [0, +\infty)$	$\frac{dy}{dx} = \beta_1 + 2\beta_2 x + 3\beta_3 x^2 > 0,\ \forall x \in [0, +\infty)$

The comparison between the three regression models is shown in Figure 4. In the charts, two relevant parameters are used to assess the quality of the fitting. The R^2 is a statistical measure, also known as the coefficient of determination, which indicates the proportion of variation in a dependent variable that can be explained by one or more independent variables in a regression model. In essence, it quantifies how well a model fits the observed data and generally a higher R^2 value indicates a better model fit. On the other hand, the MAPE measures the average magnitude of error made by a model, indicating how far predictions deviate from actual values on average. A MAPE value of 20% means the average absolute percentage magnitude of the difference between predictions and actuals is 20%. In general, the lower the MAPE, the more accurate the predictions.

Although higher-order regression models such as the cubic regression often achieve lower MAPE values (e.g., Structure: 9.7%, Furnishing: 4.1%), they also introduce non-monotonic behavior and inflection points. This is problematic in the context of weight-based predictors like OEW and engine weight, where it is physically expected that increases in weight are accompanied by increases in LCA outcomes such as GWP. Moreover, cubic models—with their added degrees of freedom—are prone to overfitting,[3] especially when trained on noisy or limited datasets. This can result in regression curves that fit the sample data very closely but generalize poorly, further compromising the model's validity. This is particularly important in subcategories like systems or operator items, where high MAPE values arise largely due to variability and imperfection in the underlying LCI data. These inconsistencies may stem from disparate data sources or modeling assumptions, and can be partially addressed using tools like the pedigree matrix or uncertainty propagation. The plots of GWP distributions highlight these uncertainties as seen in Figure 3, suggesting that the results are better represented as ranges or distributions rather than point estimates.

In contrast, linear models, despite their comparatively higher MAPE (e.g., Structure: 12.0%, Systems: 30.6%), enforce a strictly monotonically increasing relationship between predictors like OEW and LCA results. This makes them more consistent with physical intuition and engineering reasoning, especially when modeling the effect of increasing mass on GWP. While linear models may underperform statistically, their interpretability and alignment with known system behavior make them a robust and transparent modeling choice. Quadratic regressions, on the other hand, often exhibit the worst performance in terms of MAPE across most components (e.g., systems: 30.9%), even though they achieve relatively high R^2. This suggests that while the quadratic model can explain a large proportion of the variance, it may still produce significant errors in individual predictions. Furthermore, its non-monotonic curvature introduces risks of physically implausible trends without delivering the added flexibility of cubic models or the interpretive clarity of linear ones. Therefore, the choice of the underlying regression equation should be well selected and possibly enriched by setting bounds on the coefficients. A summary of R^2, MAPE, and coefficients values is presented in Table 4 for the three analysed approaches.

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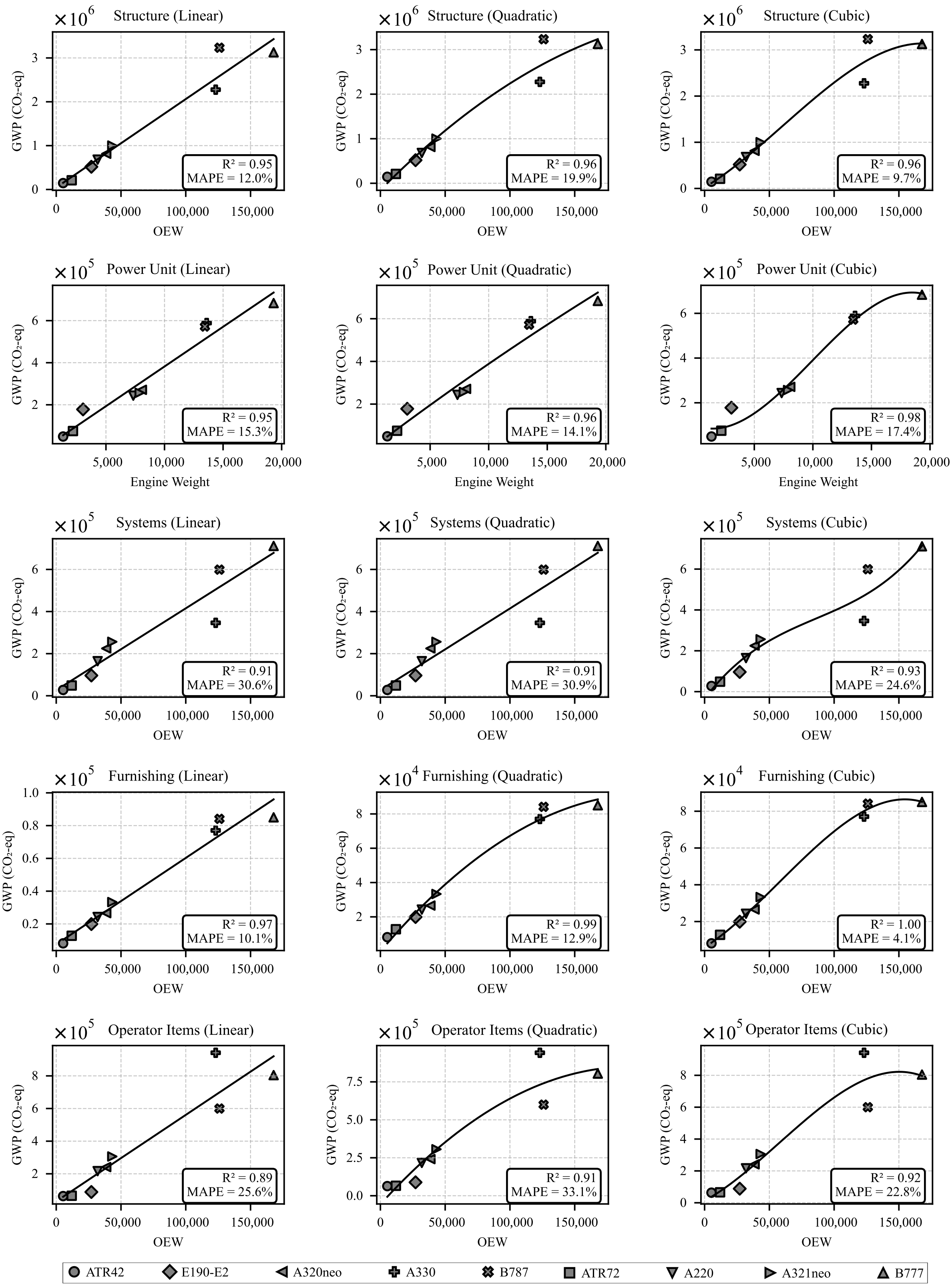

Figure 4: High-level LCA results for GWP comprising of three regression approaches: linear, quadratic, and linear. The aircraft breakdown follows the same logic as the detailed assessment: furnishing, operator items, structure, systems, and power unit.

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Table 4: Regression results by component and model order.

Component	R^2	MAPE (%)	β_0	β_1	β_2	β_3
Linear						
Structure	0.950	11.99	4.58×10^4	20.16		
Systems	0.910	30.64	2.68×10^4	3.89		
Furnishing	0.970	10.12	7.56×10^3	0.53		
Operator Items	0.890	25.64	3.12×10^4	5.30		
Power Unit	0.950	15.34	4.58×10^3	37.74		
Quadratic						
Structure	0.959	19.90	-1.51×10^5	29.40	-5.49×10^{-5}	
Systems	0.910	30.94	2.75×10^4	3.85	1.93×10^{-7}	
Furnishing	0.987	12.86	-1.04×10^2	0.89	-2.14×10^{-6}	
Operator Items	0.910	33.09	-5.60×10^4	9.39	-2.43×10^{-5}	
Power Unit	0.955	14.05	-7.28×10^3	41.50	-1.92×10^{-4}	
Cubic						
Structure	0.964	9.73	2.24×10^4	16.91	1.29×10^{-4}	-7.07×10^{-10}
Systems	0.926	24.60	-3.38×10^4	8.26	-6.46×10^{-5}	2.49×10^{-10}
Furnishing	0.997	4.07	6.00×10^3	0.45	4.32×10^{-6}	-2.49×10^{-11}
Operator Items	0.921	22.83	1.28×10^4	4.43	4.85×10^{-5}	-2.80×10^{-10}
Power Unit	0.980	17.40	9.85×10^4	-19.79	7.37×10^{-3}	-2.46×10^{-7}

5. Conclusion and outlook

This study presented a cradle-to-gate LCA of aircraft production across regional, narrow-body, and wide-body models, supported by extensive LCI development covering structure, systems, furnishings, operator items, and power units. The structure was consistently the largest contributor to GWP, while the power unit showed higher absolute values in wide-body aircraft but had a smaller share in regional TPs. Uncertainty was addressed using the pedigree matrix, though it remains to be integrated into the overall assessment. A regression-based approach using OEW and engine weight was applied, comparing linear, quadratic, and cubic models. Despite cubic regression achieving higher R^2 and lower MAPE, its non-monotonic behavior limits its applicability. Linear regression proved more stable and interpretable, particularly in reflecting the direct relationship between weight and GWP outcomes.

Future work should focus on LCI parametrisation using core aircraft design equations such as weight estimation (e.g., OEW or Maximum Takeoff Weight (MTOW)), wing loading, and thrust-to-weight ratio. This approach would establish a more direct link between design parameters and environmental performance. Given the limited availability of detailed LCI data, especially in early design phases, machine learning offers a practical tool for estimating missing information. A key outlook of this research is the development of an uncertainty-aware regression model, as relying solely on deterministic data may lead to an underestimation or overestimation of environmental impacts and overlook the variability inherent in LCA results.

For the sake of simplicity, this study focuses on single-variable regression models using either OEW or engine weight as independent variables. In this context, MCDM methods can be valuable for enhancing the presented high-level LCA, as they help balance trade-offs between competing technical and environmental criteria. Given the limited number of available data points—primarily due to the significant effort required to compile detailed LCI data—future work may explore the application of machine learning techniques to expand the datasets, utilising historical data and algorithms to forecast future outcomes. Furthermore, the models presented have not been adjusted for the varying share of composite materials in the aircraft components. Given the significant influence of material composition—particularly composites—on GWP results, this represents a relevant limitation. However, it also highlights a key direction for future work: integrating material breakdown into the regression framework to capture more nuanced environmental behavior. Furthermore, extending the proposed approach to other life cycle phases other than production, such as maintenance, flight operations, and EoL may enhance the completeness of results while avoiding burden-shifting and overlooked environmental hotspots. At last, the high-level LCA approach has been applied exclusively to the GWP impact indicator and extending the regression analysis to include the remaining impact categories is thus relevant.

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A. Appendix A - LCA results per impact category

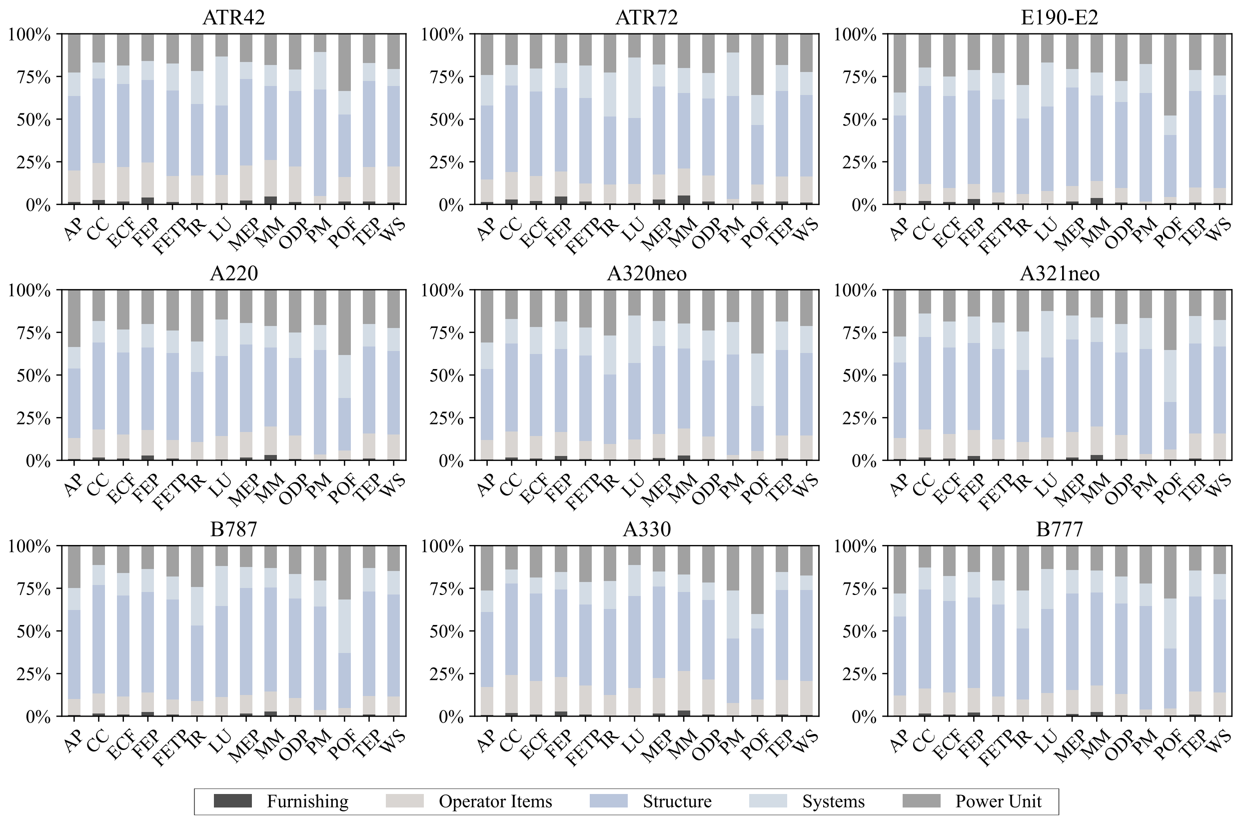

Figure 5: Impact categories results per aircraft, comprised of furnishing, operator items, power unit, structure, and systems.