MASTERS IN MANAGEMENT (MIM)

MASTERS FINAL WORK

DISSERTATION

AUTOMATION OF REDELIVERY COST FORECASTING IN AVIATION: A STUDY ON PROCESS OPTIMIZATION METHODS

NATALIA RIOS HURTADO

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Acknowledgments

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Abbreviations

AR - Action Research

BPM – Business Process Management

BPO – Business Process Optimization

EOLA – End of lease agreement

BH – Block hours

FH – Flight hours

CY – Cycles/Number of flights/Departures

SV – Shop visit

AMOS – Cloud service for maintenance operations

AOG – Aircraft on Ground

PR – Performance restoration

LLP – Life limited parts

TAT – Turnaround time

HPT – High-pressure turbine

LPT – Low-pressure turbine

HPC – High-pressure compressor

LPC – Low-pressure compressor

Resumo

Este estudo examina a otimização de um processo de cálculo de custos de redelivery numa companhia aérea brasileira que opera num ambiente altamente intensivo em ativos e regulado, onde a previsão financeira para a devolução de aeronaves e motores desempenha um papel crítico no cumprimento contratual e no planeamento de custos.
A metodologia combina Investigação-Ação (AR) e Gestão de Processos de Negócio (BPM) para redesenhar e automatizar o fluxo de trabalho anteriormente manual, através da aplicação de uma ferramenta analítica avançada. Adicionalmente, a estreita colaboração com colaboradores e stakeholders permitiu redesenhar e automatizar o processo, reduzindo o tempo de 1.200 minutos para cerca de 25 minutos, o que representa uma redução superior a 97%, ao mesmo tempo que melhora a transparência, a reprodutibilidade e a rastreabilidade.
De uma perspetiva de gestão, a abordagem combinada AR–BPM assegurou o alinhamento entre o desenho técnico e a realidade operacional. A intervenção eliminou a maioria das tarefas manuais de preparação de dados e permitiu à equipa financeira concentrar-se em análises financeiras de maior valor acrescentado. O novo processo suporta projeções diárias de utilização, em vez de estimativas mensais, melhorando a precisão dos cálculos de Performance Restoration (PR) e Life Limited Parts (LLP), e reforçando as capacidades de tomada de decisão. Investigações futuras deverão centrar-se na automatização da extração de dados a partir de sistemas operacionais, na integração de ferramentas de apoio à decisão como Power BI ou Tableau, e na avaliação do impacto organizacional a longo prazo da solução, bem como na exploração da sua replicação em outros processos intensivos em dados ou em indústrias intensivas em ativos.

Palavras-chave: Análise de Dados, Otimização, Investigação-Ação, Processo, BPM, BPO.

Abstract

This study examines the optimization of a redelivery cost calculation process within a Brazilian airline operating in a highly asset-intensive and regulated environment, where financial forecasting for aircraft and engine redelivery plays a critical role in contractual compliance and cost planning. The methodology combines Action Research (AR) and Business Process Management (BPM) to redesign and automate the previous manual workflow with the application of an advanced analytic tool. Also, a close relationship with employees and stakeholders allowed the process to be redesigned and automated, reducing the time from 1,200 minutes to around 25 minutes, representing a reduction of more than 97%, while also improving transparency, reproducibility, and traceability.

From a managerial perspective, the combined AR–BPM approach ensured alignment between technical design and operational reality. The intervention eliminated most manual data preparation tasks and permitted the finance team to focus on higher-value financial analysis. The new process supports daily utilization projections instead of monthly estimates, improving the accuracy of Performance Restoration (PR) and Life Limited Parts (LLP) calculations, and strengthening decision-making capabilities. Future research should focus on automating data extraction from operational systems, integrating decision-support tools such as Power BI or Tableau, and assessing the long-term organizational impact of the solution, as well as exploring replication across other data-intensive processes or asset-intensive industries.

Keywords: Data Analysis, Optimization, Action Research, Process, BPM, BPO.

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1. Introduction

Organizations operating in asset-intensive industries increasingly depend on computational methods to enhance efficiency, transparency, and reliability, reflecting the broader digital transformation toward data-driven decision-making (Brynjolfsson & McAfee, 2014). In the aircraft industry, where high-value assets such as aircraft engines are complex areas for the operational, financial, and contractual requirements, the need for structured and data-driven processes is essential. One of these processes is the calculation of lease termination, also called engine return conditions. This activity impacts the financial forecasting, lease compliance, and long-term maintenance planning of the company studied in this research.

In many organizations, critical calculations continue to be managed through manual, file-based workflows, most commonly spreadsheets, which remain widely relied upon despite well-documented high error rates and governance risks (Panko, 2008). These approaches often require reconciling information from multiple sources, involve logic that is difficult to trace or validate, and are vulnerable to human error. As operational complexity increases, manual data-handling methods become harder to maintain, limiting scalability, consistency, and transparency across the process.

Business Process Management (BPM) and Business Process Optimization (BPO) offer an analytical and computational foundation for redesigning processes of this nature (Dumas et al., 2018). Where BPM provides governance structures for documenting, executing, and monitoring organizational workflows, BPO incorporates quantitative, algorithmic, and data-driven techniques that enable automation and improvement. Within this evolution, open-source technologies, particularly Python programming language, have emerged as central enablers for transforming spreadsheet-based routines into automatic processes (Lee et al., 2015).

This study applies an Action Research methodology to collaborate with Fleet, Maintenance, and Finance stakeholders of an aviation firm to redesign the engine redelivery cost calculation process. This applied research seeks to address a real problem faced by an organization. Specifically, to consolidate contractual data, operational engine status from AMOS, and manufacturer LLP pricing into an automated Python-based model capable of projecting shop visits, calculating consumption, and estimating end-of-lease costs through a structured and governed workflow. Furthermore, seeking to contribute to a better theoretical understanding of how organizations can address these changes.

Thus, guiding this work is the following Research Question:

RQ: How can airline operational processes be optimized by developing advanced analytics capabilities?

The objectives of the study are therefore:

1. Analyze the current excel-based redelivery cost calculation to identify operational inefficiencies, data inconsistencies, and limitations in transparency and traceability.
2. Optimize the existing workflow through a data-driven analytical approach that reduces manual effort, improves transparency and reliability, and enables reproducible and rigorous scenario analysis.
3. Contribute to theoretical knowledge that supports further research on the studied phenomena.
4. Provide insights that inform managerial decision-making regarding technology adoption.

By integrating BPM principles with BPO's analytical capabilities, this research demonstrates how computational tools can transform critical operational processes in aviation. The results aim not only to improve the organization's internal workflow but also to provide a structured, replicable framework for applying computational process optimization to asset redelivery forecasting within the broader academic and industrial context.

In this context, the study is align with two objectives of the United Nations Sustainable Development Goals (SDGs), in particular SDG 9 (Industry, Innovation and Infrastructure), which emphasizes the development of resilient infrastructure and technological innovation, and SDG 12 (Responsible Consumption and Production), which focuses on improving resource efficiency and promoting sustainable management practices (United Nations, 2015). Since the study seeks to optimize an operational process using analytics, it contributes to improving the company's capabilities by having a more efficient and transparent workflow, which in turn supports improved operational decisions in the use of resources that are necessary for the aviation industry.

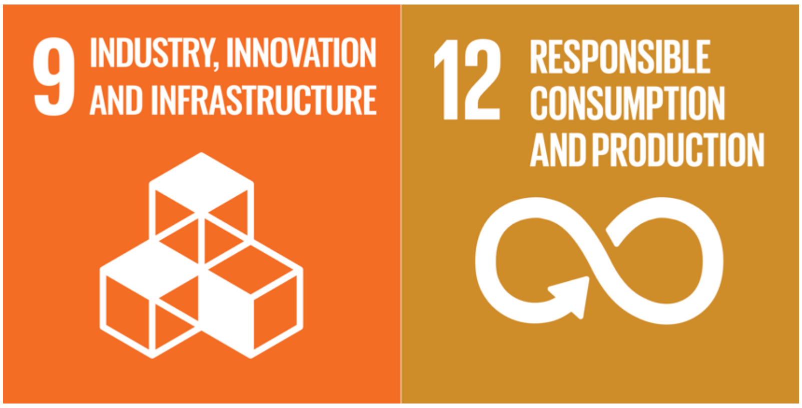

Figure 1 - Sustainable Development Goals.

2. Literature review

2.1 Business Process

Organizations operate through processes that transform inputs, such as information, resources, or materials, into outputs that deliver value to customers and internal stakeholders (Dumas et al., 2018). Based on this, business processes can be defined as a structured, measured set of activities designed to produce a specific output for a particular customer or market (Davenport, 1993). Complementing this view, business process is understood as a set of activities performed in a specific order, utilizing organizational resources to fulfill the organization's mission and structure for continuous improvement and value creation (Kaniški & Vincek, 2018). These insights suggest that business processes enable organizations to create value by understanding, structuring, and leveraging their internal capabilities.

Moreover, processes are not isolated functions since they connect different organizational areas and resources through workflows that ensure consistency and control (Hammer & Champy, 2009). As a result, business processes are the foundation of organizational performance, as they determine how efficiently an enterprise delivers value. This is why understanding, documenting, and improving processes are central to achieving competitiveness and operational excellence.

As expected, business processes can be categorized by their purpose and scope into core, support, and management processes (Dumas et al., 2018; Rummler & Brache, 1995). Based on that, management processes ensure coordination and strategic alignment across the organization through planning, control, and performance evaluation mechanisms (Dumas et al., 2018; Rummler & Brache, 1995).

A well-defined process is shaped by clear inputs, outputs, resources, responsibilities, and expected performance (Dumas et al., 2018). This clarity and transparency allow processes to be measured and optimized, establishing a clear structure for continuous improvement within the organization (Hammer & Champy, 2009). Additionally, the ability to measure processes facilitates organizations to apply analytical and computational techniques to assess efficiency, identify bottlenecks, and implement improvement initiatives (Weske, 2007). For this, processes become not only operational structures but also analytical units for managerial decision-making. As these measurable processes generate increasingly transparent and reliable data, they create the conditions necessary for more sophisticated analytics forms of improvement.

Consequently, the organizations that embed analytics into their operations improve consistency, accuracy, and performance (Davenport & Harris, 2007). This implementation reflects a transformation in which data availability and analytical capabilities enable more reliable, transparent decision-making within companies. Similarly, data-driven practices allow firms to act proactively rather than reactively (Brynjolfsson & McAfee, 2014).

2.2 Business Process Management

Business Process Management (BPM) is considered a multidisciplinary approach that uses methods, tools, and technologies to design, execute, and monitor, the improvement of organizational processes (Dumas et al., 2018). The main concern of BPM is to ensure that business processes remain aligned to business strategies and objectives, while adapting to environmental, technological, and competitive changes across the company (Weske, 2007).

BPM is the institutional mechanism that structures how organizations manage and control their operations to ensure strategic coherence (Weske, 2007). BPM provides a systematic approach to organizing and coordinating activities so that processes operate consistently with defined business objectives. It ensures that performance is both measurable and controllable, allowing organizations to monitor results through defined indicators and process models (Dumas et al., 2018).

From a business perspective, BPM connects operational efficiency with strategic intent by connecting process outcomes to organizational goals and customer value (Harmon, 2019). Viewed from a technological perspective, BPM integrates data and information systems to make strategic decisions and automation based on evidence, enabling analysis and improvement within the company (Van der Aalst, 2016). Furthermore, there is a need for transparency and accountability in BPM, as well-documented processes promote organizational learning and shared understanding of how value is created and delivered (Vom Brocke & Rosemann, 2015).

Nevertheless, process improvement initiatives often expose problems within organizations due to resistance to methodological change. Organizations operate within persistent paradoxes, such as stability versus change or control versus flexibility, that limit and shape how processes are adopted, maintained, and transformed (Smith & Lewis, 2011). These paradoxical dynamics help explain why established routines may exist with growing pressure for more automated or data driven alternatives. Incorporating this perspective into BPM highlights that improving a process is not only a technical challenge but also an organizational one, influenced by competing expectations and historical practices.

Given this evolution toward analytical and data-driven practices, a structured business approach is required to effectively govern and improve processes. BPM provides this governance system by defining a lifecycle for process identification, modeling, execution, monitoring, and continuous improvement (Dumas et al., 2018). With this structured approach, BPM allows processes to be aligned with organizational objectives, with strong KIPs according to the performance of the company, and insights derived from data and analytics translate into systematic refinement.

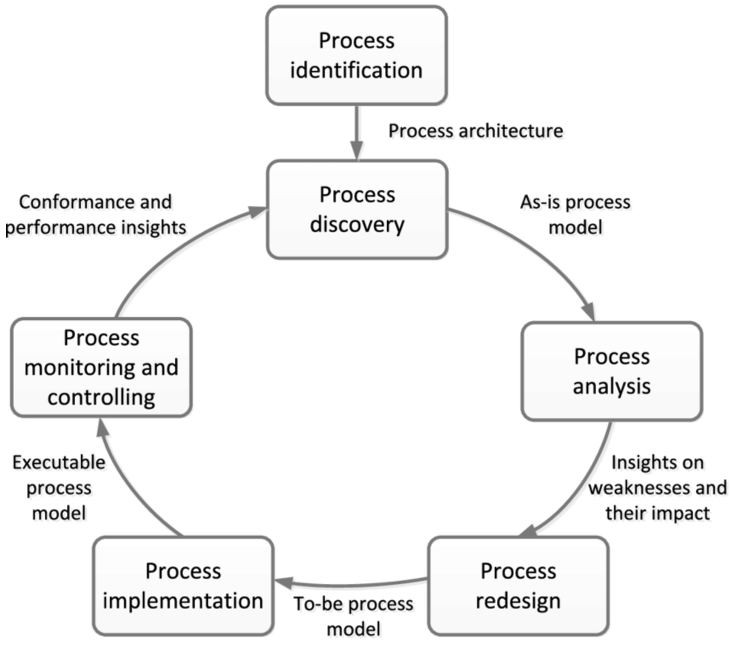

Figure 2 - BPM lifecycle. (Dumas et al., 2018)

2.3 Business Process Optimization – BPO

Business Process Optimization (BPO) is defined as a structured and systematic approach to improving an organization's processes to achieve higher efficiency, effectiveness, and adaptability by identifying, analyzing, and redesigning existing business processes (Arlbjørn & Haug, 2010). In that sense, optimization is a continuous business effort that aligns operational efficiency with organizational strategy through data driven for making decisions.

Beyond this, BPO relies on data and analytical models to improve process performance through systematic analysis and evidence to make decisions (Van der Aalst, 2016). Within this framework, BPO uses event data extracted from information systems to identify bottlenecks, inefficiencies, and deviations from optimal performance. With the application of process mining and computational algorithms, organizations can automatically or semi-automatically detect activities for improvement and predict better outcomes. This focus on data perspective transforms optimization into a continuous, technology-enabled discipline aimed at enhancing efficiency, conformance, and overall process quality (Van der Aalst, 2016).

Moreover, BPO focuses on achieving quantifiable performance improvements through methods such as simulation, operations research, and machine learning (Harrington, 1991; Kamran & Thomas, 2023). In this sense, BPO modifies or transforms the qualitative but measurable rules of BPM into a set of quantifiable KPIs by creating computational representations that can be optimized for specific goals, such as minimizing cost, correctly forecasting consumptions, or maximizing resources.

With the past of the years, the focus within BPM research shifted from descriptive and qualitative approaches to analytical and computational ones, driven by the growing availability of process data and advances in information systems, machine learning and late years AI´s (Van der Aalst, 2016). Early BPM literature emphasized qualitative redesign and organizational management, but later research began incorporating data-driven analysis, simulation, and automation (Van der Aalst, 2016).

This conceptual progression from BPM’s business foundations to the sophisticated BPO models illustrates the ongoing fusion between organizational science and computational methods. BPM defines what processes should be governed and why; BPO defines how they can be mathematically and algorithmically optimized. Together, they represent the continuum of modern process management research: from the governance of workflows to the optimization of performance.

A table of how BPO capabilities most of the time have relation on each BPM lifecycle phase is provided to better understanding:

BPM Lifecycle Phase	BPO´s capability
Process Discovery	Provides the input for optimization, it is important to set the correct measures to optimize them.
Analysis	Defines performance KPIs or metrics, along with constraints.
Redesign / Improvement	Normally machine learning or forecasting models are designed.
Implementation	Final models are scripted and delivered, also includes the trials.
Monitoring	Results could be used to enhance models delivered on implementation; derivative models or AI take this step into its own learning process.

Table 1- Interaction between BPM and BPO - (Adapted from Dumas et al. (2018), van der Aalst (2016)).

2.4 How computational methods shape BPO across industries.

Asset-intensive sectors such as manufacturing, energy, logistics, and aeronautics have increasingly adopted Business Process Optimization (BPO) supported by computational methods to improve process consistency, transparency, and analytical rigor. Rather than focusing exclusively on financial performance, these sectors benefit from the ability to model, simulate, and standardize complex operational workflows. Recent literature indicates that the convergence of BPO with computational and algorithmic tools, particularly those available in Python's open-source ecosystem, has enabled organizations to execute processes with greater precision, reproducibility, and scalability (Kamran & Thomas, 2023).

Transportation cost structures typically include distance and time-dependent costs (fuel consumption, labor, and vehicle wear), fixed fleet costs, and penalties for service delays or missed delivery windows. The Vehicle Routing Problem (VRP) and its numerous extensions provide the theoretical basis for modeling such optimization tasks (Toth & Vigo, 2014). In recent years, researchers have used Python-based optimization frameworks to translate these mathematical models into practical solutions deployable in dynamic logistics environments (Filani et al., 2021).

Companies are transforming their manual spreadsheet workflows into more structured processes, and Python has become a key technological enabler for BPO (McKinney, 2010). In the same way, BPO uses computational tools to enable employees to replace manual errors in Excel routines with automated and reproducible guides for improving transparency, traceability, and methodological practices (Kary & Myers, 2017). This makes Python particularly attractive for industries like aviation, where complex calculations, such as maintenance planning or conditions assessments, require precision, consistency, and the integration of algorithmic logic into operational workflows and processes (Lee et al., 2015; Gupta et al., 2024).

Thus, Python provides support for simulation and mathematical optimization, which are two of the key pillars of BPO. In asset-intensive sectors, Python-based predictive maintenance, often implemented through scikit-learn or PyCaret, allows organizations to anticipate equipment failures and schedule interventions proactively (Singh et al., 2022). These developments with open-source computational tools have become essential drivers of modern BPO, allowing companies to move over static analysis to a continuous algorithm-enabled improvement across industries.

2.5 What is the aviation industry doing with BPO?

One of the earliest and most impactful areas of BPO in aviation is flight and crew scheduling optimization. Airlines operate under highly intricate operational systems in which flight delays, crew availability, passenger overbooking, and aircraft rotations are strongly interdependent (Kohl & Karisch, 2004; Yan & Tseng, 2002). Historically, these scheduling tasks were managed through manual planning supported by large operations teams, as early airline planning methods relied heavily on human coordination and spreadsheet-based decision-making (Barnhart & Cohn, 2004; Gopalakrishnan & Johnson, 2005). The shift to computational optimization emerged only when operational complexity exceeded the limits of manual scheduling approaches (Cordeau et al., 2000).

Recent studies highlight the increasing use of Python-based optimization frameworks to model and solve scheduling and allocation problems, extending traditional operations research approaches in aviation planning (Barnhart & Cohn, 2004; Hart et al., 2017). These models optimize route assignments, shift assignments, and crew pairings while minimizing costs and disruption. For example, Air France and Lufthansa Technik have reported the use of in-house Python optimization engines to dynamically reallocate aircraft and crew during disruptions like AOG´s in their fleet, integrating real-time data from operations control centers (ICAO, 2022).

Maintenance, Repair, and Overhaul (MRO) processes are central to safety and cost control. The airline industry, just like for example the energy sector, is shifting from reactive maintenance (fix after failure) to predictive and condition-based maintenance, enabled by data analytics and process optimization. Airlines and aircraft manufacturers are increasingly using Python-based machine learning models to predict equipment failures and optimize maintenance schedules (Gupta et al., 2024). The most used libraries are scikit-learn, PyCaret, and TensorFlow, these are applied to large telemetry datasets collected from aircraft sensors and maintenance logs (Gupta et al., 2024).

However, the direct application of computational solutions to asset redelivery forecasting remains largely underdeveloped. Existing work tends to focus on isolated dimensions, such as maintenance optimization, disruption management, or lease compliance, without addressing the calculation process itself. While industry white papers and software providers offer practical approaches to digitize or structure cost assessments, there is limited peer-reviewed research on how manual Excel-based redelivery calculations can be transformed into automated, reproducible computational processes.

While many BPO applications in aviation emphasize cost or performance optimization, the present research targets a different, underexplored need: the lack of automated computational processes for calculating aircraft and engine redelivery conditions. Current practice relies heavily on manual Excel spreadsheets, which limit transparency, reproducibility, and traceability. This study applies BPO principles not to optimize financial outcomes, but to improve the calculation process itself by transitioning from an Excel-based workflow to an automated process that enhances consistency and methodological rigor.

2.6 Key operational concepts

Within the airline industry, the calculation of engine return conditions, commonly known as lease termination requirements, constitutes a fundamental practice. These conditions specify the technical, operational, and documentary standards that an aircraft engine must meet at the end of an operating lease to ensure regulatory compliance, asset preservation, and contractual compliance (Kinnison, 2013; McBain, 2019; IATA, 2018). In this sense, return conditions typically include minimum remaining life for life-limited parts (LLPs), prescribed performance parameters, mandated inspections, and full traceability of maintenance records (Kinnison, 2013). These technical requirements serve both regulatory and economic purposes; they safeguard the lessor's asset value while enabling a predictable transition to the next operator. Because contractual obligations vary across leasing agreements, the calculation of return conditions become a highly customized forecasting activity that integrates contractual rules, operational data, and maintenance histories.

Within these return requirements, life-limited parts (LLPs) are among the most influential cost drivers. LLPs are critical engine components that can operate only for a fixed number of cycles before mandatory replacement, as defined by the manufacturer (Kinnison, 2013; FAA, 2021). The remaining useful life of these parts directly affects whether the operator must replace them prior to redelivery or compensate the lessor financially for their consumed life. Similarly, Performance Restoration (PR) refers to the set of shop-visit activities required to restore an engine's performance to acceptable limits. Forecasting both LLP and PR obligations requires understanding of the engine's accumulated cycles and hours since its last major shop visit, which are primary determinants of consumption and remaining life.

Another key element in lease termination forecasting is the scheduling of shop visits (SVs), major engine overhauls where LLPs are replaced, and performance parameters are restored. The timing of these visits depends on operational utilization, component limits, and engine health indicators, and it directly influences the quantities used in cost projections. Airlines often rely on estimates of daily utilization, projected flight hours and cycles, and turnaround time (TAT) in the repair shop to determine whether one or more SVs will occur before the return date. These projections depend heavily on data provided by maintenance information systems such as AMOS, which supply detailed records of engine status, last shop visit dates, accumulated usage, and component limitations.

3. Method

Action research and BPM

This study applies a combined Action Research (AR) and Business Process Management (BPM) approach to analyze and improve the aircraft redelivery cost forecasting process. Action Research is used to structure the investigation as an iterative cycle of diagnosis, action planning, intervention, evaluation, and reflection, carried out in collaboration with the stakeholders (Coughlan & Coghlan, 2002). BPM is used in parallel to provide a process-oriented framework for identifying, analyzing, redesigning, and monitoring the workflow through which redelivery cost calculations are produced (Dumas et al, 2018).

This integration aims for optimal process management by continuously validating and evaluating the company's needs. AR allows defining how the intervention will be carried out, and BPM allows defining how the solution can be redesigned.

3.1 Action Research

AR is a collaborative and cyclical approach that seeks to solve real organizational problems while generating scholarly insights (Davison et al., 2012). Likewise, Coughlan and Coghlan (2002) note that AR is well-suited for studies where the researcher acts both as observer and active participant in organizational change.

AR iterative cycle is performed to test, refine, and validate optimization models in real-world environments (Coughlan & Coghlan, 2002), making it highly relevant for projection purposes, as this research intends to optimize, where continuous process improvement and feedback are vital for efficiency and compliance.

Structure of Action Research

The Action Research (AR) structure adopted in this study integrates the cyclical model proposed by Coughlan and Coghlan (2002) with the procedural principles outlined by Davison et al. (2012). By combining these complementary frameworks, the research organizes the investigation and intervention into a coherent sequence of interconnected stages, allowing a learning approach and a continuous refinement of the solutions developed in the project.

Context and Purpose /Diagnosis:

During the initial phase, it is important to understand the organizational environment and its current conditions. This involves examining the business sector, explaining the organizational needs and resources, and identifying the central problems or opportunities that motivate the research question (Coughlan & Coghlan, 2002). According to this contextual diagnosis, the researcher understands not only what processes are expected to improve, but also why these improvements matter to make decisions in the company.

Also, the purpose of the investigation must be defined. This requires an understanding of the objectives of the project, incorporating both the primary business goals and any additional questions the organization wishes to explore. In accordance with the Action Research methodology, the researcher must balance the organization's demand for actionable improvements with the scholarly contribution expected from the study (Davison et al., 2012).

Finally, this phase includes identifying key stakeholders and clarifying their expectations, roles, and potential constraints (Coughlan & Coghlan, 2002). A comprehensive assessment of resources, assumptions, and limitations is conducted, often supported by an acknowledgement of the personnel, data, technological assets, and software available for the project. Understanding the stakeholder's scenery and their resource conditions enhances alignment, strengthens collaboration, and provides a solid foundation for a constructive research client relationship throughout the AR cycle (Coughlan & Coghlan, 2002).

Data gathering:

During this phase, the data collection process was initiated by developing a clear understanding of the dataset used throughout the calculation of engine return costs. This involved compiling the initial dataset and documenting their structure, content, and specific locations within the project (Coughlan & Coghlan, 2002). As part of this process, challenges related to data accessibility, file consistency, and version control were identified. Establishing this initial data management was essential to ensure that the information supporting the cost calculation process was reliable and represented according to their actual process.

Additionally, a complete description of the collected data was developed, covering dataset characteristics such as format, number of files, variable types, and description of the variables. This ensured alignment with predefined requirements and confirmed that the available data could support the analytical needs of the study. Also, a verification of data quality was also carried out, assessing completeness, correctness, and consistency across the Excel files. It was also necessary to identify possible errors, missing values, and structural inconsistencies.

Moreover, semi-structured meetings were conducted with employees from the Finance, Fleet, and Maintenance teams to collect detailed information about the redelivery cost calculation process. These sessions aimed to capture how the process is executed in practice, including data sources used, calculation logic, validation steps, and decision points. Meeting recordings were transcribed using artificial intelligence (AI) tools. The researcher reviewed and refined the transcripts to ensure accuracy and completeness. In addition, the researcher complemented the transcripts with detailed notes taken during the discussions.

Action Planning:

Building on the insights gained from the previous phases, a set of potential solutions was developed. According to the Action Research principles, this phase involves translating diagnostic insights into planned interventions that are both feasible within the organizational context and aligned with the research objectives (Coughlan & Coghlan, 2002). The emphasis at this stage is on conceptual process redesign rather than technical implementation, outlining how the workflow could be restructured to improve consistency, transparency, and analytical reliability. The objective of this redesign is not to reduce costs but to replace the spreadsheet-based workflow with a computational, automated, and reproducible workflow that seeks transparency, consistency, and analytical rigor. During this planning phase, measurable objectives, key performance indicators (KPIs), and validation criteria are also established to ensure that the proposed solution can be systematically assessed and effectively integrated into operational practice.

Action Taking (Intervention):

In this stage, the intervention consists of implementing the automated solution for the redelivery calculation process developed in the previous phase. The proposed changes are applied within the organizational setting and examined through their execution on real process data, allowing the feasibility and relevance of the intervention to be assessed in practice (Davison et al., 2012). The new computational workflow was tested using the company's historical and current datasets to ensure that the automated logic replicates and improves the manual Excel-based procedure. The implementation was conducted in collaboration with the financial controller to validate the accuracy, transparency, and consistency of the generated output. Additionally, a detailed comparison between the manual and optimized process results was carried out to confirm alignment and to evaluate improvements in traceability, reproducibility, and ease of execution for the employees.

Evaluation:

The evaluation phase measures the impact of the implemented model on forecasting accuracy and decision-making reliability. Quantitative metrics, such as projection feasibility in cost prediction and time savings in report generation, are complemented by qualitative feedback from the participating teams. This step ensures that results are both accurate and helpful, aligning with the Action Research cycle's emphasis on evaluating outcomes and reflecting collaboratively with stakeholders to inform future actions (Coughlan & Coghlan, 2002).

Reflection and Learning:

The final phase involves analyzing the results of the action research cycle, assessing what was learned about both the problem and the research process itself (Coughlan & Coghlan, 2002). Reflection allows refine the framework, proposing generalizable insights for similar aviation or controlling contexts, documenting the steps to fill the current gap in literature and serve as tool for future researchers.

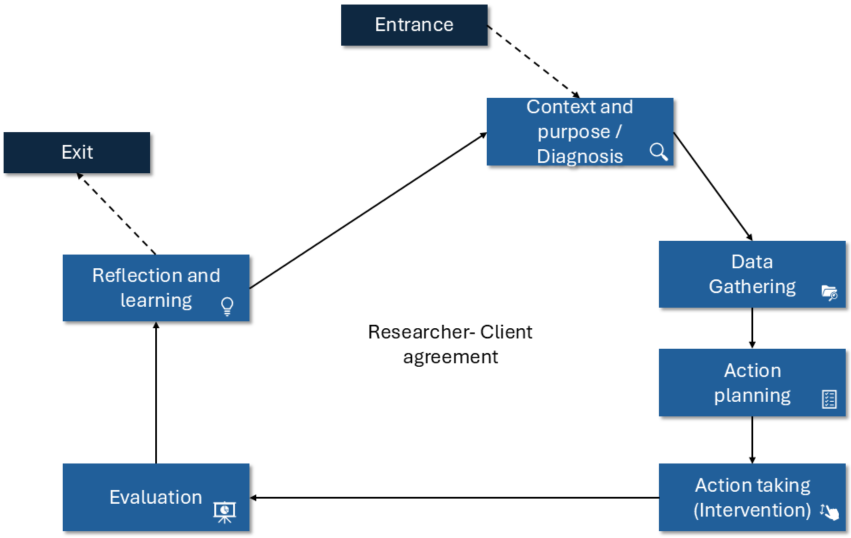

Figure 3 - AR process (Based on Coughlan & Coghlan, 2002 and Davison et al., 2012)

3.2 Business Process Management (BPM) as Complementary Methodology

To complement the Action Research (AR) approach, the study incorporates the Business Process Management (BPM) lifecycle. While AR apply a cyclical structure for organizational learning and intervention, BPM provides a process-oriented perspective that integrates a deeper understanding, redesign, and control of operational workflows. This combination ensures that the optimization of aircraft redelivery cost forecasting is grounded not only in analytical improvements but also in an explicit restructuring of the business process through which these forecasts are produced.

The BPM lifecycle consists of a sequence of phases that provide guide to organizations from process identification to continuous monitoring (Dumas et al., 2018). Each phase is useful to identify how processes function, where inefficiencies arise, and how systematic improvements can be designed and sustained. The stages of the BPM lifecycle relevant to this study are outlined and expanded below.

Process Identification:

The first phase of BPM involves determining which business processes should be prioritized for analysis and improvement (Dumas et al., 2018). In the context of this research, the aircraft redelivery cost calculation process was identified as a critical candidate due to its influence on financial planning, contractual compliance, and cost transparency. Process identification also requires understanding the boundaries of the process, where it begins, where it ends, and which departments or stakeholders are involved. Within the aviation redelivery context, this includes recognizing the interactions within the process such as finance, maintenance, and vendor.

Process Discovery:

Process discovery aims to document and represent the as-is process in a way that is the actual execution (Dumas et al., 2018). This includes interviews, shadowing, walkthroughs, and the examination of documents and software artifacts. For this study, process discovery involved reconstructing the steps taken by the financial controller when generating redelivery cost forecasts, including the compilation of Excel files, the application of manual formulas, the validation of assumptions, and the communication of results to decision-makers. During this phase, it is common to find inefficiencies, bottlenecks, and sources of variation typically become more evident as the process is reviewed (Hammer & Champy, 2009). By representing the as-is process in detail, the study forms an understanding of the system, which becomes essential for accurate diagnosis and improvement planning.

Process Analysis:

When the as-is process has been documented, the analysis phase seeks to evaluate its performance, risks, and underlying causes of inefficiency (Dumas et al., 2018). In this study, process analysis involves identifying how manual consolidation, inconsistent file structures, and calculations compromised reliability, transparency, and efficiency in redelivery cost forecasting. Using systematic analysis, the issues affecting the current process become explicit and measurable, enabling targeted and new strategies.

Process Redesign:

Process redesign translates analytical insights into a to-be process model that addresses the problems identified previously while aligning with organizational objectives and constraints (Weske, 2007). This stage focuses on rethinking how activities are structured, executed, and controlled to improve overall process performance (Dumas et al., 2018). Process redesign involves evaluating design alternatives that enhance process performance in terms of accuracy, cost, cycle time, transparency, and maintainability (Hammer & Champy, 2009). In the context of this study, redesign involved shifting from a spreadsheet-driven workflow to an automated and computational model capable of standardizing data inputs, encoding logic programmatically, and generating reproducible results.

Process Implementation:

Implementation is the stage where the redesigned process is implemented within the organization. This involves translating conceptual process models into actual systems, tools, and procedures that employees can execute (Dumas et al., 2018). In this study, process implementation includes the development and deployment of the automated workflow using the datasets, calculation rules, and operational constraints identified in earlier phases. Implementation was carried out in collaboration with the company team, to ensure that the new process aligns with organizational expectations and is validated at each step.

Process Monitoring and Controlling:

The final phase analyzed the performance of the redesigned process and identified opportunities for continuous improvement, ensuring that the new process continues to meet the objectives of generating value (Dumas, et al, 2018). In this study, this involves comparing results obtained from the manual and automated workflows, monitoring reductions in processing time, assessing gains in accuracy and consistency, and gathering qualitative feedback from the stakeholder regarding the advantages and disadvantages of the new process.

3.3 Integrating Action Research and BPM

To conclude the methodological approach of this study, Action Research and Business Process Management are integrated into a unified framework that supports both the investigation and the improvement of the redelivery cost forecasting process. AR provides a collaborative and iterative approach, where organizational problems are reviewed, and interventions are implemented. While BPM contributes to a set of process-oriented phases essential for understanding and redesigning existing workflows. Together, these methodologies can be seen as complementary components, BPM delineates what aspects of the process require change, and AR defines how those changes should be addressed, validated, and refined in collaboration with the company.

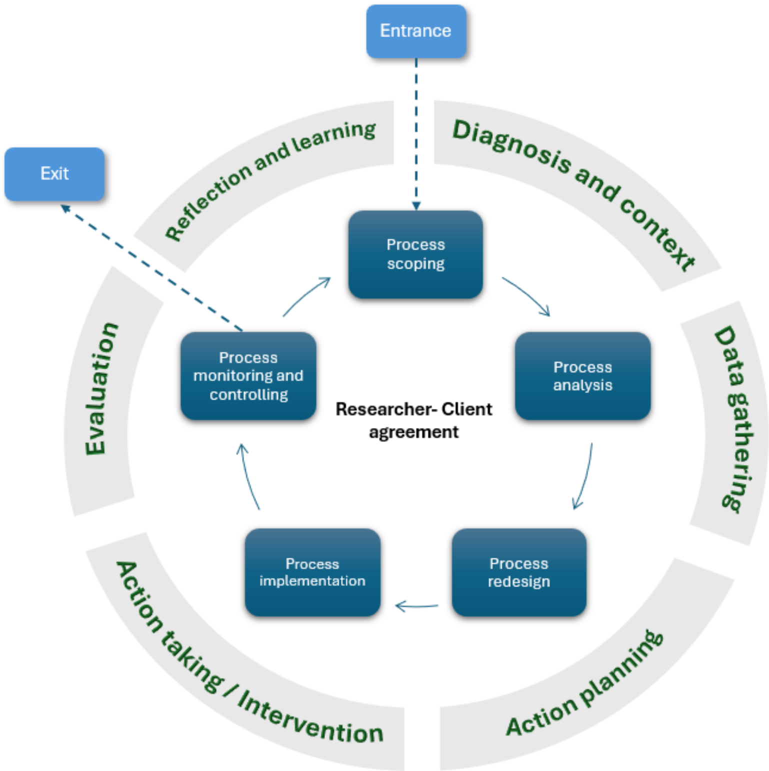

Figure 4 - Adopted Research Methodology

3.4 Ethical and Practical Considerations

Ethical considerations followed established guidance for business and management research involving organizational data, including informed consent, confidentiality, and transparency. (Saunders et al., 2019). Given the proprietary and financial sensitivity of aviation data, highlighting the private component of the company subject here, this study adheres to strict ethical and confidentiality standards. Data from maintenance systems such as AMOS, any ERP and financial records saved in excel, or any other tool are anonymized.

The researcher, in agreement with the collaborating company, maintains transparency regarding project needs, objectives, expected results, and deliverables shared with participating stakeholders, ensuring informed consent and full compliance with company policies. Communication between researchers and the participating team always is set within official channels as corporate emails, or group chats via Microsoft Teams.

4. Activities

This chapter outlines the activities carried out to analyze and improve the aircraft redelivery cost process within the airline context, supported by the application of an analytical tool. The activities were structured to develop a clear understating of the existing operational workflow, the identification of inefficiencies, data inconsistencies, limitation and traceability. To support this objective, Action Research (AR) and Business Process Management (BPM) principles were applied as guiding frameworks throughout the study, providing methodological structure for diagnosis, process analysis, redesign, and implementation.

The activities begin by establishing the necessary organizational context and diagnostic understanding that allow the process to be clearly scoped in agreement with the company. The study then progresses through data gathering and process analysis within the unified AR–BPM cycle, where key issues are identified. This is followed by redesigning the AS-IS process, which shapes the action planning, implementation, and monitoring which supports evaluation and reflection phases to understand the feedback of the company. Overall, the integrated model provides a structured and collaborative route from understanding the existing workflow to validating and refining improvements in an iterative approach.

4.1 Diagnosis and context

The company where this research takes place is a Brazilian airline headquartered in Brazil, founded in the year 2000. It operates primarily within Brazil and South America, while also reaching destinations in the Caribbean and the United States. Over the years, the organization has become one of the most important airlines in Latin America, transporting millions of passengers annually with its fleet of Boeing 737 aircraft. Its services range from passenger and cargo transportation to onboard comfort and entertainment solutions, all designed to enhance the travel experience for its customers.

The opportunity to conduct this study emerged organically through a professional connection, the airline was known to the researcher and facilitated an initial conversation about their operational needs. At that moment, the company was seeking external support to improve specific internal processes, while the researcher was looking for an organization where a methodological intervention could generate both practical impact and academic contribution. This mutual alignment of interests created a natural “entrance” into the company, enabling the establishment of a collaborative environment in which both parties could benefit from the project.

Within this context, the process selected for analysis is the calculation of return conditions for leased aircraft, a critical operational and financial activity for the organization. The purpose of this process is to estimate the future cost of aircraft redelivery at the end of the leasing period, ensuring that each aircraft is returned to the lessor in the same technical condition in which it was initially received. This activity has significant implications for financial forecasting, cost recognition, and compliance with lease agreements, directly influencing the company’s balance sheet and long-term maintenance planning.

This is important for the company because the calculation allows the company to anticipate future expenses, allocate adequate provisions, and maintain credibility with leasing partners. However, despite its importance, the process currently faces several structural inefficiencies and integration challenges that obstruct its reliability and timeliness.

4.1.1 Process scoping

To define the scope of the redelivery cost calculation process, meetings were held with the relevant organizational teams to obtain a clear understanding of the actual workflow. This scoping activity focused on identifying the sequence of activities involved, the time required for each step, the key data inputs, and the main bottlenecks affecting the process. Through this analysis, the process boundaries, critical dependencies, and stakeholders involved in the calculation were clearly established.

The execution of the process required collaboration with different organizational areas, fleet management and maintenance; both provide essential inputs for the calculation. Their involvement was critical to ensure that the information feeding the model is complete, reliable, and aligned with operational needs.

Stakeholders and Data Sources

- **Fleet Management Department:**

This area provides the Contract Detail files for each leased aircraft, containing key parameters such as lease duration, redelivery date, applicable tariffs per flight and flight hour, and annual escalation rates (similar to inflation indices). These data define the price component (P) of the return cost model.

- **Maintenance Department:**

Through systems AMOS, the Maintenance team supplies real operational data, including the current technical status of aircraft and engines, date of last repair, and accumulated usage since that point. These data define the quantity component (Q) representing the number of flight cycles or flight hours that will have been consumed at the time of aircraft return.

When integrated, both sources allow the organization to compute the P × Q model, projecting the expected redelivery cost for each aircraft.

Resources: Although the cost calculation process is currently performed in Excel, the company also provides access to the Python programming language across all departments. Since Python is a language rather than an application, employees must use Visual Studio, or another compatible Integrated Development Environment, to develop and execute scripts. If required, updates or adjustments to these tools can be requested from the company's service desk via email.

This approach allows the organization to leverage existing software resources without incurring additional licensing costs, optimizing the use of tools already available internally. By maximizing current capabilities, the company avoids unnecessary expenditures while maintaining flexibility for potential updates or upgrades when needed. It is important to note that the employees responsible for performing the calculations have experience with coding and programming applications.

4.1.2 Process analysis

Enough information was gathered to map the process, and additional guidance from a finance team member contributed to forming an initial understanding of how it operates.

High-level process map developed based on interview insights:

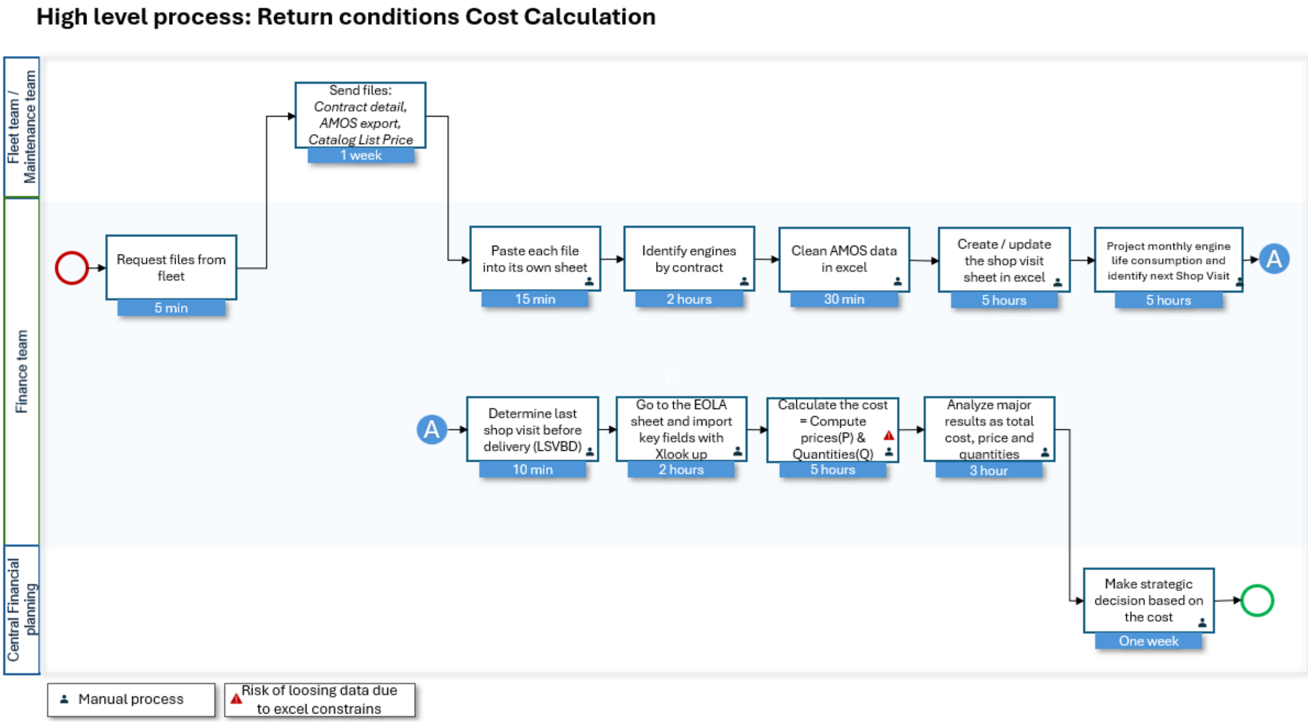

Figure 5 - High-level process map (AS-IS)

Current Situation and Identified Issues

Based on the interviews conducted, the measurement of activity execution times, and the shared understanding developed through close collaboration with the company, a set of operational and data-related problems were jointly identified in the current redelivery cost calculation process. These issues represent a consensual diagnosis reached during the diagnostic discussions between the researcher and organizational stakeholders.

- **Constraints with Excel:** Excel is not a tool that allows handling large databases, so it is prone to failure if we have a model with many calculations.
- **Fragmented Information:** Data is distributed across two independent systems and departments, with different formats and structures.

- **Data Quality Problems:** Contract details frequently contain missing or inconsistent information.
- **Manual Integration:** The process requires labor intensive reconciliation in Excel through lookups using aircraft tail numbers or engine serial numbers, creating large, complex, and error-prone models.
- **Limited Traceability and Efficiency:** The absence of a unified database or automated projection tools increases the workload and reduces transparency in the estimation process.

4.2 Data gathering

The data-gathering phase aimed to obtain a complete and accurate view of the information used in the existing end-of-lease engine cost calculation. This process integrates contractual, operational, and manufacturer data, the collection effort required close collaboration with fleet, maintenance, and finance teams. Following the principles of Action Research and BPM, data were gathered iteratively, allowing gaps and inconsistencies to be identified and resolved through continuous refinement.

a. Primary Data Sources

Three datasets were jointly identified as essential for understanding and modelling the current workflow:

i. **Contractual Data (Fleet)** – Provided the contractual framework for each aircraft and engine, including return conditions, tariff structures, escalation rules, and assigned engine serial numbers. This data defines the pricing parameters used in the cost model.

ii. **Operational and Maintenance Status (AMOS)** – Supplied engine hours and cycles since the last repair, shop visit dates, and component life limitations. This information described the technical drivers of consumption and the timing of future maintenance events.

iii. **Catalog List Prices (Manufacturer via Fleet)** – Contained current and historical LLP prices used for cost estimation and the calculation of annual escalation factors.

iv. **Flight Plan** – Flight-by-flight operational data from the company may include real figures plus available forecasting for future years.

The following is a description of the most representative variables of the files:
For more detailed information, refer to appendix 1.

CATEGORY	DATA FIELD	DESCRIPTION
IDENTIFICATION	MSN (Manufacturer Serial Number)	Aircraft manufacturer serial number
IDENTIFICATION	ESN (Engine Serial Number)	Contractual engine serial number
AMOS STATUS	Last Shop Visit Date	Date of last major shop visit
AMOS STATUS	Hours Since LSV	Flight hours accumulated since last repair
AMOS STATUS	Cycles Since LSV	Flight cycles accumulated since last repair
AMOS STATUS	LLP Remaining Life	Remaining LLP cycles before next shop visit
QUANTITIES	PR Quantity (Hours)	Flight hours since last repair until return date
QUANTITIES	LLP Quantity (Cycles)	Flight cycles since last repair until return date
RESULTS	Forecasted Shop Visits	Projected shop visit dates until return
RESULTS	PR Cost (P×Q)	Performance Restoration cost
RESULTS	LLP Cost (P×Q)	LLP replacement cost
RESULTS	Total EOLA Cost	Sum of PR + LLP (can be negative in mirror cases)

Table 2 - Description of redelivery cost calculation process variables

b. Iterative Refinement

Data collection unfolded across several iterations rather than a single extraction. As discrepancies emerged, such as mismatched engine assignments, irrelevant “light repair” events in AMOS, or unclear escalation rules, updated files were requested and definitions were clarified with subject-matter experts. Additional guidance from Finance helped validate how specific fields affected the calculation logic. Each iteration improved data completeness, consistency, and alignment with the requirements of the computational model.

c. Integration of Quantitative and Qualitative Insights

Alongside the datasets, qualitative input from Fleet and Finance experts was essential to interpret contractual tones, confirm modeling assumptions, and understand practical bottlenecks such as inconsistent file formats or manual reconciliation steps. These insights complemented the quantitative data and informed both the diagnosis of the current process and the design of the improved Python-based workflow.

d. Outcome of the Data-Gathering Stage

This collaborative and systematic approach provided a reliable foundation for mapping the existing process, identifying opportunities for improvement, validating the shop-visit projection logic, and constructing the initial version of the end-of-lease cost model. The findings from this stage completed the diagnosis phase of the Action Research cycle and enabled the transition to structured action planning.

4.3 Action planning

Building on the diagnosis and data-gathering stages, the action planning phase focused on designing a structured, evidence-based intervention to optimize the current end-of-lease engine cost calculation process. Guided by the research question: How can airline operational processes be optimized by developing advanced analytics capabilities? This phase translated the identified inefficiencies into a set of actionable, measurable, and collaboratively developed improvements. Following the principles of Action Research and BPM the plan integrates organizational needs, theoretical foundations from BPO, and the technical constraints of the existing workflow.

a. **Objectives**

The action plan aims to accomplish three interconnected goals:

1. Transform the manual Excel-based workflow into a computational process capable of scaling with fleet size, contractual complexity, and data volume.
2. Automate key steps of the redelivery cost model, including data integration, shop-visit projection, consumption calculation, and cost estimation (P × Q).
3. Improve transparency, reproducibility, and traceability, addressing recurrent issues such as version inconsistencies, manual formula errors, and fragmented information sources.

b. Scope of the Intervention

The intervention targets the core components of the redelivery calculation process, focusing on:

- Integration of the three foundational datasets: Contract Detail, AMOS operational status, and Catalog List Price.

- Replication and automation of the shop visit (SV) forecast logic, including life-limit calculations for LLP and PR components.
- Automated estimation of quantities (Q), hours and cycles consumed between last repair and return date.
- Automated calculation of prices (P), contractual tariffs for PR and manufacturer LLP prices, adjusted using annual escalations.
- End-to-end generation of EOLA cost outputs, including mirror/100% logic and contract-specific variations.

Non-essential elements, such as user interface design, system integration beyond Python, or deployment within organizational systems, are intentionally excluded from this cycle but proposed as future work.

c. Planned Actions and Activities

A structured set of actions was defined to address the workflow gaps uncovered during diagnosis. These actions form the basis of the computational implementation:

1. Data Integration and Consolidation

- Develop Python routines to import, structure, and validate the three datasets.
- Standardize key identifiers (aircraft mark, MSN, ESN) to avoid mismatching and look up errors.
- Remove irrelevant AMOS data (e.g., light repairs) and isolate LLP-relevant modules (HPT, LPT).

2. Reconstruction of the Calculation Logic

Translate the Excel logic into transparent, modular Python functions:

- Remaining life calculations for LLP and PR components.
- Daily utilization projections (FH and CY).
- Monthly reduction of remaining useful life until reaching zero.
- Application of TAT (default 90 days, adjustable).
- Identification of whether a shop visit occurs before return-date.

3. Automation of the P × Q Cost Model

- Automate PR escalation based on the contract signature date or escalation amendment.
- Compute LLP price escalations from the manufacturer's historical index.
- Apply mirror-in/mirror-out or 100% return obligations as per contract.
- Generate individual and fleet-level results.

4. Validation and governance mechanisms

- Define KPIs for performance and correctness (e.g., variance vs manual Excel model, processing time, error rate reduction).
- Establish data-quality checks and exception rules (e.g., missing serial numbers, inconsistent dates, unaligned escalation factors).
- Introduce versioning controls for datasets and Python outputs.

5. Collaborative review with stakeholders

- Schedule review sessions with Finance and Fleet teams to confirm accuracy and interpretability.
- Define a feedback loop to refine assumptions such as utilization, TAT, or escalation parameters.

Gantt chart

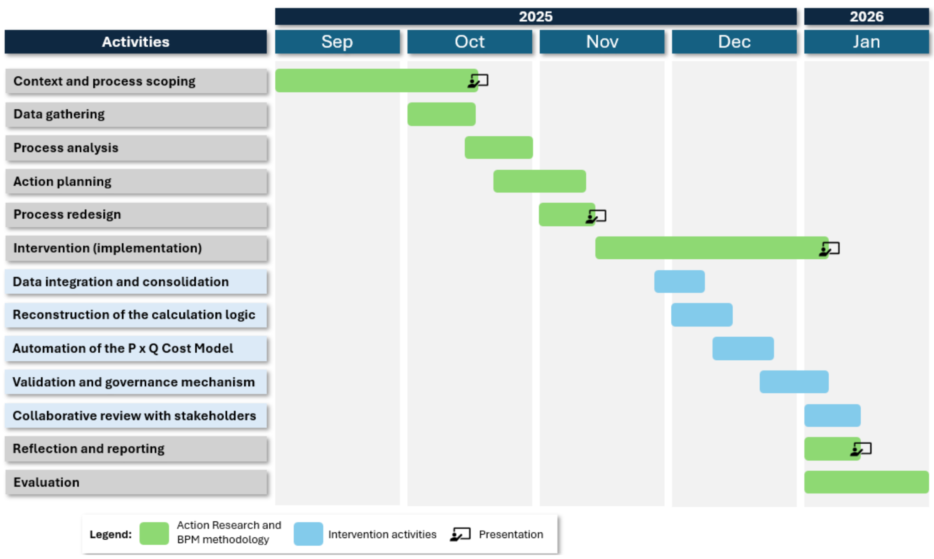

Figure 6 - Gantt Chart Activities

Figure 6 presents the Gantt chart outlining the planning and execution timeline of the study. The schedule reflects the sequencing of activities structured according to the Action Research cycle and supported by Business Process Management principles. The project starts in September 2025 and finishes in January 2026, progressing from context definition and process scoping through data gathering, analysis, action planning, redesign, and implementation. The intervention phase has the details of the specific technical activities, including data integration, reconstruction of the calculation logic, automation of the cost model, and validation with stakeholders. The final stages focus on evaluation, reflection, and reporting, ensuring that findings are systematically assessed and aligned with both organizational objectives and academic requirements.

d. Stakeholders, Roles, and Responsibilities

Area	Responsibility
Finance	Validate cost outputs, provide business rules, test scenarios
Fleet	Provide Contract Detail file, clarify escalation rules and mirror/100% logic
Maintenance (AMOS)	Provide engine status, confirm component limits, validate shop-visit projections
Researcher	Translate Excel logic into Python, perform integration, document the model, coordinate AR cycles

Table 3 - Stakeholders, roles and responsibilities

The collaborative nature of AR ensures shared ownership of results and continuous verification.

e. Expected Outputs

The planned actions are expected to be delivered:

1. A functioning Python model replicating and enhancing the Excel workflow.
2. A unified and clean data structure suitable for forecasting and future automation.
3. A documented, reproducible methodology describing the logic behind each calculation.

4. Scenario-generation capability, enabling dynamic testing for utilization changes or contract variations.

5. A transparent P × Q calculation, reducing ambiguity and dependence on expert tacit knowledge

4.4 Intervention

Process redesign

Based on the action planning outcomes, a redesigned version of the redelivery cost calculation process was developed to address the inefficiencies identified during the previous phases. This redesign formalizes the transition from a manual, Excel-based workflow to an automated, data-driven computational model aligned with the objectives defined jointly with the company.

As a result of this redesign, the operational effort required from the finance team is significantly reduced, with processing time decreasing from approximately 1,200 minutes in the original process to around 25 min in the redesigned workflow for the data management activities. Given that results and the first implementation of this type of automation within the organization, the redesigned process intentionally incorporates human supervision, whereby a designated employee oversees the automated steps to verify data integrity, validate intermediate results, and confirm the overall consistency of the outputs before they are used for decision-making.

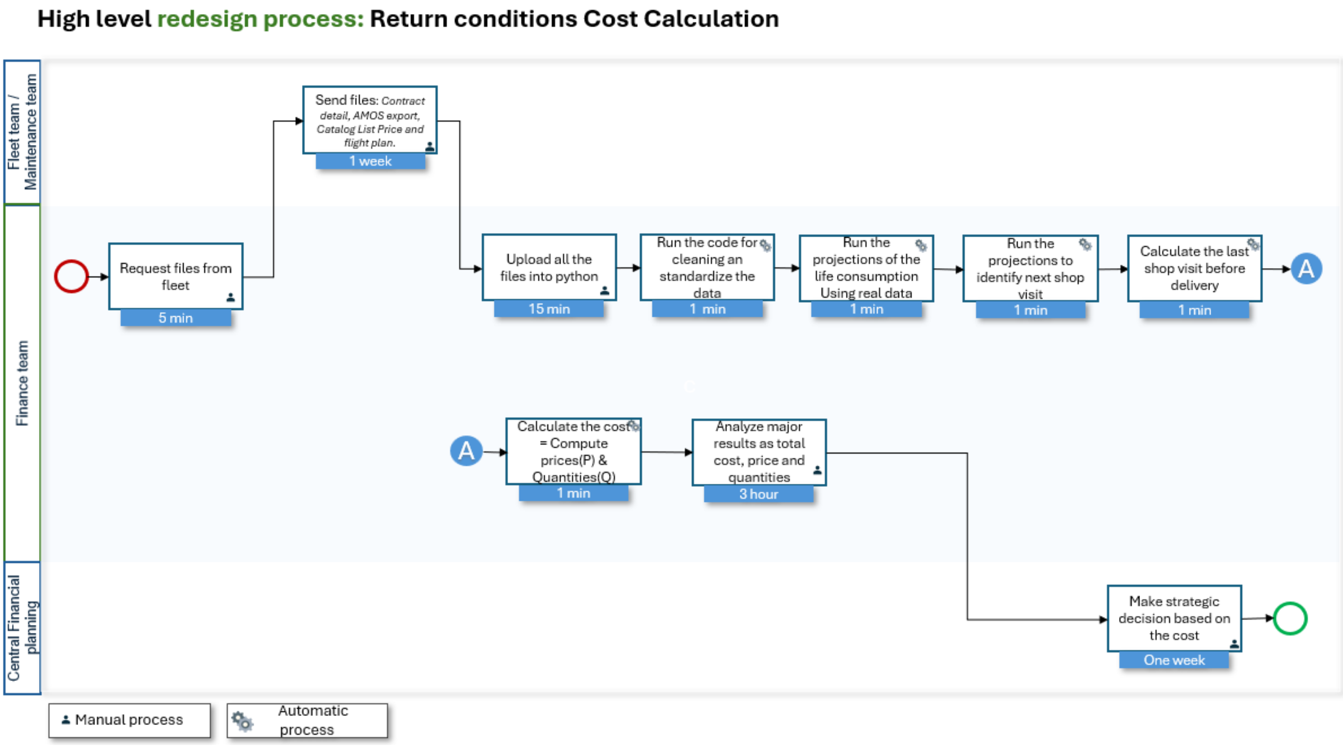

Figure 7 - High-level process map (TO-BE)

Now, the researcher continues with the implementation of the computational model in Python to automate the calculation of engine return conditions. The development and implementation of the code were explicitly aligned with the redesigned process for return-condition cost calculation, ensuring that the automated workflow reflects the sequence of activities, decision points, and control mechanisms defined in the process redesign.

The implementation relies primarily on the pandas library for handling and transforming tabular data, including loading excel files, merging datasets, and performing aggregations. NumPy is used to support efficient numerical calculations and conditional logic, while the os and math libraries are employed for file management and specific mathematical operations required in maintenance and utilization projections. Together, these libraries allow efficient execution, improved transparency, and easier maintenance compared to the previous process in the spreadsheet-based solution. For a summary of the code used, please refer to Appendix 2.

The outcome of the intervention is an engine-level output that consolidates contractual, operational, and maintenance data and quantifies redelivery exposure through Performance Restoration (PR) and Life Limited Parts (LLP) components. While the computational steps are automated, the process is currently implemented as a semi-automatic workflow, in which an employee supervises the execution of the model and validates the plausibility of the results before they are used for decision-making. This supervision was intentionally maintained to ensure control and reliability in the process.

Throughout the intervention, the development of the model was carried out in close collaboration with the finance team. Progress review meetings were held approximately every fifteen days to assess the outputs, validate calculation logic, and correct formulas when discrepancies with the original Excel model were identified. These iterative review cycles allowed the code to be refined incrementally and ensured that the automated calculations accurately reflected the business rules applied by the organization.

The intervention phase lasted approximately two months, encompassing initial implementation, iterative validation, and alignment with the redesigned process. By integrating the automated model within a supervised and process workflow, the intervention achieved a balance between efficiency gains and operational control, establishing a solid foundation for future iterations toward higher levels of automation.

Excel output:

EOLA_LLP_cost	EOLA_Total_PR_plus_LLP
6,078,216.4	9,468,428.1
7,058,858.0	13,251,844.7
7,156,531.6	13,540,972.2
1,037,290.7	2,177,539.3
627,083.7	1,347,248.9
367,435.7	643,054.9
6,245,545.9	11,104,733.4
6,324,119.8	8,273,649.5
1,001,097.2	1,775,603.4
732,033.7	1,303,253.8
4,945,154.0	9,045,850.6
1,124,782.1	1,851,068.9
4,405,112.1	6,058,380.8
4,701,553.1	6,466,078.0
996,041.5	1,369,862.7
7,766,752.2	10,681,667.4
3,248,992.5	4,468,361.6
8,412,993.5	11,570,447.3
8,679,790.3	11,937,374.8

Table 4 - Excel output (EOLA LLP Total Cost)

```
DONE
Final output: C:\Users\natal\OneDrive\Escritorio\FINAL WORK MIM\Python\outputs\FINAL_engine_level_EOLA.xlsx
Rows: 266
EA TSO matches: 170
EA CSO matches: 170
PR not-null: 254
LLP not-null: 258
```

Figure 8 - Python output

4.5 Evaluation

The evaluation phase assessed the effectiveness and practical impact of the redesigned and automated redelivery cost calculation process. Following the Action Research and BPM approach, this assessment combined technical validation with qualitative feedback obtained through an interview with the employee responsible for supervising and reviewing the automated workflow. In addition to validating that the automated solution was successful, this phase confirmed that the redesigned process was implemented.

In general, the intervention and the underlying process redesign successfully resolved several of the key problems identified at the beginning of the study. The automation of the calculation logic and the consolidation of information eliminated the fragmentation previously caused by multiple independent excel files. According to the reviewer, all relevant contractual, operational, and cost data are now centralized in a single structured output, which functions as a unified database. This outcome demonstrates that the redesigned process effectively replaced the manual workflow, directly addressing prior issues related to manual reconciliation, limited traceability, and inefficient information access. Additionally, the output will be integrated into Power BI as a next step to support visualization and enhance the decision-making process.

The evaluation also confirmed improvements in accuracy and methodological robustness, addressing earlier limitations of the excel workflow. Constraints related to spreadsheet size and performance, such as the need to approximate utilization on a monthly basis or apply rounding to avoid model overload, were eliminated. The Python-based model enables daily utilization projections and performs calculations without rounding constraints, resulting in more precise estimates for Performance Restoration (PR) and Life Limited Parts (LLP). Furthermore, manual data preparation tasks previously required to enable excel lookups, such as extensive data cleaning and restructuring, are now handled programmatically, reducing manual effort and processing time within the redesigned process.

To complement the quantitative validation of the automated model, a semi-structured interview was conducted with the employee responsible for supervising and reviewing the redesigned process. The objective of this interview was to assess whether the main operational and data-related issues identified during the diagnostic phase were effectively addressed through the intervention. The questions focused on key problem areas previously associated with the manual spreadsheet workflow, including scalability constraints, information fragmentation, data quality, manual effort, and traceability. The responses provide qualitative evidence of the practical impact of the new process from an end-user perspective and support the evaluation of the intervention within the Action Research framework.

Question	Answer
1**. Constraints with Excel** Compared to the previous Excel-based process, does the automated model handle larger datasets and complex calculations more reliably and without performance issues?	"Yes, the model allowed the data to be uploaded quickly, and the system responded immediately without performance delays"
2. Fragmented Information To what extent has the new process reduced the need to gather and reconcile information from multiple files, systems, or departments?	"The new process achieved its main objective by consolidating the information into a single, unified database, which is the most important improvement for reviewing and analyzing the data. However, the process of requesting the original information remains unchanged, meaning that there is still a dependency on other departments for data provision"
3. Data Quality Problems	"Yes, the automated process makes the analysis much simpler and allows the

Does the automated process make it easier to identify and manage missing or inconsistent contractual and operational data?	results to be reviewed more clearly, making it easier to identify and manage missing or inconsistent contractual and operational data”
4. Manual Integration How has the level of manual work (such as look-ups, reconciliations, and data cleaning) changed since the implementation of the automated process?	“This was the aspect that changed the most. The process now takes significantly less time, representing one of the most important improvements compared to the previous manual workflow”
5. Limited Traceability and Efficiency Compared to Excel, does the new process improve traceability of calculations and reduce the time required to produce redelivery cost estimates?	“Yes, the new process significantly improved traceability and drastically reduced the time required to produce redelivery cost estimates. In addition, the calculation logic was enhanced, resulting in a more efficient and reliable overall process”

4.6 Reflection

The study provides several insights into how advanced analytics can be used to improve complex data- intensive operational processes in the airline industry. The implementation of an automated solution revealed the extent to which execution time, accuracy, transparency, and data consolidation are influenced by the underlying process design. In particular, the findings demonstrate the value of applying Business Process Optimization (BPO) principles, demonstrating that alignment with the redesigned process effectively addressed the limitations initially observed the manual workflow.

The adoption of an Action Research methodology enabled continuous collaboration with stakeholders to develop a shared understanding of the process targeted for optimization. This ongoing interaction ensured that the redesigned workflow reflected operational realities and facilitated iterative validation of results. This approach reduced the risk of misalignment between the theoretical model and practical needs, ensuring a relevant solution that was applicable to the company. In addition, the study revealed a deeper organizational issue, the absence of formal process documentation, which limited the company's ability to accurately understand operational challenges and identify bottlenecks within the area. This limitation reinforced the need to apply Business Process Management (BPM) principles alongside Action Research, to structure, document, and systematically analyze the existing processes in this type of companies.

Also, the results confirm that automation aligned with process redesign and supported by stakeholder collaboration, can remove structural limitations that are present in manual workflows, such as fragmentation, limited traceability, and high dependency on repetitive data handling. Considering a BPO perspective, the intervention proof that formalizing calculation logic, standardizing data inputs, and reducing manual intervention improve both process performance and analytical reliability. Moreover, the experience encouraged the organization to recognize the potential for replicating similar optimization approaches in other processes constrained by data management complexity.

On the other hand, the company encountered potential long-term difficulties once the intervention concluded. First, modifications to the original source databases, like changes in structure, formats, or availability, may require updates to the Python code. Although the implementation was robust, addressing such changes would require employees with programming expertise, potentially creating a dependency on specialized technical profiles within the organization. Second, the redelivery cost calculation process itself is not static but evolves in response to changing business needs. For more requirements, reporting objectives, or decision-making priorities, the current logic and outputs of the model may need to be revised, which would also need further code adaptations.

This study is the basis for future developments that the company wants to make. As a potential next phase, stakeholders identified the opportunity to design and integrate Power BI dashboards and to enable automatic data extraction from operational systems, further reducing manual intervention. They indicated that an intervention of this nature is necessary and that it is useful to incorporate a new analytical tool.

5. Discussion

This study examines how airline operational processes can be optimized through the development of advanced analytics capabilities, using the redelivery cost calculation process as a case study. Rather than assessing whether such optimization is possible, the discussion focuses on how optimization was achieved in practice and which organizational, analytical, and process elements proved most relevant. By focusing on the redelivery cost calculation process, the study evaluates the role of advanced analytics in supporting complex financial forecasting activities within an airline operational context.

The results indicate that the research objectives were addressed through a combination of analytical automation and process redesign. The manual workflow was replaced by a computational process capable of scaling with increased data volumes and contractual complexity. Key components of the redelivery cost model, including data integration, cost projections, and P × Q calculations, were automated in alignment with the company's financial logic.

Furthermore, transparency, reproducibility, and traceability were increased by formalizing calculation rules and consolidating outputs, by that means reducing issues related to version inconsistencies, manual errors, and fragmented data sources. These outcomes illustrate how the joint application of Business Process Management (BPM) and Action Research (AR) as methodological frameworks, together with Python as the analytical tool, facilitated the optimization of the operational process and provided a concrete answer to the research question of how such optimization can be achieved in practice.

These outcomes are supported by quantitative results from the evaluation phase. The automated workflow reduced processing time from approximately 1,200 minutes to around 25 minutes, representing a reduction of over 97%. Manual activities such as data cleaning, lookups, and reconciliation were eliminated, and utilization calculations were improved from monthly to daily projections, increasing the accuracy of PR and LLP estimates. Employee feedback also suggests that the implementation did have a generally positive impact.

As a result, the employees were able to redirect their efforts away from data preparation and toward financial analysis and interpretation of results. This shift is relevant in controlling and finance contexts, where analytical judgment and scenario evaluation add more value than manual data handling. Also, the findings suggest that automation can improve efficiency and the quality of decision-making by allowing the financial team to focus on their core competencies.

These findings contribute to answering the research question by illustrating how advanced analytics, when integrated with a redesigned business process, can be applied to optimize complex analytical workflows in airline operations. The results confirm that automation and computational modeling improve efficiency, scalability, and analytical reliability without compromising control or decision quality. This interpretation is consistent with prior research that identifies spreadsheet-based processes as prone to error, limited in scalability, and difficult to govern in data-intensive contexts (Panko, 2008). Furthermore, Business Process Management studies support the argument that formalizing logic through computational models enhances transparency and reproducibility (Dumas et al., 2018).

At the same time, the findings extend existing aviation research, which has predominantly focused on optimizing operational execution such as maintenance or scheduling, by demonstrating that significant value can also be generated through the optimization of analytical and forecasting processes. Unlike studies that emphasize cost reduction as the primary outcome of optimization, this research shows that improvements in process quality, traceability, and decision support represent equally relevant performance dimensions, reinforcing the practical relevance of advanced analytics for financial planning and asset management functions.

Although the results are positive, the study also presents limitations. First, the evaluation period was constrained by time, limiting the opportunity to observe the model's performance over additional months of operational data. A longer period of observation could provide further insights into stability, robustness, and adaptability under changing business conditions. Second, although the model was validated collaboratively with the team, long-term feedback could strengthen conclusions regarding the adoption and user dependence.

Additionally, another key insight that emerged during the BPM process was that the company did not have formally defined or documented processes. The absence of documented workflows makes it difficult to control time allocation and clearly assign responsibilities at both the employee and organizational levels. This type of study helps identify the company's actual capabilities and needs, moving beyond informal or unsupported requirements and providing a more solid basis for process improvement and decision-making.

According to this, future research could extend this work in several directions. One would be to assess the long-term organizational impact of automation on decision-making quality and process governance. Another opportunity lies in integrating automated data extraction directly from operational systems and improving visualization through business intelligence tools such as Power BI. Additionally, comparative studies across different airlines or asset-intensive industries could help generalize the findings and refine best practices for transitioning from spreadsheet-based process to computational process models.

6. Conclusion

This study explored how advanced analytics can be used to optimize a complex analytical process within an airline, using the redelivery cost calculation process of a Brazilian airline as a case study. By combining Action Research (AR) with Business Process Management (BPM), the study addressed the limitations of a manual workflow and implemented a redesigned, computational process aligned with organizational needs.

The findings indicate that integrating computational analytics within a structured process redesign can improve efficiency, transparency, and analytical reliability in data-intensive financial processes for this type of company. The AR–BPM methodological approach ensured that the solution worked within the operational reality, supported stakeholder engagement, and facilitated effective implementation. In this sense, the study shows that airline operational processes can be optimized using advanced analytics within a structured process redesign, supported by stakeholder collaboration, allowing scalable automation, improved transparency, and more reliable decision-making. Rather than focusing solely on automation, the research highlights the importance of aligning technology, process design, and organizational context to achieve better outcomes.

While the findings are limited by the duration of the evaluation period and the dependency on data structures and technical expertise, the study provides a practical and methodological foundation for further development. Overall, this research demonstrates that advanced analytics, when is used in a participatory and process-oriented framework, offer a viable path for improving analytical processes in asset-intensive industries and supporting more informed financial decision-making.

Finally, this study contributes to the development of responsible and efficient operational practices aligned with sustainable development goals (SDG). By improving transparency and traceability in the redelivery cost forecasting, using a new workflow, the proposed approach supports more informed decision-making regarding asset utilization, maintenance planning, and contractual compliance, contributing indirectly to SDG 12 (Responsible Consumption and Production). Also, the adoption of advanced analytics and process-oriented methodologies supports SDG 9 (Industry, Innovation, and Infrastructure) by demonstrating how digital tools, such as Python, can modernize legacy processes and improved organizational capabilities in complex and regulated environments such as aviation.

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Appendix

Appendix 1 – Detail table for the variables

CATEGORY	DATA FIELD	DESCRIPTION
IDENTIFICATION	Aircraft Mark	Operational aircraft identifier used internally
IDENTIFICATION	MSN (Manufacturer Serial Number)	Aircraft manufacturer serial number
IDENTIFICATION	ESN (Engine Serial Number)	Contractual engine serial number
SOURCES	AMOS Export	Operational status: last shop visit, hours, cycles
SOURCES	Catalog List Price	Catalog with LLP prices and limits
CONTRACT	Return Scheme (100% / Mirror)	Defines if return is 'as new' or 'same condition'
CONTRACT	Engine Escalation Date	Date a new escalated PR tariff begins (amendment)
AMOS STATUS	Last Shop Visit Date	Date of last major shop visit
AMOS STATUS	Hours Since LSV	Flight hours accumulated since last repair
AMOS STATUS	Cycles Since LSV	Flight cycles accumulated since last repair
AMOS STATUS	LLP Remaining Life	Remaining LLP cycles before next shop visit
COMPONENTS	Applicable Modules	Modules used in LLP calc: HPT, LPT.
COMPONENTS	Module Limits	Life limits per module (e.g., 20,000 cycles)
UTILIZATION	Daily Utilization (Projection)	Average flights per day (used for forecasting)
UTILIZATION	TAT (Turn Around Time)	Estimated time engine stays in repair shop
TARIFFS	PR Engine Rate	Performance Restoration rate per flight hour
TARIFFS	LLP Price	Price per LLP component
TARIFFS	PR Escalation (%)	Annual escalation rate for PR
TARIFFS	LLP Escalation (%)	Average LLP inflation based on 10-year history
TARIFFS	Escalated PR & LLP Rates	Final escalated rates for PR and LLP at return year
QUANTITIES	PR Quantity (Hours)	Flight hours since last repair until return date
QUANTITIES	LLP Quantity (Cycles)	Flight cycles since last repair until return date
RESULTS	Forecasted Shop Visits	Projected shop visit dates until return
RESULTS	PR Cost (P×Q)	Performance Restoration cost
RESULTS	LLP Cost (P×Q)	LLP replacement cost
RESULTS	Total EOLA Cost	Sum of PR + LLP (can be negative in mirror cases)
ENGINE TYPES	Engine Family	Engine type (e.g., CFM56-7B, LEAP)

Appendix 2 – Code summary

```
# 1) Ensure engine-level granularity (one row per engine)
engine_long = aircraft_lease.merge(aircraft_list, on="Reg Marks", how="left")
engine_long = engine_long.melt(
    id_vars=[c for c in engine_long.columns if c not in
            ["1st Engine Serial Number", "2nd Engine Serial Number"]],
    value_vars=["1st Engine Serial Number", "2nd Engine Serial Number"],
    value_name="engine_serial_number"
).dropna(subset=["engine_serial_number"])

# 2) Add AMOS core information (life limits and utilization since last shop)
engine_long = engine_long.merge(
    amos_core.groupby("engine_serial_number")
    .agg(
        min_cycles_remaining=("Cycles Remaining (LIFE LIMIT)", "min"),
        tso_aggregate=("tso_aggregate", "max"),
        cso_aggregate=("cso_aggregate", "max")
    ),
    on="engine_serial_number",
    how="left"
)

# 3) Identify last shop visit before lease end (maintenance projection)
engine_long["last_shop_before_lease_end"] = np.where(
    engine_long["min_cycles_remaining"] <= 0,
    CALC_DATE,
    engine_long["LSV"]
)

# 4) Compute Performance Restoration (PR)
engine_long["PR_quantity"] = (
    engine_long["tso_aggregate"] +
    engine_long["Utilization/FH_per_day"] *
    (engine_long["Lease Ending Date"] - CALC_DATE).dt.days
)

engine_long["PR_price"] = (
    engine_long["Eng ESV Adj Rate"] *
    (1 + engine_long["ESV Escalation"]) **
    engine_long["years_escalated"]
)

engine_long["EOLA_PR"] = engine_long["PR_price"] * engine_long["PR_quantity"]

# 5) Compute LLP exposure
engine_long["LLP_quantity"] = (
    engine_long["cso_aggregate"] +
    engine_long["Utilization/CY_per_day"] *
    (engine_long["Lease Ending Date"] - CALC_DATE).dt.days
)

engine_long["LLP_price"] = (
    engine_long["Cost_sum"] *
    (1 + LLP_ESC_RATE) **
    engine_long["years_escalated"]
)

engine_long["EOLA_LLP"] = engine_long["LLP_price"] * engine_long["LLP_quantity"]

# 6) Apply mirror clause if applicable
mirror_mask = engine_long["Adjustment Basis"].str.contains("Mirror", case=False, na=False)

engine_long.loc[mirror_mask, "EOLA_PR"] -= (
    engine_long.loc[mirror_mask, "TSO (Core) EA"] *
    engine_long.loc[mirror_mask, "PR_price"]
```