A Holistic Approach to the Life Cycle Assessment of a Propeller System

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Abstract: This study aims to demonstrate the value of life cycle analysis in legacy aircraft based on data fusion from asset usage and respective monitoring parameters to support management decisions across all operational levels, being the extend of the useful life of assets or the configuration management. The research includes a case study focused on the propeller system, which serves as a reference for applying the methodology to the entire aircraft and its components.

The proposed analysis integrates state-of-the-art models covering three dimensions: Life Cycle Investment, Sustainability-Oriented Life Cycle Assessment, and Operational Risk Analysis. These models are interconnected to identify cause-and-effect relationships across the different spectra, providing a holistic view of asset performance and degradation.

The methodology considers all operational and maintenance activities, from acquisition to decommissioning, with the objective of increasing asset availability, optimizing resource allocation, reducing component cannibalization, and extending Remaining Useful Life (RUL).

A key feature of the approach is real-time data updating, enabling continuous and accurate information refreshment. This dynamic data environment supports the development of machine learning models and the integration of Generative Artificial Intelligence (GenAI), enhancing predictive and prescriptive capabilities, increasing reliability, and improving risk analysis and forecasting.

Keywords: Life Cycle Analysis; Reliability; Propeller System; Aircraft

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1. Introduction

The need for combining engineering expertise with financial insights is driven by the exponential pace of technological advancement, the geopolitical context and today's socio-economic challenges. This article stems from a collaborative project between the Defence and Academic Sectors in Industrial Engineering field. The main objective of this research is to develop an innovative tool to aid high-level decision-making, involving the entire chain of command. The parameters considered to achieve the desired results involve all operational staff, from the workshop floor to the accounts department. The aim is to apply the methodology to all aircraft and their respective fleets, starting with proof of concept in Propeller Systems. This methodology will provide an overview of all flows and KPIs for an asset within the organization. In addition to this general overview, it will also provide a detailed assessment of any component of any subsystem, considering the basis of its structure. All necessary data will be collected to measure the performance of these assets. As well as all data relating to Life Cycle Cost (LCC) and Life Cycle Assessment (LCA). Moreover, the financial information, it will provide operational KPIs and details on all risks associated with the acquisition and operation of assets, as well as assessments from a sustainability perspective.

This methodology aims to provide immediate insights into the current assets performance. As it is developed and implemented, Deep Neural Networks (DNN) will be employed, including Generative AI (GenAI), enabling the mapping of various distinct pathways based on the organization's objectives. This will correct potential deviations, given the risk analysis and the need for adjustments.

2. State of the art

During the preliminary stages of this research, it became evident that there are several gaps in the literature, which underpins and justifies the efforts that will be undertaken throughout this research to address them. This article highlights some specific examples of these gaps.

Although topics, such as Life Cycle Assessment (LCA), Life Cycle Cost (LCC) and Reliability, Availability, Maintainability and Safety (RAMS) Engineering have become increasingly relevant to the industry, it is quite challenging to identify comprehensive medium and long term studies that directly link these concepts at an operational level. Muazu *et al*. (2021), through a study they conducted, related LCA to Environmental Risk Assessment (ERA), the authors concluded that both complemented each other. However, despite this complementarity, some barriers to the integration of LCA and ERA were identified, namely "the lack of data (e.g., on toxicity) and differences in model structure of LCA and ERA. Most of the proposed approaches presented in the reviewed studies are inclined towards LCA or ERA, resulting in the omission of important components from the other, and leading to the inability of these approaches to address properly the needs of both LCA and ERA simultaneously. There is no clarity on the available information or data required to progress in this area and a clear pathway for practitioners to follow when integrating LCA and ERA is also lacking. Holwerda *et al*. (2021) directly address the gap that this work aims to fill by the end of the research. They discuss several possible life cycle analyses that can be performed, known as Life Cycle Thinking (LCT). The authors state that "a large majority of existent literature focuses on LCT methodologies and case studies. At best, assumptions are made – implicitly or explicitly – about the adoption of LCT methodologies to support sustainable practice. However, empirical research on the practical application of LCT outcomes in decision-making is scarce". The authors also conclude that greater assistance is needed to operationalise LCT results to achieve sustainable policies and operations. This research has the potential of enabling that LCT can be operationalised and monitored in the medium to long term.

As more research is conducted on projects of this scale and complexity, the existing gap becomes clearer: the need to reach conclusions that relate the results obtained in studies of the various types of life cycle of the same asset in a specific and simultaneous way. In other words, there is a necessity to develop a method that relates the various types of life cycles and to identify the cause-and-effect relationships. Saraswat & Yadava (2008), through their work aimed to provide an overview of RAMS engineering in industry, and concluded that despite the variety of work carried out in these four areas, there are few conclusions that link the obtained results. Several key issues are raised in the NATO document “Methods and Models for Life Cycle Cost Calculation” TREATY (2007) on LCC analysis. The authors point out that “Life cycle costing should not be considered as a one-off task but should be recognised as an ongoing activity throughout the life cycle to evaluate all programme changes and exploit cost saving opportunities. Although this report focuses on the importance of conducting life cycle cost analysis, it should be recognised that there are limitations of such analysis. Some of the limitations are Life cycle costing is not an exact science. A life cycle cost analysis does not provide an exact number of the costs; it merely gives an insight in the major cost factors and an insight into the magnitude of the costs:

- The life cycle cost estimate is inherently uncertain; its accuracy depends on the quality of the inputs, which are often themselves estimates or based on expert judgment.;
- Life cycle cost models require large volumes of data; however, only limited data are typically available at the time of estimation. Therefore, multiple assumptions must be made, and the resulting cost estimate is highly dependent on those assumptions—any change in them may significantly affect the outcome.;
- Life cycle cost results are used for multiple purposes and are not always directly comparable; for example, estimates developed for comparative or trade-off analyses may not be suitable for budgeting purposes.

These limitations should be carefully considered when conducting a life cycle cost analysis.

The authors highlight important limitations in the analysis of life cycle costs. One of them, which is the methodology presented in this paper that aims to overcome, is the widespread use of generalised costs, since one of the objectives is to create an adaptable model that seeks to consider all costs related to the activity of assets, such as their systems and their respective components. The second is the uncertainty in forecasting future costs. In this case, the research proposes a risk analysis in the projection of values, considering the history of the components and the constant updating of the data considered. In addition to this factor, this is where DNN with GenAI, come in. In other words, the introduction of GenAI will help to overcome the problem of black swam events, because the deep dive in working orders historic permits to identify the events outside the PdM tools. Based on historical data and other variables that may constitute the AI tool, a probabilistic study can be developed to enable projections for future values. However, this method is often contested because, although historical data can be used to predict the future behaviour of equipment in specific scenarios, there is always the chance of unique operational circumstances arise. This may occur exclusively at that moment of the life cycle, wich makes it difficult to identify outlier events.

To better understand the problem, a practical and simple example can be used to extrapolate. Considering risk and history as a probabilistic basis for estimating future costs, a direct comparison can be made with the algorithms used in Condition Based Maintenance (CBM) and AI tools in Predictive Maintenance (PdM). On the one hand, because the cost of maintenance interventions directly enters the life cycle analysis of the asset in question; On the other hand, because the methodologies can be transposed and replicated. In this way, similar mathematical gaps can be found.

In fact, by viewing life cycle analysis as a holistic management task, it will be possible to build much more accurate physical asset management systems. The emerging need to integrate asset management with technology and data management for system optimisation leads to an evolution in the quality of KPIs chosen to provide data that feeds algorithms to aid decision-making. Ferreira & Gonçalves (2022) emphasise the need for monitoring for PdM to predict the Remaining Useful Life (RUL) of equipment. RUL is a clear example of an indicator that has become increasingly reliable due to advances in technology and more reliable analysis and decision-making methods. It is a direct part of CBM and PdM and, as such, asset management.

Since this project will be developed with military physical assets, it is important to note the research conducted by Scott *et al*. (2022), which emphasise the need and urgency to implement sensorisation and accept the credibility of the data collected; this subject is equally relevant in non military assets. The evolution of the reliability of these sensors (which is already happening) is important, since pilots are being removed from aircraft and the world is moving towards a future where autonomous vehicles predominantly operate. The quality of the data collected ensures that these aircraft can operate autonomously. But more than that, with the accuracy and quality of the sensors that enable data collection from these vehicles, increasingly more opportunities are arising for expert monitoring of the asset life cycle. Also, in the study of Scott *et al*. (2022), the authors state that "military and civil domains may see benefit from greater cross-collaboration, enabling a dual-use case for PdM technologies, while also providing higher returns on funding and resources". Byington *et al*. (2002) evaluate the adjacent possibilities between the failures diagnosis and prognosis. Referring to the ability to predict the future condition of an asset, the authors emphasised that an "advanced prognostic capability is desired because the ability to forecast this future condition enables a higher level of CBM for optimally managing total LCC". The authors also conclude that the "ability to predict the time to conditional or mechanical failure (on a real-time basis) is of enormous benefit and health management systems that can effectively implement the capabilities presented here offer a great opportunity in terms of reducing the overall LCC of operating systems as well as decreasing the operations/maintenance logistics footprint". All these mentioned gaps and facts are based on the predominant matter of physical asset management, with the analysis of the various life cycles being a key point for real and effective management. The way in which the terms are perceived can influence how investments are conceived and how profits are derived from these actions. When interpreting the data collected, issues of mindset and how each one views the life cycle can determine whether or not good decisions are made.

In line with this reasoning, Farinha (2018) highlights an important point, noting that "regarding management itself, the introduction and certification of many organizations by ISO 55000 will be a revolution when compared with the current vision of asset management. The word "cost" will be replaced by the asset's fixed initial investment and the variable asset investment over time". The author mentions some of the times and stages that must be met during the life cycle of an asset:

- t1- Acquisition decision
- t2 - Terms of reference
- t3 - Market consultation
- t4 - Acquisition

- t5 - Commissioning
- t6 - Starting production/maintenance
- t7 - Economic/lifespan issues
- t8 - Renewal/withdrawal

In another study, Farinha (2024) demonstrates the optimisation potential that the implementation of maintenance policies and standards can offer to an organisation, considering the quantitative support for decision-making.

Considering all these broad themes, it is possible to assess the importance that the proposed methodology could have and the impact it could cause on organizations and the scientific community.

3. Methodology

3.1 Scientific approach

In order to contribute to the sharing of knowledge and scientific innovation, efforts will be made to improve the application and integration of the various existing LCA and LCA models. Not from the theoretical perspective of mathematical formulation, as these have already proven to be robust, but rather in the acquisition of the data that feeds them, by establishing a direct link with data collected via sensors used, for example, in maintenance. Furthermore, innovation is sought in data processing and the predictive analysis of maintenance costs with the aid of maintenance algorithms. Thus, in addition to optimising all investments related to the acquisition and operation of the assets under study, it will also be possible to improve the efficiency of the associated maintenance and maximise its lifecycle. Finally, by analysing the models applied, it will be possible to support and inform decision-making regarding whether and when to renew or replace this equipment. Figure 1 is a diagram that provides a simplified illustration of the data analysis, learning and managing process throughout a typical life cycle, from the acquisition decision to disposal.

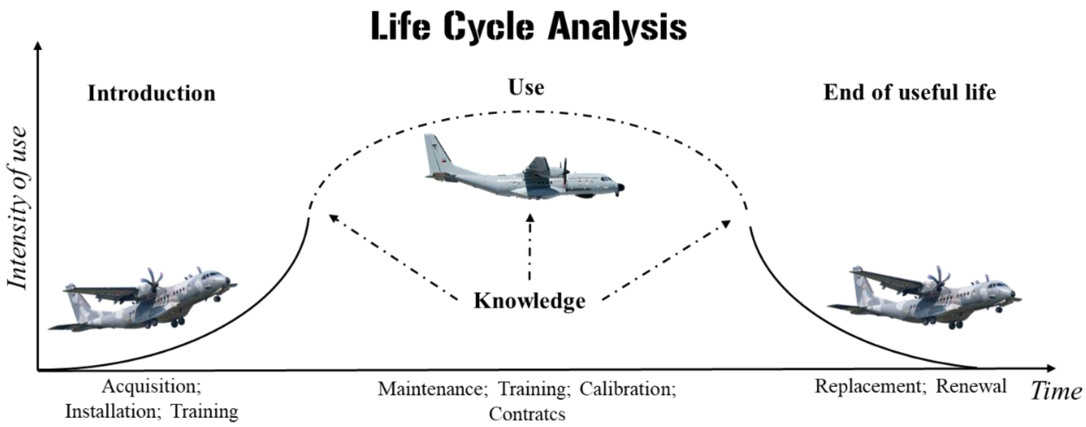

Figure 1 - Life cycle analysis

This research consist of five main phases:

- State-of-the-art research with an in-depth bibliographic analysis;
- Data collection and processing;
- Models' preparation and application with the parameters considered most appropriate, based on processed data;
- Analysis of the correlation among variables and models;
- DNN training and application of AI tools.

A review of the literature also played a major role in the choice of this approach. It was a topic that had been discussed and on which an intuitive consensus had been reached within the organisation. This fact demonstrates and underscores its suitability. Thus, it is possible to structure in advance what is expected to be the outcome and the development of this method. The social constraint was taken into account, since the asset is managed by an organisation and its management can be unique and decisive in achieving results. The sampling process is characteristic of the qualitative method, as the process is non-probabilistic. It will be selected using specific indicators of the asset under study. These indicators are in line with the study's requirements, as the life-cycle models applied take them into account. This may be considered a purposive (judgmental) sample, where participants are intentionally selected based on their knowledge of the models being applied. The information collected will enable the interpretation of the relationship among multiple variables, in terms of the asset's performance and the transformation of its life cycle. Ideally, these variables will be exploratory data and may be considered to originate from secondary sources of empirical information. It is the organisation that collects them directly and provides them to the researcher. The sources of evidence expected to be used in this study will be observations, documents and records, and physical artefacts. Observations will be made regarding the condition of the equipment and how it operates. The documents and records will provide access to the equipment's operational history. Physical artefacts, on the other hand, will allow for the verification of the results of potential deterioration, which has been recorded and studied by the organisation. These will also provide for the adoption of precautions and considerations in the approach to maintenance management. Once again, the mixed nature of qualitative and quantitative research methods is demonstrated. One of the main goals of the study's conclusion is to identify the most appropriate point in the life cycle for renewing or replacing the asset by a new equivalent. This involves determining the most suitable life cycle model for the asset, in line with the manager's objectives. Once the model has been determined, the objective is to design a decision-support tool that can be applied to other physical assets. It is also hoped that, by obtaining maintenance data, patterns will be identified that allow maintenance costs to be optimised and clearer forecasts of future costs to be made. Thus, equipment availability will be maximised and it will be possible to meet the Defence Sector's need for a tool that helps optimise investment in its assets.

3.2 Methodology implementation

Given that the first stage was more theoretical, involving a survey of the state of the art with an in-depth bibliographic analysis, this second step involves data collection and processing. Although all other stages are important, this specific stage of the project will be decisive and will determine the quality of the results obtained. It addresses the gaps that have been identified. There is a wealth of data and numerous types of data available. However, much of it is raw data. Considering the practical work carried out in partnership with the Defence Sector, the purpose is to identify KPIs to assess the life cycle and the ideal replacement period. These indicators must be interpreted to enable the information to be processed so, they are introduced into the models. The models to be applied are the following (de Almeida Pais *et al*., 2021; Farinha *et al*., 2023; Mendes *et al*., 2023; Raposo *et al*., 2019):

- Uniform Annual Income (UAI);
- Minimization of Total Average Cost with (MTAC) with and without Reduction to Present Value (MTAC-RPV);
- Life Cycle Recovery (LCR);
- Life Cycle Investment (LCI);
- Life Cycle Investment Assessment Method (LCIAM).

To apply these models, several parameters must be addressed:

- Time period (*j=1, 2, 3,…,n*);
- Acquisition cost (*CA*);
- Cessation value (*VC*);
- Lifetime corresponding to *VCn* (*N*);
- Exploration value (*CE*);
    - Operating Cost (*CO*);
    - Maintenance Cost (*CM*).
- Apparent rate (*iA*).
- Average Availability (*A*);
- Benefits value (*B*);
- Non-production costs (*NP*).

The UAI calculation methodology is represented in equation (1).

$$UAI_n = \frac{i_A \times (1+i_A)^j}{(1+i_A)^j - 1} \times (CA + \sum_{j=0}^{n} \frac{CM_j + CO_j}{(1+i_A)^j} - \frac{V_n}{(1+i_A)^j}) \tag{1}$$

The MTAC method is obtained from equations (2), (3) and (4).

$$Cn' = \frac{\sum_{j=0}^{n} CM_j + CO_j}{n} \tag{2}$$

$$Cn'' = \frac{CA - Vn}{n} \tag{3}$$

$$MTAC = Cn' + Cn'' \tag{4}$$

The MTAC-RPV method is based on the equations (5), (6) and (7).

$$Cn' = \frac{1}{n} \times \frac{\sum_{j=1}^{n} CM_j + CO_j}{(1+i_A)^j} \tag{5}$$

$$Cn'' = \frac{CA - \frac{V_n}{(1+i_A)^j}}{n} \tag{6}$$

$$MTAC - RPV = Cn' + Cn'' \tag{7}$$

The LCI method includes profits derived from the assets, as well as fees and expenses. The LCI method can therefore be calculated using equation (8) (already modified to include non-production costs).

$$GR_n = \sum_{j=0}^{n} \frac{B_j}{(1+i_A)^j} - \sum_{j=0}^{n} \frac{CO_j}{(1+i_A)^j} - \sum_{j=0}^{n} \frac{CM_j}{(1+i_A)^j} - \sum_{j=0}^{n} \frac{NP_j}{(1+i_A)^j} \tag{8}$$

The LCR method, on the other hand, not only considers the depreciation of the asset that was acquired or will be acquired based on the rates, but also the value of a new equivalent at the same rates. This way, in addition to organizations being able to consider the costs of renovating and maintaining assets, it is easier to find the best time to replace them, based on the variation in the market value of the new asset. Equation (9) relates the Apparent Rate to the depreciation of the physical asset, where C_{0D}^{t} represents the value of the asset in period *t* and C_{0D}^{t-1} represents the value of the asset in the previous period.

$$C_{0D}^{t} = C_{0D}^{t-1} \times i_A C_{0D}^{t} = C_{0D}^{t-1} \times i_A \tag{9}$$

Equation (10) represents the same relationship, but this time from the point of view of acquiring equivalent new equipment, where C_{0N}^{t} represents the value of the new physical asset at time *t* and $C_{0N}^{t-1}$the value of the new physical asset at time *t-1*.

$$C_{0N}^{t} = C_{0N}^{t-1} \times i_A \tag{10}$$

The total net present value, considering the devaluation of physical assets (NPV_{TD}), depends on the net present value of the movement in financial production (NPV_{FpD}) and the net present value of the financial expenses movement (NPV_{Fe}), as can be seen in eq. (11).

$$NPV_{TD} = NPV_{FpD} + NPV_{Fe} - C_{0D}^{t} \tag{11}$$

Similarly, equation (12) presents the total net present value considering a new physical asset (NPV_{TN}), where NPV_{FpN} represents the net present value of the financial production movement considering the acquisition of the equivalent new equipment. NPV_{Fe} is calculated using equation (13).

$$NPV_{TN} = NPV_{FpN} + NPV_{Fe} - C_{0N}^{t} \tag{12}$$

$$NPV_{Fe} = -\sum_{j=0}^{n} \frac{F_j}{(1+i_A)^j} - \sum_{j=0}^{n} \frac{M_j}{(1+i_A)^j} \quad (13)$$

All these models can be integrated into the LCIAM assessment, if the current Net Asset Value (*NPV*) is modified to the Integrated Net Present Value (*INPV*). The current *NPV* formula is expressed in equation (14).

$$NPV_n = CA + \sum_{j=0}^{n} \frac{CM_j + CO_j}{(1+i_A)^j} - \frac{V_n}{(1+i_A)^j} \quad (14)$$

On the other hand, the *INPV* method includes the following parameters:

- Investment in technological upgrade (*IUT*);
- Technological depreciation (*DT*);
- Sustainability depreciation (*DS*);
- Residual Value of the upgraded part (*R*).

INPV is presented in equation (15).

$$INPV_n = CA + \sum_{j=0}^{n} \frac{CM_j + CO_j + IUT_j + DT_j + DS_j}{(1+i_A)^j} - \frac{V_n + \sum_{j=0}^{n} R_j}{(1+i_A)^j} \quad (15)$$

However, it is certain that there will be a need to modify and introduce new types of data to ensure its complementarity. At this point of the research will seek to fill one of the biggest gaps in literature, which is the possibility of finding points of interconnection between the various types of life cycle analysis of physical assets, thereby making this assessment permanent and simultaneous. For example, to understand the environmental impact of operations involving the studied assets, it is necessary to include the sustainability depreciation parameter. Or even to reflect changes (improvements) that have been implemented to the assets since its acquisition, technological upgrades will be included as parameters. When selected, these indicators must cover all parameters of sustainability, availability, operation, maintenance, technological updates and more. It will also be crucial to understand the parameters that characterize the need for cannibalization and stock calculation. Rationalization will be the key, and effective stock rationalization will only be possible by applying lean principles and striving to implement a Just In Time (JIT) methodology, without compromising the availability of components and aircraft. In addition to all the models and parameters indicated so far, many others will also be included, where applicable. These are, among others, the Mean Time to Repair (MTTR), the Mean Time Before Failure (MTBF), the Availability, and the Mean Time to Failure (MTTF) for consumable or irreparable damage. It will presumably be necessary to find additional applicable parameters as understanding of the asset's operation increases. Particularly because many of the performance parameters are measured differently, since flight hours predominate (and this is where there is greater deterioration of the equipment), but operating hours and component age must also be considered. Another calculation that will have to go hand in hand with the methodology and all life cycle models will be the Return on the Investment (ROI). Given the type of asset, the return on investment will also be required to reflect the political and social return that could also present a challenge to overcome, and which is expected to add value to the current state of the art. Nevertheless, once again, such steps will only be possible if the appropriate indicators are carefully selected, processed, and interpreted. In addition to the link between the various possibilities for analyzing an asset's life cycle, a platform will be made available where managers can select a specific life cycle analysis. If the user wants to find out the minimum average cost of an asset's operation, this can be found in the MTAC-RPV. If the user wants to find out about the environmental impact, it is possible to analyze the modified models with the inclusion of the sustainability depreciation parameter (INPV). Everyone involved must be able to answer these three questions about the collected data:

- Why is it being collected?
- How is it being collected?
- What is it being collected for?

This procedure will be extremely important, as it will keep everyone aware of their role and how it can impact the proper functioning of the system. In addition, this deep understanding of the entire process will lead to a reduction in errors caused by human interpretation. Discrepancies in interpretation among different users will be reduced by standardizing the process and minimizing subjective assessments. The quantitative and qualitative features that define the work to be performed and that will allow the data to be interpreted and processed, suggest that the approach to data processing is considered the most appropriate. The data is obtained through the history of all components (cannibalization, availability, maintenance, flight hours, lifetime, end of life due to irreparable defects, among others).

The methodology presented in this paper, part of Predictive Life Cycle Analysis for Aircraft Navigation Equipment (PLANE) project, is an innovative methodology that uses the variables of the asset's life cycle, namely Operational KPIs, including Maintenance, Economic, Spare Parts, Risk, and maintenance historic.

Figure 2 provides a simplistic diagram of the methodology to be applied.

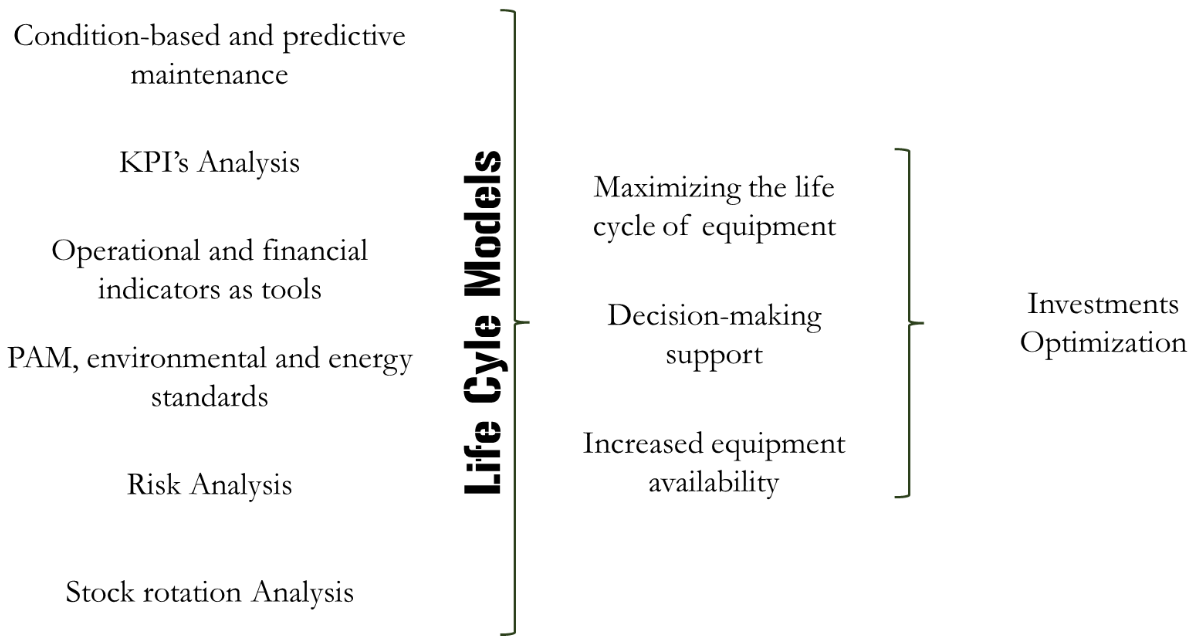

Figure 2 - Simplistic diagram of PLANE methodology.

Integrating AI into PLANE will primarily target increasing efficiency and improving hypothesis formulation. By training DNNs, like Long Short Term Memory (LSTM), Gated Recurrent Units (GRU) among others, the goal is to develop predictive models capable of understanding both trends and potential variations in the parameters of life-cycle models during asset operation. It will also be important to help visualize potential relationships between them through asset performance. The application of these tools, such as GenAI, will enable the creation of new models and combinations based on Large Language Models (LLMs) training, because in near past these resources were not available, including the hardware processing. This means that, until recent days, those approaches were not possible to be implemented because the lack of processing means.

The goal is to assist users in interpreting data, reformulating logistics strategies and specifications as needed. This could involve, for example, simulating potential combinations of different aircraft part serial numbers to optimize operations—whether to minimize costs, reduce environmental impact, maximize availability, mitigate risk, or even suggest the best approach to achieve the most efficient performance across all these areas simultaneously. The possibilities are endless and will enable managers to optimize resources, boost efficiency, and anticipate hypothetical scenarios.

4. Conclusions

This paper presents not only the state of art of life cycle analysis but presents proposals to help to manage physical assets, namely propeller systems of aeronautical assets. Through this study, knowledge about life-cycle analysis will be deepened, but, above all, it will be established as a standard tool that can be replicated and adapted to any asset in any sector. The implementation of best practices, the rationalization of resources and investment analysis can take any organization to a new level of management. This project aims to deepen knowledge of life cycle analysis, but above all, to establish it as a standard tool that can be replicated and adapted to any asset in any sector. The implementation of best practices, the rationalization of resources and investment analysis can elevate any organization to a higher level of management, thereby contributing to a more sustainable management of physical assets.

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