CHALMERS
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Lifecycle Revenue Analysis and Predictive Forecasting

Revenue analysis of new sales and spare parts for Marine Safety Systems

Master's thesis in Product Development

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DEPARTMENT OF INDUSTRIAL AND MATERIALS SCIENCE
CHALMERS UNIVERSITY OF TECHNOLOGY
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Cover: A Marine vessel, since the thesis focus on marine safety system.

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Abstract

The marine safety systems industry is defined by its critical aftermarket segment, with revenue generation that is more reliant on aftermarket activities like spare parts sales and services. As the trend goes with other sectors, the marine industry is increasingly reliant on data, with manufacturers seeking data-driven revenue optimization tools, analytics, and forecasts for the entire product life cycle. This masters thesis develops a data-driven framework for life cycle revenue analysis and predictive forecasting for a global safety systems provider in the marine sector. In the thesis, a mixed method approach was adopted, literature review, qualitative interviews, and quantitative data modeling with Power BI. This modeling focused on sales order data from ERP with a subset of vessels and products and tracked revenue generation across the market life cycle, enabling the forecasting of revenue generation and product demand. Also, a structured decision model for End-of-Life (EOL) was developed to capture decaying trend lines for sales and revenue volume while adhering to product category-specific thresholds. In addition, a simulation of pricing strategy was modeled to analyze the recovery of margins across the life cycle.

As spotlighted in the key analysis and results, spare parts revenue tends to peak after several years of the vessel delivery and initial sales, although the patterns differ across fire and gas systems. The EOL model effectively mitigated the risks of phase-out by utilizing defined decline thresholds, thereby offering valuable contributions to aftermarket planning and inventory optimization. Within Power BI, the defined and limit-sensitive control frameworks utilizing historical quantity trends demonstrated actionable short-term forecasting capabilities, which expedited decision-making processes. This study adds to the existing body of knowledge from an academic and practical perspective: in the form of case study integration from the marine industry to life cycle revenue theories, ERP-based forecasting, and data-driven decision-making dashboards for the case company. Other capital goods industries with long service life cycles would benefit from the methodology and insights presented, which offer a replicable approach to planning and revenue optimization.

Keywords: product life cycle management, life cycle revenue, forecasting, spare parts, data analytics, power BI.

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I would like to express my sincere gratitude to all those who supported me throughout this thesis journey on life cycle revenue analysis and predictive forecasting for marine safety systems. I am deeply grateful to my industrial supervisor, Johan Apelberg at Consilium Safety Group AB, for his valuable guidance, strategic insights, and continuous encouragement. I am equally grateful to my academic supervisor and examiner, Professor Dag Henrik Bergsjö from Chalmers University of Technology, for his constructive feedback and academic direction. I also extend my appreciation to the professionals at Consilium who generously contributed their time and insights through interviews and discussions, as your inputs formed a vital part of this work. This thesis would not have been possible without your support.

Vigneshwaran Thiagarajan, Gothenburg, August 2025

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis, listed in alphabetical order:

ARIMA	Auto Regressive Integrated Moving Average
BI	Business Intelligence
B2B	Business to Business
CRM	Customer Relationship Management
DAX	Data Analysis Expressions
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
EOL	End of Life
EMWA	Exponentially Weighted Moving Average
ERP	Enterprise Research Planning
ETS	Exponential Smoothing
IMO	International Maritime Organization
KPI	Key Performance Indicator
LRM	Lifecycle Revenue Management
LSTM	Long Short Term Memory
LTB	Last Time Buy
MAD	Mean Absolute Deviation
ML	Machine Learning
OEM	Original Equipment Manufacturer
OR	Operations Research
PLM	Product Lifecycle Management
R&D	Research and Development

Contents

List of Figures

1

Introduction

The first chapter presents the background and thesis motivation, which covers life cycle revenue analysis and predictive forecasting specific to marine safety systems. In addition, it explains the context and significance of the problem being researched relative to the industry and business, which leads to developing the research aim and the research questions. Moreover, it defines the boundaries of the study scope and describes the approach in which the problem will be solved. In the end, the chapter proposes the design of the report to get oriented for the upcoming chapters.

1.1 Background

The marine industry is characterized by long product life cycles, where vessels typically operate for 20 to 40 years, particularly in the case of commercial ships such as tankers, container vessels, and bulk carriers (Jungen et al., 2021). As a result, the installed safety systems are often maintained and upgraded rather than replaced, which is also seen as a customer behaviour and in turn creates ongoing revenue streams through spare parts sales, service, and system upgrades. However, when it comes to managing these life cycle stages strategically, it is complex, as it involves product support planning, pricing decisions, spare parts availability, and end-of-life (EOL) transitions (Liang et al., 2024). As a result, the company must balance long-term commitments to safety and compliance with profitability and operational efficiency.

The case company specializes in marine safety systems, particularly fire and gas detection solutions installed on a variety of commercial vessels such as tankers, container ships, cruise liners, and bulk carriers. These systems are critical to ensuring onboard safety and are subject to strict regulatory standards.

This thesis will address the need for understanding and forecasting the life cycle revenue associated with the case company's marine safety systems across different stages of the product and market life cycle. Therefore, by analyzing historical sales data with vessel and product level dimensions and stakeholder insights, the thesis aims to generate actionable recommendations for pricing, product life cycle management with a focus on end-of-life decisions, forecasting strategies, and new product development.

1.2 Aim

The aim of this thesis is to explore how insights from the life cycle revenue of products in different market stages can be used to support strategic decision-making. The main goal here is to analyze revenue patterns across life cycle stages of marine safety systems from new system sales to spare part sales and developing models for forecasting approaches that can guide pricing, aftermarket planning, and end-of-life transitions, which can further guide new product development decisions. The study attempts to bridge the gap between historical revenue data and the long-term life cycle strategy of products and their sales.

1.3 Limitation

The boundaries set for this thesis encompass some practical constraints that have to do with the limitations of data and the systems in question. This work utilized proprietary internal sales data from the CRM and ERP systems of the case company, specifically Dynamics 365 and the legacy M3 ERP, which generated records of invoiced sales orders. Relevant metadata was retrieved from the IHS Maritime Portal as well as from manually curated product categorization files. Although these systems had their unique advantages regarding data retrieval, other system-centered constraints posed challenges due to the systems structural limitations. Especially for older sales data associated with vessels delivered prior to 2015, the consistent mapping of vessel-level attributes was only possible to a limited degree. Thus, full segmentation was not attainable.

Furthermore, interaction with the Power BI environment used for analysis was limited to front-end elements guided by Azure Analysis Services. In practical terms, this meant no new tables or calculated columns could be added, and all modeling logic had to be executed via DAX measures. Even though real-time analytics are powerful in-demand and streamed data contexts, this particular modeling constraint curtailed advanced modeling and necessitated simplifications in the forecasting logic residue.

The remainder of the analysis, however, abides by the companys information security policies by not disclosing sensitive financial figures or visuals while providing the company with useful insights based on the reasoning that has structured the analysis. Furthermore, qualitative insights from internal interviews across multiple departments will be used to complement data-driven analysis. So the conclusion from this work, will need to be interpreted based on the above boundaries as a matter of fact.

1.4 Research Questions

In order to accomplish the stated aims and goals, this thesis is guided by a specific set of research questions that aim to structure the inquiry around the relationship between product and market life cycle revenue trends and strategic decision-making. These questions are based on both the theoretical focus of the case company and the practical world in terms of product life cycle management and forecasting on industrial contexts.

1. **What is the effect of life cycle revenue analysis on resource allocation and investment decision on aftermarket services and new product development?**

   This question looks into the study of how insights generated using data over time impacts strategic and operational decision-making. It analyses how revenue flows may validate or change investment expenditures in augmenting spare parts sustainment, engineering capabilities, or advancements in innovations. This question also accounts for how intelligence gathered over a products life cycle assists in setting priorities between preserving legacy systems and speeding up the new systems development. This study also investigates how much life cycle analytics seek to balance business expenditure and resources against income and revenue.

2. **How can revenue trends from historical sales data be utilized to develop data-driven criteria for end-of-life (EOL) decisions on products?**

   The focus of this question is to construct a systematic approach to determine which products are likely at the tail end of their commercial life cycle. The goal is to examine how historical sales data impacts criteria such as observed revenue drop, reduction in unit sales, and time since the last sale. Thus, the thesis attempts to define repeatable indicators that enable proactive planning for phase-out, discontinuation, and aftermarket support decisions. These insights are essential in forming the model for End-Of-Life and decision support tools that are created in the study.

3. **How can strategic pricing models from life cycle revenue analysis contribute for new marine safety products to enhance long-term profitability with effective strategic pricing?**

   This question is concerned with extracting information from life cycle revenue changes and using them to inform pricing for new system sales or projects. The objective is to determine how much emphasis on early revenue indicators, along with aftermarket redistribution warrants in pricing logic, with the aim of enhancing profit across the product life cycle. Particularly, the study investigates if and how loss leader strategy, bundled pricing, or life cycle-based differentiation strategies are utilized. This question links revenue analytics to marine safety product development with innovation in pricing.

4. **How do revenue generation patterns vary across different product life cycle stages and among various commercial vessel categories?**

This question, by illustrating how revenue distinctly changes against the life cycle maturity and vessel usage, lays the groundwork for further explorative inquiries. The objective is to classify revenue trajectories by identified product category, type of system, and type of vessel. Recognizing this variation enables performance benchmarking, assists in contextualizing profit phases, and supports tailored strategies for different market segments. This forms the practical basis for the above-formulated application questions.

The approach to research in this thesis was meant to be iterative and exploratory. Instead of settling on one particular output, the framework was synthesized through a cycle of empirical study, stakeholder participation, and data analysis. The primary outputs include several analytical frameworks and decision-support systems, which are expert-validated within the case company. Primary focus was placed on actionable outcomes instead of proposed insights, thereby advancing academic knowledge alongside practical value in revenue management from a life cycle perspective.

1.5 Case company Description

This thesis has been done in collaboration with one of the major industrial leaders in the global marine safety market. The firm is involved with the design, advanced development, and life cycle sustainment of fire and gas detection systems for commercial vessels, with capturing critical importance in supporting international safety regulations and operational safety on container ships, tankers, bulk carriers, cruise vessels, ferries, offshore platforms, and a diverse fleet.

Consilium Safety Group operates in more than 55 countries, where they provide aftermarket services such as the supply of spare parts, maintenance contracts, software upgrades, alongside new installations and system retrofits. Their business model is focused on a long product life cycle as serviced and supported installed systems, even decades after delivery. An extended life cycle focus makes aftermarket planning and evaluation of product end-of-life (EOL) assessment strategically imperative.

At a corporate level, the firm utilizes Microsoft Dynamics 365 as a standalone system to manage sales, service, and finance functions of the different global divisions as a unified ERP platform. Some of the firm's market companies use Ocra as an addition to Dynamics 365 to manage the commercial functions. Prior to adopting Dynamics 365, M3 ERP was used to streamline transactional operations. Both systems complement the company's immense historical sales database. As part of this study, it was crucial to access both historical data from M3 ERP and current data from Dynamics 365 so that an entire product service life cycle analysis could be performed. Furthermore, other sophisticated resources such as Microsoft Power BI are used in business intelligence for analytics, dashboards, and reporting.

In order to comply with academic impartiality and corporate confidentiality, the case company becomes anonymized in this report and is referred to as "the organization" or "the case company" throughout this document.

1.6 Outline of the report

The thesis is made up of seven chapters. In the first chapter, the topic of research is introduced alongside its background, objectives, and the questions that the research seeks to address. In chapter two, the research methodology is described with respect to the research framework: data collection plan, interview protocols, analytical methods, and ethics.

Chapter 3 has been devoted to the presentation of the theoretical framework, which encompasses literature within five distinct but interconnected domains: life cycle revenue management, spare parts strategy, forecasting, end-of-life planning, and strategic aftermarket planning. In Chapter 4, the key findings derived from both qualitative interviews and quantitative analysis conducted using Power BI are presented in a detailed manner.

In Chapter 5, the synthesis chapter, the presentation of decision-support tools and planning frameworks made in Power BI is provided. In Chapter 6, the strategic implications of the findings are discussed, while reflecting on the methodological strengths and limitations, offering deeper insights regarding the thesis contributions by answering the research questions. Finally, Chapter 7 summarizes the study, reflecting on the results and proposing avenues for subsequent investigation and future work.

2 Methodology

The purpose of this chapter is to explain how the methodological framework was constructed to meet the research aim and answer the questions posed in the thesis. It certainly covers the research strategy, design, and research process, data collection techniques, methods of processing data, forecasting, and EOL analysis methods, and other aspects of research quality and ethics. The chapter provides rigor as well as transparency regarding systematic planning, executing, and validation of the research.

2.1 Research Strategy

This thesis implements a mixed-methods research strategy, which includes quantitative and qualitative approaches to examining life cycle revenue patterns alongside predictive forecasting for marine safety systems at the case company. The quantitative part consists of detailed analyses of sales order data to identify predictive revenue model and life cycle-based insights. Qualitative analysis was informed by semi-structured interviews with internal stakeholders which added contextual relevance to the research outcomes.

According to Bryman and Bell (2011), quantitative research is primarily focused on numerical data collection and hypothesis testing, while in contrast qualitative research focuses on interpretive analysis of words and meanings within a specific context. The mixed-method approach thus leverages the complementary strengths of quantitative rigor and qualitative depth, effectively addressing complex, applied business research challenges (Eisenhardt, 1989).

In addition, this thesis aligns with the design science perspective articulated by Hunziker and Blankenagel (2024). In design-oriented business research, the emphasis is on creating practical tools and frameworks, such as dashboards for forecasting and EOL decision-making models, to solve organizational problems. This places the research within the realm of applied business research, where theoretical understanding is used to generate actionable outcomes.

Also, the research study follows abductive reasoning as described by Dubois and Gadde (2002) and applies systematic combining, meaning the empirical data and the theoretical framework are constructed simultaneously. It is not a straight path;

rather, a series of iterative loops encompassing analysis of empirical data as well as refinement of subsequent theories. It is a continuous cycle of integrating fresh theoretical insights from observations and evolving frameworks with them as new data becomes available. This flexibility and iterative process are effective when dealing with evolving business environments and the need for more adaptive strategic tools.

In the conclusion, the strategy for this research in the thesis rests on three synergistic pillars:

1. mixed methods that integrate quantitative analysis with qualitative stakeholder interviews

2. a design science approach focused on creating actionable decision-making frameworks and

3. an abductive iterative framework that supports continuous updates to the theory and empirical evidence throughout the research process.

2.2 Method Theory

This section develops a rationale for the methodologies used in this thesis, concentrating on the literature review, interviews, data collection and analysis, forecasting, and EOL analysis.

2.2.1 Literature review

A literature review is defined as a systematic method that identifies, gathers, and analyzes past research on a particular subject. As cited by Bryman and Bell (2011), the literature is to highlight knowledge gaps, validate research questions, and support construct elaboration in the study scope. Carrying out a literature review entails locating relevant materials, assessing their relevance, and synthesizing results in order to formulate contextual importance.

2.2.2 Interviews

Interviews are categorized as qualitative research methods. As defined by Bryman and Bell (2011), research interviews fall within three primary categories: structured, semi-structured, and unstructured. In this thesis, semi-structured interviews were applied which grant freedom to advance discussion while still dealing with set questions so that respondents give more comprehensive answers, and new ideas can be further examined.

2.2.3 Data Processing

Data processing entails organizing, cleaning, and preparing collected information ready for analysis. As Sreejesh et al. (2014) noted, data processing is critical for maintaining the quality, reliability, and validity of the research results. Some of the techniques is data cleaning, aggregation, segmentation, and transformation, which are often done with Excel, Power BI, or other analytical and database management tools.

2.3 Research process

The empirical research and the theoretical research were integrated to provide a balance of both sides, and these considerations were combined into the systematic iterative structure of the thesis. The problem and the objectives that guided the entire research process was defined with the practical issues of the company. After that, a literature review was conducted to build a good foundation and also to ensure no significant gaps in the existing literature. Alongside this there was also an empirical component where quantitative data (sales records, life cycle information) and qualitative data (stakeholder interviews and document reviews) were collected. The iterative way of doing things follows (Dubois & Gadde, 2002) systematic combining model and enables refinement of the gaps in the data collection. The iterative loop approach ensures a constant balance between the theory and empirical findings, making sure that the outcomes of the research are usable and effective.

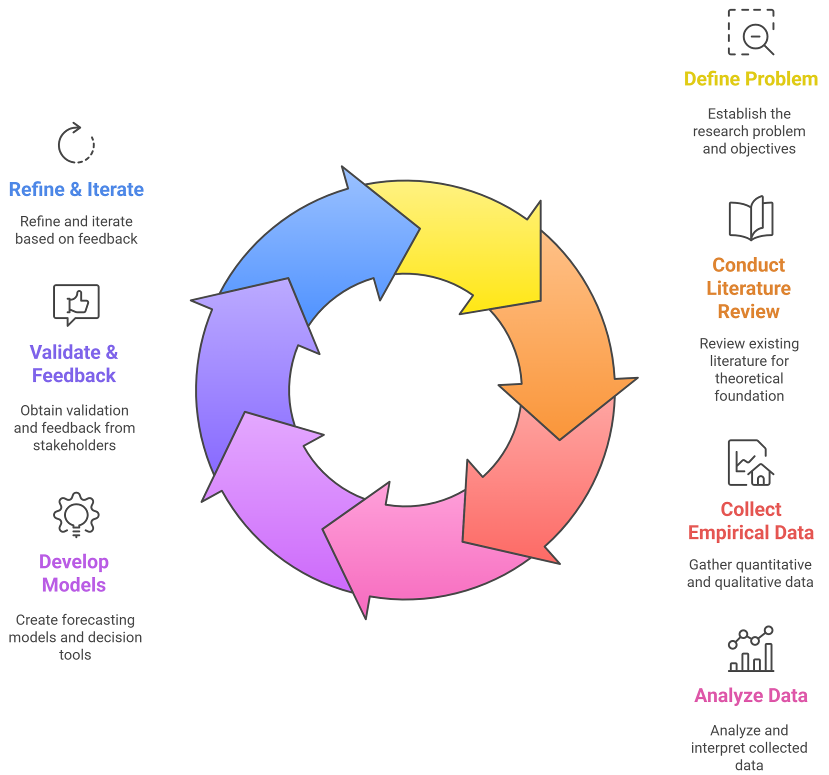

Figure 2.1: *Visual representation of the research process - Systematic Combining*

The Figure 2.1 illustrates the research process having back and forth flow while integrating empirical research, the theoretical framework, and analysis of the data.

2.4 Applied Method

This part describes the practical application of the research methodology, detailing how the literature review, interviews, and data processing were executed in the context of this thesis.

2.4.1 Literature Review and Document Study

The literature review was done on different academic databases and search engines, beginning with Chalmers Library and later proceeding to Google Scholar as well as other pertinent databases. Search phrases included life cycle revenue, forecasting, End-of-Life (EOL) management, and spare parts optimization. Also, these are listed in the A.1. Even though a lot of literature existed on general life cycle revenue and forecasting methods, limited specific studies directed towards the maritime sector were available. The literature review is based on existing industrial product life cycle scenarios which were subsequently adapted to fit into marine safety systems. Furthermore, case company's internal files, such as Consilium's product life cycle matrix from the product team, pricing policies, and other relevant internal documents were studied to incorporate practical company insights with the theories. Also, the complete list of literature is listed in the bibliography.

2.4.2 Conducting Interviews

Interviews were carried out in a semi-structured format with various stakeholders from different departments within the organization. The focus of the interviews was to elicit rich detail on life cycle management, sales, aftermarket services, and forecasting. The interviews were recorded, transcribed, and analyzed for thematic relevance. Figure 2.2 shows a list of the departments and roles of the participants from whom the data was collected.

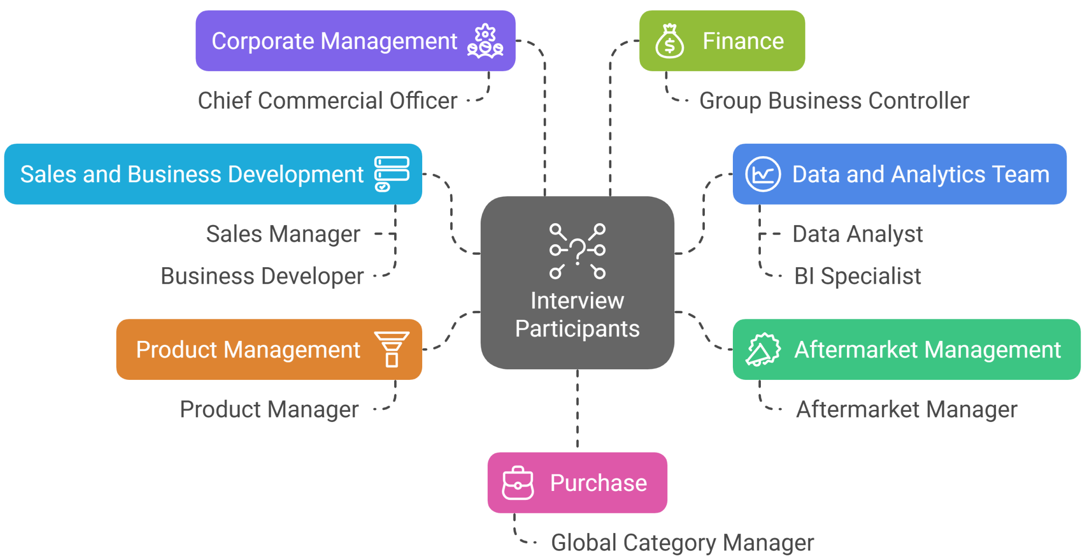

Figure 2.2: *Interview participants - Department and Roles*

2.4.3 Quantitative Data Collection and Processing

The thesis data was obtained from the case company's integrated Enterprise Resource Planning (ERP) systems and Customer Relationship Management (CRM) systems. The current operational ERP system, Microsoft Dynamics 365, and CRM system, Lime were connected to through Azure Analysis Services, which provided a live link to a consolidated sales data model. The company's Business Intelligence (BI) team had previously integrated sales data from the ERP system into Power BI, which made those records available. The finalized dataset contained detailed sales order transaction data, along with pertinent attributes capturing product identifiers, IMO numbers of the vessels, types of vessels, business dimensions (sales categorized as new building, retrofit, service, spare parts), and customer segmentation tiers.

The data was structured and connected into a star schema for further analysis, with the sales order lines serving as the central fact table, connected to dimension tables for Product, Vessel, Date, and Business Attributes. To enable further sales data analysis in Power BI, the model ensured that all computations were done at the front end, as altering the data model, such as adding new tables or calculated columns, was disallowed.

As a result of the complexity and size of the data set, the first step was to specify the measures of interest and concentrate on transactions that could be considered complete. Data cleaning included identifying and correcting issues such as missing transaction history, inconsistencies in product classification, and differing terminologies across versions of the ERP system, for example dealing with non-system dependent values, incomplete product labels, and system naming tagging with definition (such as 'new installation', 'spare part', or 'retrofit') to life cycle definitions. Additional DAX measures were created to cater to on-demand reporting for measures like growth over previous periods, moving average calculations, revenue per life cycle segment, and anomaly detection. All further forecasting and life cycle revenue analyses were built off the centralized model, which had been structured and cleansed.

2.5 Research Quality and Validity

To increase the credibility and trust of the research outcomes, multiple approaches related to reliability, validity, and triangulation were put in place. The research reliability was ensured using the same and uniform processes of handling information and documenting it so that others can repeat the research. Multiple analytical methods and data source utilizing enhance the depth and accuracy of the findings; thus, validity was achieved.

With Dynamics 365 quantitative data combined with qualitative information obtained through interviews and internal documents, triangulation was found to be one of the key strategies applied. This strategy minimized bias and enabled cross-verification of findings throughout different data sources. Furthermore, validation meetings alongside feedback sessions with stakeholders from the company enabled real-time input while serving as an internal quality control mechanism.

2.6 Ethical Considerations

Ethical principles concerning research with human subjects as well as organizational data were considered. All interview participants were informed of the purpose of the study, and all voluntarily consented to being participants. For confidentiality purposes, participant identities were concealed in the report.

Information gathered from the internal systems and documents of the organization was treated with a high degree of confidentiality and consideration, and only used for scholarly activities. Ethical measures such as openness, consent, and appreciation of the participant's role were upheld throughout all stages of the research.

2.6.1 Data Confidentiality and Visual Representation

For confidentiality reasons, sensitive commercial information like actual numerical data, revenue figures, profit margins, and product identifiers has been omitted from this thesis. Moreover, the report includes limited screenshots of the Power BI dashboards and visuals created during the analysis. Instead, they are described in terms of the functionalities of the dashboards, while visual and analytical insights are conveyed through aggregated language and abstracted structural descriptions.

All representations are also anonymized. Only the modeling frameworks, the analytical processes, and the decision-making logic are presented. This approach fulfills the requirements of GDPR as well as the case company's internal confidentiality policies. Proprietary information may be illustrated with placeholder figures and schematic descriptions of the structure or workflow, but exposed structure is avoided.

3

Theoretical Framework

The purpose of this chapter is to present the literature and the theories that support this research. It covers primary research areas, which include life cycle revenue management, spare parts strategy, demand estimation, EOL decision-making, and strategic aftermarket planning as regarding marine safety systems. In addition, this chapter explains how the relevant academic literature was identified and selected, including developed knowledge prior to explaining the research gap that this thesis attempts to fill.

3.1 Overview

In many industrial and safety-critical domains like the marine industry, products have a long operational lifespan during which the equipment is offered for sale, and incur maintenance service fees long after the initial purchase is made. This prolonging lifespan shifts the focus to effective proactive aftermarket strategies, forecasting methods, life cycle management, and continuous customer relational management to sustain revenue and customer satisfaction. There is an observable trend where organizations are moving from a pure transactional selling system to a service-oriented, value-driven approach. Thus, aftermarket servicing and planning alongside life cycle revenue management are becoming increasingly important.

This chapter seeks to construct a robust theoretical framework for the thesis by analyzing scholarly publications in five interconnected thematic areas. Each theme has elements that, when blended together, provide deep insight into how firms can improve their aftermarket services, planning accuracy, and forecasting aids, especially in B2B interactions for marine safety systems. Combining foundational and recent literature, this chapter attempts to review the most advanced literature and theories in each area and collect the relevant theories for this study.

3.2 Methodology for Literature Review

A systematic literature review was undertaken in order to appreciate the scope of the relevant academic literature within five thematic areas. The search concentrated on highly cited, peer-reviewed documents published mostly from 2015 to 2025. Priority was given to literature contributing B2B, industrial, marine, or aftermarket contexts through empirical, conceptual, or methodological means.

The materials were sourced from Chalmers Digital Library and also from databases such as Google Scholar, Scopus, Web of Science, IEEE Xplore, and ScienceDirect. For each theme, tailored keyword search strings were created. These strings featured concept words such as life cycle revenue and demand forecasting accompanied with contextual words like aftermarket, marine, or PLM. Then the results were screened based on the following inclusion criteria:

- Theme relevance in relation to the marine and industrial aftermarket contexts
- Methodological rigor and empirical grounding (where applicable)
- High citation count or recent publication in high-impact journals
- Application-oriented insights applicable to life cycle or aftermarket decision-making

A record of search terms, databases used, total hits, and the number of relevant papers retained is maintained in a review matrix (see Appendix A.1). This approach ensured transparency and repeatability in the review process.

3.3 Thematic Domains

This study draws from five areas of research which taken together provide a basis for analyzing life cycle revenue and forecasting methodologies of marine safety systems:

1. **Life cycle Revenue Management** - Studies how businesses sustain and reap revenue from a given product over its life cycle, paying particular attention to the relation of revenue and profit in its later years as it approaches obsolescence.

2. **Spare Parts Strategy and Aftermarket Revenue** - Centers on the contribution of spare part logistics, inventory management, and service agreements to long-term profitability in the context of B2B aftermarket.

3. **Forecasting Methods** - Analyzes classical, statistical, and machine learning methods for forecasting demand for spare parts, specifically with intermittent and long-tail demand typical of aftermarket situations.

4. **Product life cycle and EOL Decision Making** - Studies processes and models for managing last-time buys and support phase transitions for products that have reached the end of their commercial life.

5. **Strategic Aftermarket Planning and PLM** - Takes a holistic view incorporating Marketing and Service Management that merges PLM with Service

Management, focusing on feedback loops and cross-functional integration for planning services throughout the life cycle.

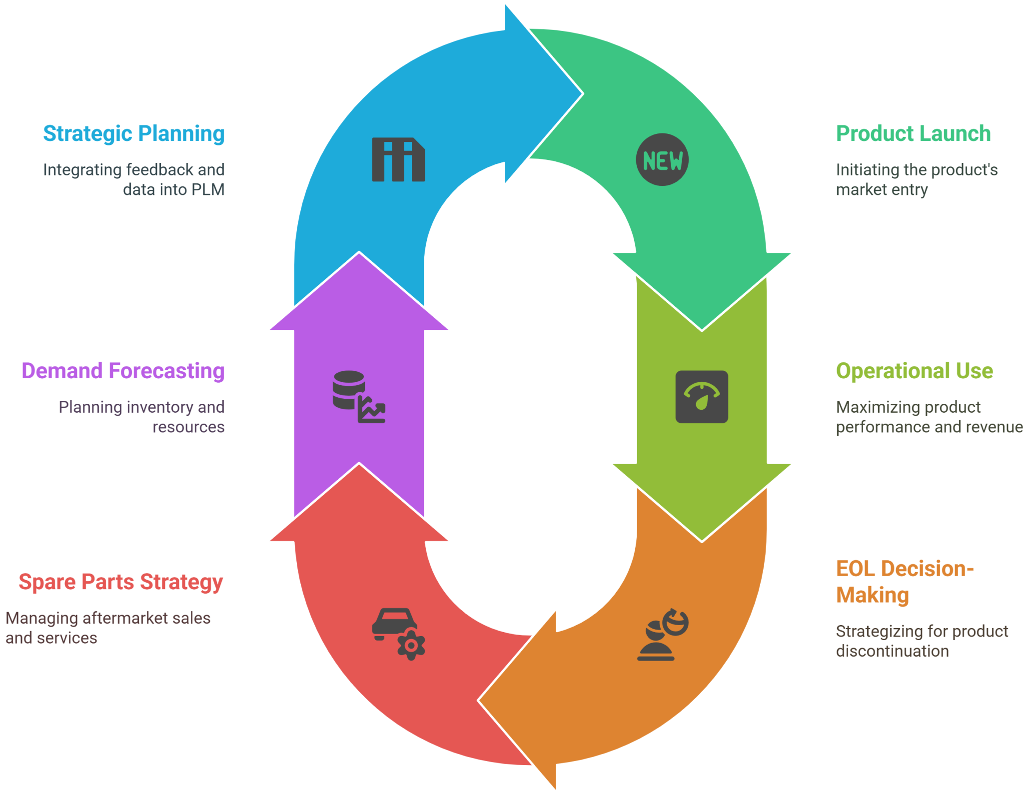

Figure 3.1: *Thematic Domains and Their Interconnection*

These domains were chosen because of their relevance to the case companys context, as shown in Figure 3.1 and as well as the broader industrial trend towards servitization and data-centric decisions.

Why these domains matter?: As said earlier, the marine industry has long life cycles in terms of both product and market, which leads to critical aftermarket needs that comes with certain challenges - fragmented life cycle data of products, reactive EOL planning, and complex spare parts & revenue forecasting. So combining these domains supports proactive, profitable management of products and systems within the regulated environment.

Each theme is analyzed in depth in the following subsections.

3.4 Life cycle Revenue Management

Life cycle Revenue Management (LRM) encompasses the systematic management of revenues associated with a product from its sale to its end-of-life (Eggert et al., 2014). An illustrative example of this would be established in B2B and Industrial domains like marine safety, where products are not only in use for two decades, but a stream of operational profit needs elaborate post-sales strategies in order to ensure profitability.

Sales are one of the toughest models to manage. In order to maximize revenue, companies are driven toward services, inspections, compliance, component upgrades, and even additional services beyond basic demand (Faramarzi et al., 2024). This strategy model guarantees an income stream in contrast to a decline, even if the product has reached its maturity stage.

In addition, Kowalkowski et al. (2017) noted that aftermarket activities serve as the primary revenue source for participants in the products declining and mature stages. Alignment with regulatory provisions and life cycle scheming is essential to maintain these revenue streams (M.Z. Babai & Syntetos, 2013).

3.4.1 Life cycle Stages

Vorst and Yohn (2018) outlines four life cycle revenue stages: introduction, growth, maturity, and decline; each with distinctive revenue patterns and managerial difficulties. These life cycle phases can be analyzed by the companies for developing strategies to increase the profitabilty at each stage focused.

- Introduction Phase: Characterized by high development costs and limited early-stage sales. Also investment made in marketing and gaining market share.

- Growth: Revenue scales up as adoption increases and bundled service offerings gain traction. With this, companies can focus on scaling production and operations.

- Maturity: Core product sales plateau while services take precedence.

- Decline: Product support becomes more costly; strategic use of retrofits and replacements becomes vital.

When these life cycle phases are considered in a more important way, it can improve revenue forecasting and also the planning for the long run (Kus & Zurakowska-Sawa, 2017). A surge pricing model that adjusts pricing dynamically across life cycle stages can help protect margins and maintain service competitiveness (Sun et al., 2024).

3.4.2 Servitization and Business Model Transformation

The shift turning towards embedding services into core facets of the business model alongside the traditional sales model fuels long-term revenue and customer retention prospects (Faramarzi et al., 2024). Kowalkowski et al. (2017) noted that in the matured markets which has aging installed base, firms differentiate themselves through outcome-based service contracts and digital service augmentations. While revenue is increased from servitization, Eggert et al. (2014) noted that uncontrolled service cost management can severely harm profit potential. This is termed the service paradox.

3.4.3 Digital Technologies and Life Cycle Monetization

Grubic and Peppard (2016) noted that remote diagnostics and IoT monitoring allow for predictive and continuous maintenance, thus changing episodic service requirements to ongoing contracts. Firms can strategically monetize digital services throughout their lifespan using a digital value capture framework which integrates design, development, and scaling (Linde et al., 2021).

3.4.4 Aftermarket Analytics and Installed Base Optimization

With the addition of aftermarket intelligence, companies are now able to proactively provide upgrades to annotated part failure prediction and refocus customer tailored needs (Ucar et al., 2024). In the context of marine safety, where unscheduled downtime has severe safety regulatory implications, these analytics serve strategically important compliance and commercial objectives.

LRM shows how to best leverage its existing global installed base. Examples of these opportunities include the creation of sectional upgrade kits, region-agnostic service packages, and retrofit works associated with compliance trends. Furthermore, incorporating service considerations into product design from the outset and leveraging data to forecast aftermarket requirements will enable smoother, more reliable revenue capture throughout the product life cycle.

3.5 Spare Parts Strategy & Aftermarket Revenue

Effective spare parts control is predictably and uniformly important across various aftermarket strategies. In industrial contexts, parts supply aids in compliance with operational safety requirements, helps in minimizing operational downtime, and is vital for assured revenue streams in the long run (Durugbo, 2020). Customers like shipping companies and offshore operators expect reliability from Original Equipment Manufacturers (OEMs) in terms of parts availability for decades. This makes the spare parts policy an operational imperative and optimal pricing instrument at the same time (Zhang et al., 2021).

In safety-critical areas, exposed to severe operational and branding risks, inefficient availability of spare parts oversight can lead to dire consequences. Therefore, companies must balance these factors by defining optimal policies for controlling the inventory, life cycle-stocking strategies, and service level agreements that dictate the boundaries of cost and service quality (Hu et al., 2018).

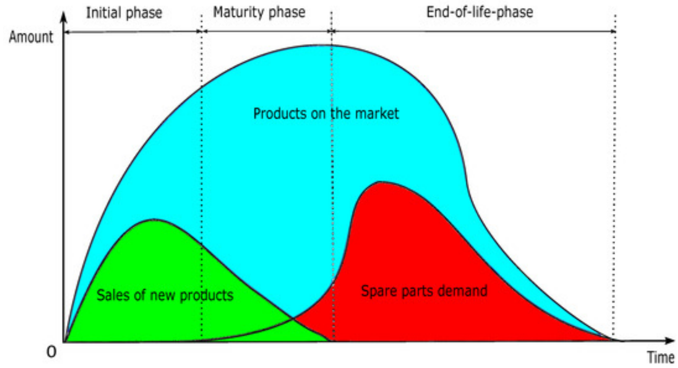

Figure 3.2: *Relationship between new product sales and spare parts demand over the product life cycle (adapted from Zhang et al., 2021)*

Demand changes according to the life cycle of a product, and its spare parts are no different. Zhang et al. (2021) illustrates such trends with a model depicting the demand for spare parts, sales of new products, and the number of installed products within a market system. The aftermarket activities become more pronounced and vital towards the latter parts of the maturity stage of the product life cycle, as well as during decline, as seen in Figure 3.2

3.5.1 Strategic Dimensions of Spare Parts Planning

Each Strategy for Spare Parts Management cuts across different verticals of planning:

- Stocking Policies: These include classifying parts by their importance and usefulness, along with demand frequency, and are backed by policies such as make-to-order and make-to-stock.
- Life cycle Phase Management: Parts are required as demand evolves is associated with the product life cycle parabolic curve. The beginnings include low and less predictable demand; mid-life has stabilization, and end-of-life requires a last-time buy plan (Zhang et al., 2021).
- Inventory Optimization: Use of Operations Research (OR) methods makes it possible to make better decisions regarding order sizes, placement of depots, and level of safety stock to achieve a set availability level and cost (Hu et al., 2018).
- Distribution Strategy: In international markets, multi-echelon networks ensure prompt delivery. This is particularly the case with regard to marine systems, which have to maintain service to fleets spread over a number of ports and oceans.

Servitized firms redesign their supply chains to enable high service levels, especially under uptime contracts, due to increased collaboration with suppliers and strategic stock deployment (Saccani et al., 2014).

3.5.2 Maintenance Strategy Alignment

Policies for maintenance have a dominant effect on the use of spare parts. Schedule-based inventory systems become easier with the adoption of condition-based and preventive maintenance programs (Alrabghi & Tiwari, 2015). Inventory holding costs and emergency provision cost tend to drop as well. Such foresight allows companies to design service contracts that utilize terminology aligned with predictive maintenance and thus reduce variability in demand while increasing satisfaction for customers.

Formulating a comprehensive strategy for spare parts can significantly elevate the value of installed base information. Also, integrating spare parts strategy with life cycle planning helps in ensuring that product life cycle support is profitable and aligns with changing needs.

3.6 Forecasting & Its Broader Business Significance

Across all industries, strategic forecasting has become foundational as it allows for informed decision-making. Whether it leads to accurate resource allocation, inventory usage, capacity maximization, or even budgeting, an accurate forecast always adds value. Accurate prediction in the context of sales and revenue planning assists productivity and financial performance alignment attainment (Hoyle et al., 2020).

In business-to-business (B2B) settings, sales forecasting is critical due to the tight interdependence within B2B supply chains. Long sales cycles associated with B2B necessitate careful consideration of predictive estimates. Hoyle et al. (2020) explains how CRM and ERP systems have started being integrated into forecasting; however, they note that most organizations do not use them to their full analytical capacity, which leads to suboptimal forecasting.

3.6.1 Forecasting in Aftermarket and Spare Parts Contexts

Predictive spare parts forecasting in aftermarket scenarios is particularly difficult due to irregular demand patterns, extended product life cycles, and servicing requirements that evolve due to system failures, maintenance activities, or routine inspections (Pinçe et al., 2021).

Van der Auweraer et al. (2019) highlights the importance of ensuring that product life cycles are well integrated into the operational profile of the installed base pertaining to systematic forecasting. In particular, factors such as product age, usage, and service history are relevant to enhance forecasting precision.

3.6.2 Forecasting Techniques

There are three categories of forecasting methods: statistical, machine learning (ML), and hybrid or ensemble approaches. This classification, according to Spiliotis (2023), is within the context of how the technique attempts to construct a model of the underlying data-generating mechanism. The approach to forecasting is determined by the amount of available data, the characteristics of the demand pattern, and the presence of explanatory variables. Each approach has benefits and pitfalls, and its applicability is often restricted to the given business environment and product or service being forecasted.

- Statistical Methods enforce the use of a structured model, like ARIMA or exponential smoothing, which attempts to quantify the trend and seasonality components in historical data. Components of time series forecasting, such as ETS (Exponential Smoothing) and ARIMA, are some of the oldest and most useful because they can be justified, adjusted to different situations, and are so simple that they require very little information (data) (Makridakis et al., 2020). These techniques are applicable when demand patterns are stable but become problematic in the presence of volatility or sparse observations.

- Intermittent Demand Models are especially pertinent in cases such as spare parts predictions, where demand is fragmented. Custom models like Crostons method and its variants: SyntetosBoylan Approximation, enhance the efficiency of zero-inflated datasets because they separately estimate the size and frequency of demand events (Hasni et al., 2019; Paterson et al., 2017). Evaluative comparisons conducted by Ratnayake and Ali (2023) have shown that under alternating conditions of demand, outcomes were also adequate for EWMA, Holt-Winters, and Theta methods.

- Machine Learning Methods capture nonlinear relationships using flexible learning algorithms like neural networks and decision trees. ML models such as LSTM neural networks and support vector regression are particularly powerful when demand is influenced by external variables like environment, usage, product type, or external factors (Ifraz et al., 2023; Kim et al., 2023). On the other hand, ML models require more data, careful feature refinement, and validation to ensure dependability (Spiliotis, 2023).

- Hybrid and Ensemble Methods combine multiple approaches to mitigate model-specific weaknesses and improve robustness. Makridakis et al. (2020) found that ensemble methods yield more accuracy in competitive settings than individual model approaches. In rapidly changing and uncertain situations, merging forecasts from routinely different models often yields better results i.e., improved accuracy. Averaging forecasts, employing weighted ensembles, and stacking models are some of the ensemble approaches that can decrease the bias and variance in forecasting for diverse demand series.

3.6.3 Forecasting using Installed Base

In forecasting, estimating future demand by analyzing the characteristics of currently used products is referred to as installed base forecasting. Key concepts such as lifetime base and warranty base are identified by Thai Young Kim and Heij (2017) and serve as important aids in modeling demand patterns serving during the latter part of a products life cycle.

Unlike models which purely rely on history data, these encompass service intervals, failure rates as well as decommissioning timelines, thus allowing better alignment with aftermarket realities. Predictive accuracy is enhanced by exogenous variables like fleet profiles, usage metrics, and inspection schedules through demand forecasting models (Ifraz et al., 2023).

Especially in planning for spare parts, companies can attain precision in forecasting by merging installed base data with statistical or machine learning frameworks due to the heightened responsiveness that emerges.

3.6.4 Evaluation and Practical Implications

M.Z. Babai and Syntetos (2013) emphasizes that forecasting assessment should also consider business impacts, in addition to accuracy-this includes service level, inventory turnover ratio, and order reliability. In aftermarket scenarios, the accuracy of forecasts directly affects availability and costs.

As noted in their work of Ratnayake and Ali (2023), the criteria for model selection need to balance how well it performs with the effort to put it into practice and make it understandable. They further explain that while implementing advanced ML models may increase accuracy, simpler models would achieve greater understanding and integration into existing workflows.

All in all, a robust forecasting approach includes measuring statistical precision, understanding the data from the installed base, and integrating flexibility to business constraints. This allows organizations to anticipate life cycle changes, adjust inventory levels, and enhance performance over time.

3.7 Product life cycle and EOL Decision Making

Managing the product's EOL encompasses the strategic approach of taking a product off the market, analyzing how to manage aftermarket support during a given transition period, and post-transition (Paterson et al., 2017). In the marine safety segment, EOL is of utmost importance because of the prolonged equipment service life coupled with legislative requirements of continued servicing. Inadequately planned transitions expose the business to dissatisfaction, reputation risk, and service revenue loss risk (Özyörük et al., 2022).

3.7.1 EOL Inventory and Obsolescence Management

Final EOL decisions normally incorporate last-time buy or LTB planning, procurement lifetime inventory, and obsolescence monitoring, each of which is pertinent to end-of-life decisions. Optimization models like the one developed by Özyörük et al.

(2022) support strategic decision making by providing optimization guidelines for service commitments in light of holding costs and inventory service balancing.

In particular, Bazerghi and Van Mieghem (2024) underscores the proprietary relationships within the ecosystem of OEMs and suppliers as relevant in the discussion of phase-out component negotiations, illustrating LTB and supplier relations with adept timing and collaboration.

These strategies enhance the accuracy of predictive models of component obsolescence, especially with electronics, using life cycle curves and market life cycles indicators (R. Solomon & Pecht, 2000). Such predictive approaches can assist in more timely purchases and service-changing designs to fulfill service equity.

3.7.2 Upgrade Strategies and Customer Transition

From an EOL planning perspective, upgrade strategies play a crucial role in easing system transitions and strengthening customer relationships. These strategies encompass trade-in promotions, modular retrofits, and outcome-based upgrades, which fundamentally change the focus from ownership to value performance. In the case of the industrial B2B sector, where service reliability matters, Visnjic et al. (2018) mentioned that incorporating upgrades as bundled service outcomes like uptime or total cost of ownership increases adoption significantly.

Also, Pourakbar et al. (2012) points out that strategically tailoring upgrade pathways with end-of-life inventory and service scheduling could control excess inventory, stabilize service operations, and inappropriately incentivize customers against operational goals. Their work in the consumer electronics sector showcases how proactive participation through offers reduces aftermarket complexity, eases transitions, and maximizes the value in the remaining life cycle. These approaches, when coupled with specific targeted communications, not only shield revenue streams from services but also strengthen brand loyalty in the course of product phase-outs.

3.8 Strategic Aftermarket Planning and PLM

Strategic Aftermarket Planning involves making proactive decisions until the delivery of the final product, whereas Product Life Cycle Management (PLM) denotes the processes and systems looking after the product data and making vital decisions on the product from its inception until the information needs to be discarded. When both approaches are integrated, as cited in Li et al. (2015) and Wiesner et al. (2015), ensure that revenue opportunities associated with services are optimized constantly during the use phase, meaning that revenue potential is designed and integrated into the product from the start.

3.8.1 Data Integration and Organizational Synergy

PLM should enhance windows of interaction where interdepartmental engineering, services, and marketing functions exchange information. Wiesner et al. (2015) argue that effective service-product integration requires shared data models, such that a products digital twin reflects not only its technical configuration but also its maintenance history and usage environment. Cavalieri and Pezzotta (2012) extends this concept within Product-Service Systems (PSS), where service deliverables are co-designed with products.

Integrating digital twins with big data into an advanced PLM system greatly enhances model resilience according to Li et al. (2015). Using data, the proposed monitoring architecture can maintain track of the product's birth (design), usage, service period, and product abandonment. In this case, the proposed model offers real-time condition monitoring, predictive servicing, and personalized upgrade offerings.

3.8.2 Strategic Value and Innovation Enablement

Aftermarket strategies planning and product life cycle management (PLM) alignment allow the emergence of new revenue models, including outcome-based contracts, subscription services, and modular upgrades. Grubic and Peppard (2016) investigates the enabling role of remote diagnostics as a digital service for continuous value creation and product differentiation in mature markets.

Cavalieri and Pezzotta (2012) stresses the importance of planning services as early as the requirements engineering level in order to integrate factors such as maintainability, upgradeability, and data capture.

The combination of PLM and aftermarket strategy has numerous advantages, including the creation of systematic feedback loops from the field to R&D, enhanced service readiness at product launch, and value creation from smart services based on usage data.

3.9 Research Gap and Motivation

Across the five themes reviewed, a clear knowledge gap emerges at their intersection, which directly motivates this masters thesis. The literature confirms that:

- Aftermarket services and life cycle revenue are crucial for financial success in industrial markets;
- Spare parts and forecasting must be optimized to support those services efficiently;
- End-of-life must be managed to retain customer trust and capture remaining value; and
- These elements should be integrated through strategic planning and PLM.

However, few studies have combined these perspectives into an integrated framework for a specific industrial context such as marine safety systems.

Most existing research examines these themes in isolation for example, inventory optimization in spare parts (Theme 3) or servitization strategy (Theme 1) or at most pairs of two themes (such as forecasting and inventory, or PLM and service integration). There is a lack of comprehensive frameworks or case studies that concurrently address how life cycle revenue management, spare parts strategy, forecasting methods, EOL decisions, and PLM-based planning can be aligned. In practice, as our literature review shows, these domains are deeply interdependent: poor demand forecasts undermine spare parts availability, which in turn hurts service contracts and life cycle revenue; conversely, a strategic push for service revenue can fail if not supported by proper EOL parts planning and data feedback through PLM.

For the marine safety systems industry in particular, there is scant published research. Marine and offshore contexts have unique characteristics stringent regulatory requirements, safety-critical products, and conservative customer attitudes which mean that best practices from general manufacturing may not directly apply or need adaptation. This thesis addresses that gap by studying a real company in this sector, assessing how well current academic best practices are implemented, and what modifications are needed for this context

3.9.1 Research Motivation

The motivation for this thesis is thus twofold. First, from a practical standpoint, the partner company is experiencing challenges (e.g., forecast, pricing strategy, customers keeping old equipment longer than expected, etc.) that span multiple domains reviewed. This indicates a need for an integrated solution: a life cycle Revenue Analysis and Predictive Forecasting framework that ties together forecasting techniques with life cycle planning decisions. No existing single framework from the literature directly provides this, especially tailored to marine safety products, motivating original applied research.

Second, from a theoretical standpoint, this work will contribute by demonstrating how the concepts from each theme can be synthesized. It will show, for example, how a data-driven forecasting model (perhaps using installed-base data) can feed into a life cycle revenue model (estimating after-sales revenue over time), or how end-of-life strategies can be evaluated not just on cost but on lost future service revenue. By doing so, the thesis will fill the identified gap with a case-backed framework, extending academic knowledge into a new application domain.

3.9.2 Thesis contribution

This study will develop a structured framework that integrates the five themes, something that may be the first of its kind for the marine safety sector. It will provide the company with actionable insights: how to integrate forecasting into historical sales data and what that implies for inventory and service levels; how to adjust spare parts and service offerings across the product life cycle to maximize revenue; and when and how to phase out products while transitioning customers to newer systems.

Academically, the thesis will contribute a detailed case that illustrates the interplay of life cycle revenue management and predictive analytics. It will validate whether the recommendations gleaned from disparate literature streams do indeed synergize in practice, and document any trade-offs or unforeseen interactions between them. Ultimately, the research is driven by the goal of helping the company turn its aftermarket into a growth driver by using forecasting and life cycle management, and in doing so, advancing the understanding of effective Product-Service life cycle Management in a high-stakes industry.

4

Results

This chapter integrates key qualitative and quantitative data findings, including stakeholder interviews, alongside the outcome of the analysis and data modeling. The analysis is performed using a Power BI model built on a star schema architecture, along with thematic reflections from interviews with the sales, product, and aftermarket teams, and also the literature reviewed. This analysis seeks to identify trends among sales, margins, and life cycle transitions of components of a marine safety system while considering the firm's pricing, aftermarket, and end-of-life (EOL) strategies.

4.1 Expert Insights and Information Gathering

This section focuses on qualitative results from stakeholder interviews and internal documentation reviews conducted at the case company and their perspectives on life cycle revenue, spare parts strategy, forecasting challenges, EOL decisions, and customer behavior.

4.1.1 Stakeholder interviews

In order to capture the strategic, operational, and technical aspects within the organization, semi-structured interviews were conducted with key stakeholders from the commercial, technical, and aftermarket sides. The goal of the interviews was to capture qualitative perspectives regarding revenue, forecasting, PLM, as well as control through data analytics. The synthesized results are organized into groups according to the responsibilities of the stakeholders.

4.1.1.1 Aftermarket and Revenue Trends

Aftermarket services revenue, including spare parts, is monitored using financial dimensions in the ERP system and were consolidated in a tool called Okra. This allows for consolidations by market company or sales category (e.g., spares, service contracts), business area, and marine segment. While granular revenue analysis is possible, indirect sales through intermediaries such as ship chandlers present challenges to accuracy and, in some cases, may be even impossible due to a lack of data clarity.

Sourcing origin dictates pricing strategies for spare parts through set purchasing department inputs, margins differing per sourcing origin (in-house or external). Prices for almost all the parts/systems undergo annual reviews to account for cost inflation, exchange rate fluctuations, and market position. Life cycle pricing is tactical: products that are EOL approaching usually have their prices set higher to entice customers towards retrofit solutions or new system installations.

The most significant contributors to aftermarket revenue are fire and gas detectors, which are often changed/replaced due to harsh marine conditions and maintaining compliance with regulations, resulting in frequent replacements. For instance, cruise vessels outfitted with thousands of detectors experience perpetual replacement demand.

While forecasting demands is based on a heuristic approach, taken using parameters like 1% annual failure rate detection the problems arise due to the absence of data at consumption-level per vessel, along with the extended period needed for trends to be recognized. Backup assistance, including support and spare parts availability, is provided for all equipment for a minimum of ten years, and in some cases, up to thirty years, especially for naval contracts. This demands advanced planning concerning strategic stock, communication with customers, and tracking life cycles.

4.1.1.2 Strategic and Commercial Management

"Spare part pricing is always a balancing act between profitability and customer retention."

The performance in terms of revenue is evaluated on a monthly basis on a dashboard displaying crucial financial indicators, which encompass order intake, gross margin, and EBITDA across the market companies. Moreover, these figures are monitored as a whole, aggregated by product group and regions, which helps the leadership in identifying in tracking trends, spotting potential issues, and strategically planning for defined actions.

Strategies associated with pricing, changes over the products life cycle. For newly built ships, competitively low prices are set to win the trust of clients. Later on for spare parts, the pricing model emphasizes profitability and consistency in service delivery. These strategies are set based on competitive benchmarking alongside customer readiness and cost recovery.

Revenue optimization faces multiple challenges due to fluctuations in the market, changes in regulations, and the difficulty integrating legacy product pricing with modern expectations in the fast-paced world. Evolution of customer expectations, technological innovation, or any updates affects the strategy as well. Customers are retained through structured EOL approaches such as backward compatibility, retrofit offers, and, in some cases, incentives to upgrade.

4.1.1.3 Product life cycle and EOL Planning

"One of our challenges is not having a clear trigger for when something should go into phase-out. It ends up being more reactive than planned."

At the case company, life cycle planning is carried out along a continuum as a matrix integrates new sales and transitions to end-of-life. Organizational inertia and the lack of clear, systematic triggers often lead to reactive decision-making. Common EOL drivers include regulatory change and component obsolescence.

Performance evaluation of new products is usually made from resources including sales data, non-conformity reports, and feedback from sales teams provided to Product Line Managers. As a baseline, obsolete spare parts are supported for 10 years, extending to 30 years in special cases, such as naval contracts. When it comes to challenges in EOL planning for spare parts and other systems arise in the case of supplier discontinuation of critical components and difficulties maintaining documentation and compatibility.

In an attempt to decrease disruption, the firm restricts customers from acquiring outdated parts by raising the prices of EOL products and funneling them towards newer substitutes. However, some phase-outs can lead to inefficiencies with inventory or support challenges. A key opportunity lies with improving anticipation efforts towards coordination between product development, aftermarket, and procurement teams.

4.1.1.4 Forecasting, Procurement, and Finance

Optimity is the forecasting tool used by purchase team for demand forecasting . Optimity uses statistical forecasting, such as exponential smoothing, to calculate the most probable quantity needed for production. The data from the Dynamics 365 ERP system is linked to Optimity, and forecasting is made from the data of sales orders, production consumption, and transfer orders between warehouses. Basic market information or customer-specific information may require additional overrides.

The estimation serves operational planning purposes, especially procurement, for the short and medium-term horizons. Forecast accuracy is monitored using KPIs such as errors in the forecast, the Mean Absolute Deviation (MAD), and fulfillment rates. Demand responsiveness is improved over time because Optimity adjusts alpha and gamma values, increasing responsiveness as Agile Marketing increases in demand.

Procurement planning is closely linked with product life cycle strategies to avoid supplier transitions mid-life cycle. Hence the suppliers of critical components are given long-term agreements that are subject to audits and contingency clauses with adaptation to regulatory requirements. Financials are tracked with Cross 1.1 (materials and direct services) and Cross 1.2 (internal time and materials) to enable profit analysis of both individual services and products.

4.1.2 Internal Information Gathering

Alongside the stakeholder interviews, other internal documentation and systems which can aid to the thesis work were analyzed to augment and corroborate the findings from the interviews. This encompasses policy files, life cycle matrices, pricing approaches, and other data derived from internal business system operations.

- EOL and life cycle Related Documents: An internal life cycle matrix captures the clear progression stages associated with a new product introduction to EOL, which includes steps and responsibilities pertaining to spare parts support. These stages assist in planning and communication with customers, especially for high risk or mission critical products.

- Pricing Policy: Strategic documents on pricing reveal that the company follows a structured price-cube model refined according to the products position in its life cycle. Price evaluation and changes yearly account for suppliers costs, influences of currency, and prevailing demand levels. Close to EOL, price increases are implemented to control the spares inventory and encourage retrofitting.

- Dynamics 365 is the organizations main ERP system, complemented with Power BI for business analytics, and Optimity is the demand forecasting tool used by the Purchase department.

4.2 Life Cycle Revenue Analysis of Sales Data

This subsection has an analysis of the invoiced sales order data of the case study for the different life cycle phases. Using data from the company's ERP, this analysis aims to reveal revenue patterns across different sales types (New Build, Retrofit, Spare Parts), product groups, and segments in the marine vessels over time. This forms the basis for the detailed subsections that follow. These findings are interpreted in light of revenue management theory complemented by insights obtained from internal stakeholder interviews.

4.2.1 New Build Phase: Revenue Trends and Low-Margin Characteristics

Sales order records indicate that new build transactions, particularly in the earlier years, exhibit low or even negative gross margins. This does not reflect operational ineffectiveness, but rather an intentional pricing approach confirmed in interviews with commercial managers. New builds are sold at competitive prices to gain initial customer acquisition as well as aftermarket business, particularly in standardized vessels segments, for example, tankers.

This directly supports commercial goals by allowing easier access to capture customers as well as encouraging the use of the companys marine safety systems by lowering the upfront costs linked to the proprietary marine safety systems. It also has a strong connection to the installed base approach where acquiring the vessel early in its life cycle enables dominance in aftermarket services and parts sales.

Eggert et al. (2014) explains this through life cycle revenue management when claiming that the first installation provides the groundwork, which leads to consistent revenue through high margin consumables. Balcan et al. (2007) supports this by stating that below cost pricing can be justifiable as long as there are later sales of its associates. Supporting the above, the case company currently actualizes this in their model through high post-installation supplemental part purchases by the customers.

In this analysis, the effects of this pricing strategy are evident in historical sales data, where new orders of builds generally attained breakeven margins after several years. This aligns with strategic planning objectives that focus on sustaining long-term customer engagement and aftermarket revenues as opposed to preferring near-term margin benefits. The simulation model applied to estimate life cycle profitability, including break-even analysis and margin recovery, is outlined in Chapter 5, which will give the stakeholders in view of the break-even timelines alongside the lifetime revenue of a particular vessel type.

4.2.2 Operational Phase: Spare Parts Dominance

Sales of spare parts are the most dependable and lucrative within a product's life cycle. From analysis of 2015 to 2024, there was observable growth in spare parts revenue, with 2024 anticipated to be a peak year for both sales volume and gross margins. Throughout this period of time, the aftermarket business maintained robust margins ranging from 78% to 89%. But here, the cost of the products also seemed to rise once they started aging since their release.

From a product standpoint, consumables such as detectors, sensors, bases, and printed circuit boards are among the top contributors to spare part revenue. These items are frequently replaced because of wear and tear, safety adherence, and rapid technological advancements that render them outdated. From interviewees, marine conditions and classification society requirements enforce mandatory replacement intervals, ensuring recurring demand streams.

Zhang et al. (2021) identified consumable components as a critical driver of life cycle profitability in complex systems. This view is supported by the case company's sales data. Products that are regulatory relevant and compatible investments sustain long-term revenue resilience.

Annual reviews are conducted to evaluate pricing frameworks for spare parts, which adjust based on supplier costs, inflation, exchange rates, and market benchmarks. Pricing decisions, according to the managers, are primarily influenced by the need to maintain service levels, minimize subscriber attrition, and ensure customer retention. Strategic price hikes are applied to legacy models to stimulate the adoption of newer systems.

Furthermore, the study revealed a consistent gap of 2-3 years between vessel delivery and the start of spare part purchases, which marks the beginning of the replacement life cycle. Consequently, this gap aids in forecasting demand. Cruise and tanker vessels dominate sales volume due to their complex systems and marine safety regulations within the industry.

In sum, the operational phase demonstrates the firm's capability to leverage its installed base and refine low-margin first sales to high-margin recurring business. These effects bolster the strategic importance of aftermarket optimization and life cycle-aware product management.

4.2.3 EOL Phase: Decline Triggers and Life cycle Fallout

EOL behavior was studied with Power BI visual analytics to evaluate the ongoing performance of products in various life cycle stages. The company's ERP classifies items as 'Released', 'Discontinued', 'Inactive', 'Prototype', or 'In Development'. These classifications served as analytic filters, with primary focus given to Released products that were presumed to be actively supported.

For the selected products, unit sales data were plotted over several years using Power BI's time series and forecasting functionalities. Figure 4.1 reveals the time-series analysis conducted in Power BI forecast models for products marked as Released. The analysis indicated persistent year-over-year sales declines for several products, reinforcing the argument for alignment with life cycle management. This made it possible to track revenue growth, identify seasonal patterns, and discover sustained declines. Some products exhibited distinct annual declines in sales volume or total stagnation, which is incompatible with their "Released" status. These included legacy system components and outdated modules somehow classified as released.

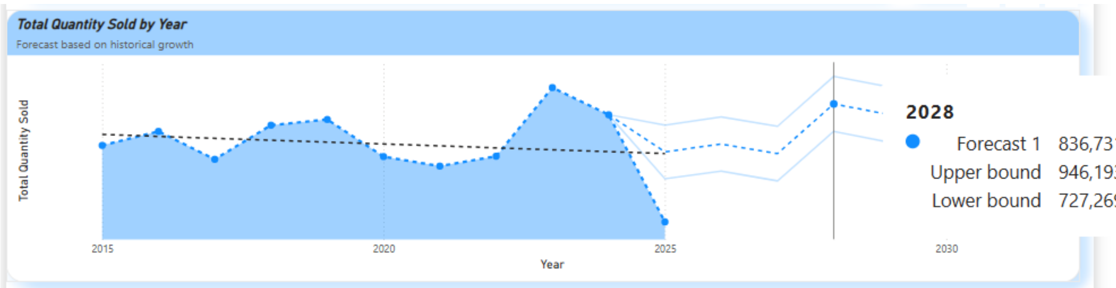

Figure 4.1: *Plot of unit sales over time followed by forecasted values in Power BI.*

Power BI's forecasting capabilities were utilized in this instance to visualize historical data and predict future sales trends. Products that displayed a continuously descending trajectory in their sales forecast were flagged as possible candidates for phasing out. On the other hand, products that were predicted to have stable or growing sales were considered to be in a healthy operational phase.

These results highlight issues regarding a formalized product life cycle status versus market activity. Interviewees acknowledged that there is a life cycle matrix that is not frequently updated based on sales patterns. Decisions pertaining to end-of-life (EOL) date tend to be influenced by EOL product suppliers or technical obsolescence, instead of predictive sales models and demand thresholds.

This contradicts life cycle planning frameworks put forth by Doyle et al. (2012) and Özyörük et al. (2022), which advocate for data-driven EOL policies based on demand forecasts using leading indicators. The absence of consistent transition criteria can result in inefficient inventory utilization, surplus support costs, or customer dissatisfaction due to unrealistic expectations.

To overcome these issues, the sales evaluation underscored the necessity of creating an evolving and systematic End-of-Life (EOL) model based on usage patterns, diminishing demand, and sales stagnation. This model was incorporated into the thesis and is summarized in Chapter 5 with its classification rules and visual indicators alongside stakeholder commentary.

4.2.4 Revenue by Product Type and Vessel Category

Examining sales order data stratified by product line, including the type of vessel, reveals more granular insights into life cycle revenue. This slice analysis demonstrates the heterogeneity of revenue behaviors based on the function of the product as well as the context of vessel deployment.

From the product type perspective: In the top-performing product categories grouped by sales volume and margin contribution, consumables detectors, sensors, and bases emerged first. These items sustain recurring replacement cycles which are triggered by onboard inspections and safety wear regulations. On the other hand, capital-intensive items such as control panels, system cabinets, and electronic modules exhibit front-loaded revenue spikes during new build installations with limited post-deployment recurring engagement. Their revenue lifespan closely aligns with initial delivery, not the support cycle.

The challenges faced by legacy systems were notable with ERP-based product tagging. Additional fragmentation due to incomplete categorization and a misaligned consistency structure hindered data granularity in lower-tier breakdowns. Regardless, available sales data confirms the conclusion that long-term revenue stability is mostly driven by consumable components tied to compliance requirements as well as wear and tear.

From a vessel category perspective: Revenue-generating life cycle patterns differ greatly by vessel type. Tankers are the largest contributors to total revenue, especially in the spare parts segment. Their standardized construction, coupled with operational intensity, sustained aftermarket demand everywhere. Cruise ships, with lower total revenue, show extremely stable consumable revenue due to high equipment density, rigorous safety certification cycles, and frequent dry-dock schedules.

LNG carriers and container ships meaningfully contribute across all life cycle stages, from installation of the systems to the sustained support provided. Their life cycle profiles depict balanced performance and predictable demand. In contrast, fishing boats and naval ships, transacting at low volume, appear relatively stable but sporadically surge with high-margin retrofitting.

One important data restriction stems from the inability to trace sales to vessels delivered before 2015 due to the absence of a historical link in the ERP system. This limitation particularly impacted the breadth of longitudinal trend analyses for enduring products.

From these analyses, the underlying consumption behavior is captured at the intersection of product and vessel attributes, which has significant implications for determining their pricing, support resource allocation, and inventory management.

4.2.5 Pricing Strategy and Margin Recovery

Revenue during different life cycle phases is greatly affected by the pricing approach taken. With data analysis, it became apparent that with most new builds, gross margins were either significantly low or negative at the onset. However, these losses were later compensated for during the operational phase through high-margin spare part sales.

Interview excerpts confirmed the observation and indicated that the case company does intend to sell new systems at a loss to capture market share, but makes up for losses through spares downstream. The staged recovery strategy, mapped in Figure 4.2, highlights a margin curve across life cycle phases. It captures the staged recovery approach where early pricing sets a baseline for profitability across numerous phases. This approach follows the reasoning of life cycle pricing, which posits that profitability is managed over multiple transactions instead of on a single transaction basis.

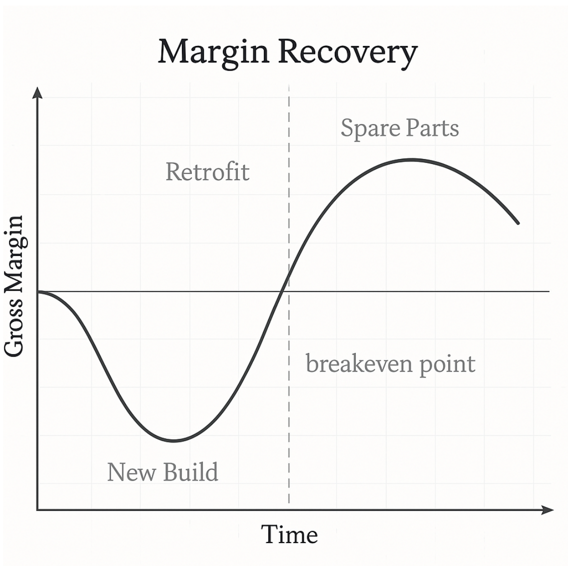

Figure 4.2: *Schematic illustration of gross margin recovery across the sales type.*

Price changes happen every year and are influenced by supplier prices, inflation, competition in the market, and planned margin goals. Stakeholders noted how prices for products that approach their end-of-life are sometimes raised intentionally to incentivize customers to adopt newer platforms or retrofit solutions. This also aids in controlling inventory as well as legacy support cost reduction.

The breakeven horizon is observed in sales data close to three years post-delivery, after which cumulative margins turn positive. This behavior is observed in several high-volume vessel segments, product categories, and numerous high-volume segments. That said, this insight is purely based on trends in the sales data; the actual pricing simulation model with warranty period and spare parts growth rate, and the logic behind life cycle margin projections are detailed in Chapter 5.

Essentially, the company's pricing strategy exhibits refined mastery of life cycle economics by utilizing entry-level accessibility for new builds and capturing sustained margins in spare parts. This enhances long-term profitability alongside customer retention, which is pivotal in heavily regulated sectors like marine safety systems.

4.2.6 Forecasting Gaps and Life Cycle Data Challenges

Insights gained from analyzing sales data also revealed gaps in forecasting capabilities as well as gaps in data accuracy. While Power BI uses exponential smoothing in its forecasting, the seasonality and accuracy tend to be subject based on other factors, and also, anticipating demand at the life cycle level is still rudimentary for the long term.

A significant hurdle is missing vessel-level consumption data. At present, there is no automated connection between the sales order data and usage events onboard certain vessels, making it difficult to forecast curves for spare part demand or estimate saturation points for crucial components. Many stakeholders pointed out this limitation, emphasizing that a large number of forecasting determinations are still made based on heuristics or are simply reactive.

Moreover, incomplete tagging and item migration from legacy ERP systems led to poorly maintained product hierarchies, which, in turn, hampers the ability to analyze historical sales data accurately and derive meaningful trend insights. The accuracy of segmenting performance based on product life cycle maturity or customer demographics is compromised due to poorly mapped or inconsistently tagged records.

Although Power BI rendered basic projections for unit sales, its native forecasting capabilities lack contextual variables like failure rates, maintenance cycles, or environmental exposure, which leads to incomplete and readily misinterpreted projections.

More refined integration between ERP systems, forecasting systems, and life cycle indicators would allow for anticipating future demand with greater accuracy. Improving data accuracy and implementing dashboards on a per-vessel basis with accurate installed-based information could enable proactive decisions on pricing, supply chain management, planned obsolescence, and life cycle exit strategies.

As a final note, the sales order analysis validates the existence of a life cycle-based revenue pattern: starting with lower-margin system sales, progressing to high-margin aftermarket revenue, and ultimately transitioning to a decline phase. Such findings reinforce the need for proactive model-based strategic pricing, end-of-life planning, and forecasting dashboards as outlined in the subsequent chapter.

5

Synthesis

This chapter demonstrates the Power BI dashboard solution developed to address primary business concerns as defined in the earlier results and analysis from Chapter 4. These concerns are lack of life cycle visibility, unsystematic EOL decision-making, poor linkage between system installation and spare consumption patterns, and limited simulation of profitability modeling throughout the product life cycle, among others. Consolidation of inputs from ERP sales data, IHS vessel data, and curated product hierarchies is integrated into a business intelligence tool. Each of its four core modules is introduced in this chapter as a functional prototype to enhance data-driven decision-making for Product Line Managers, Aftermarket teams, and other stakeholders.

These modules are:

- Life cycle Revenue Planning Dashboard
- Pricing & Life cycle Profit Simulation Module
- Product Life cycle Status & EOL Risk Dashboard
- Spare Parts Analytics Dashboard

Each module has been designed as a synthesis of analytical insights, and stakeholder expectations, and, where possible, initial input on enhancement and next steps is provided.

5.1 Life cycle Revenue Planning Dashboard

The result of the analysis is the comprehensive life cycle revenue data collection within a single Power BI dashboard, monitored at both product and vessel levels. This dashboard, as shown in Figure 5.1, captures the outcomes and converts them into streamlined real-time monitoring and decision support systems.

Problem Addressed: In previous attempts, the case company did not have an aggregated and systematic view of revenue performance at the product and vessel level. Revenue from new builds, retrofits, and spare parts was stored in silos across systems, and life cycle maturity was not quantifiably monitored. This constrained strategic decision-making in prioritization, investment, and aftermarket planning.

Proposed Solution: The life cycle Revenue Planning Dashboard integrates information from the ERP system, IHS vessel registry, and the product hierarchy mappings to present sales performance at different intervals. It also allows for flexible visualization of historical revenue and margin trends across various sales types. Thus, offering high-level insight into:

1. Yearly, quarterly, and monthly sales performance
2. Product group, system type (e.g., fire/gas), customer group, and vessel category filters
3. Vessel-level revenue capturing through IMO number filtering
4. Projective forecasted revenue trends based on historical data

Key Functionalities:

- Monitor and assess life cycle maturity across vessel-product combinations.
- Determine revenue contribution by vessel type and product group.
- Exponential Smoothing Forecasting growth or stagnation using historical trend analysis.
- Filter by delivery year (i.e., vessels delivered after 2015).

This module serves as the initial interface for life cycle planning, establishing a baseline from which EOL risks, break-even analysis, and spare parts consumption can be further examined.

Early Testing and Usage: The dashboards real-time connection to the ERP data model provides order line visibility at all product granularity levels. It allows filtering down to individual vessels based on IMO number and product/item numbers. Internal showcase meetings with the aftermarket team and stakeholders showed high usability for uncovering revenue gaps and driving focus on prioritized high-value customers or segments.

Potential for Further Development:

- Benchmark revenue curves against life cycle archetypes by system type.
- Integrate predictive models for revenue decay or acceleration.
- Implement alert systems for anomalous product performance.

This dashboard aligns with the overarching objectives of the research concerning revenue trend analysis, segmentation, and forecasting. Moreover, it provides the foundational layer for the other tools in the solution suite.

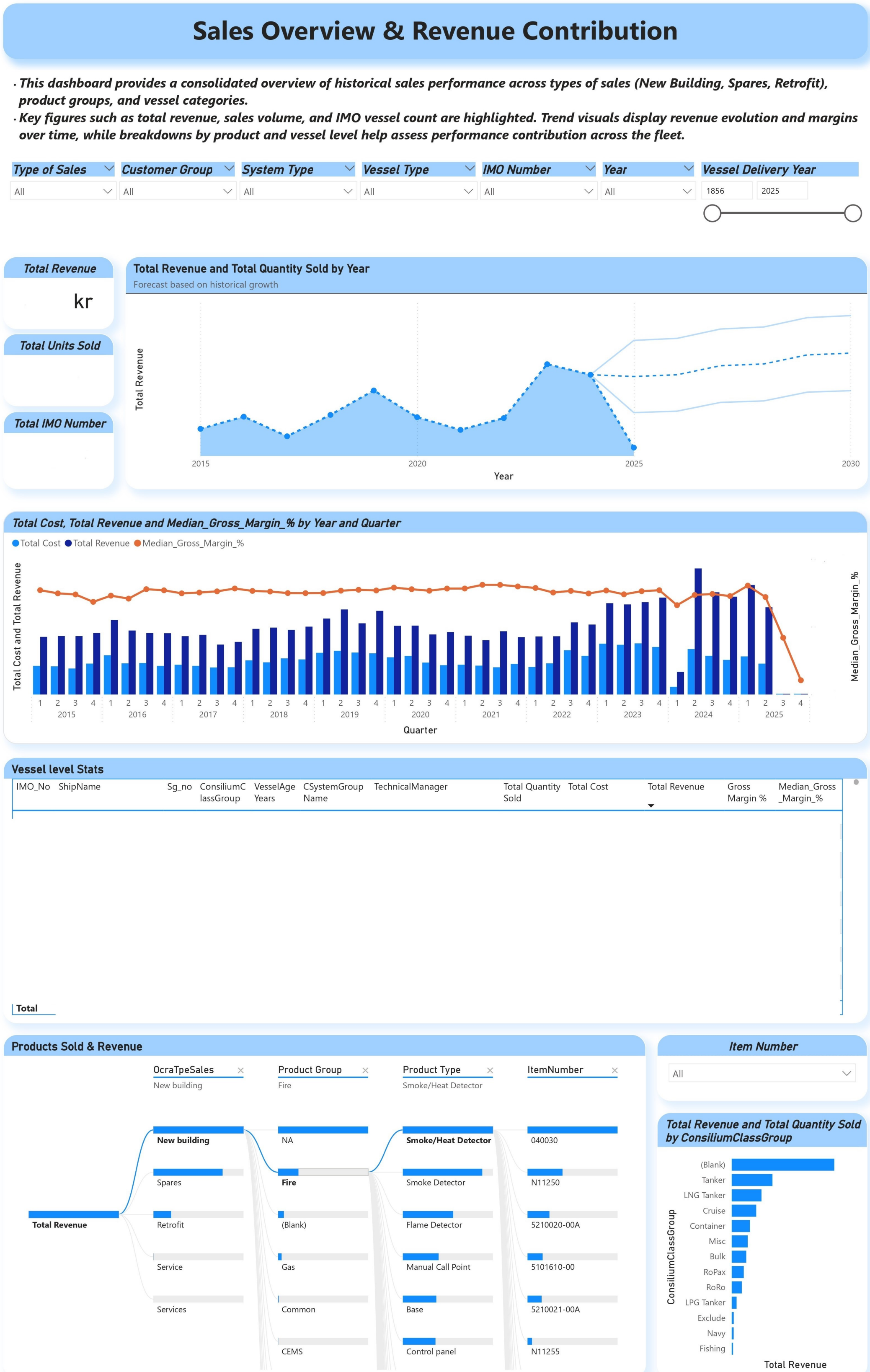

Figure 5.1: *Sales and Revenue Contribution Dashboard overview*

5.2 Pricing & life cycle Profit Simulation Module

The case company is struggling with accurately gauging the aftermarket profitability of new build projects, particularly those constructed at break-even margins to remain competitive in the marketplace. There was no systematic method to estimate the contour and time frame of profit recovery via aftermarket service contracts for parts sales, nor was there a simulation model to test dynamic pricing over time.

The Pricing & life cycle Profit Simulation Module allows the simulation of cumulative life cycle profitability per vessel by applying historical sales data alongside user-defined variables with predefined inputs. It captures the break-even point estimation at which the initial investment loss is recovered by spare parts revenue from the vessels that are built. The break-even estimator uses key inputs such as average new sales revenue per vessel, average spare part revenue per vessel, spare parts revenue growth rate, product life assumptions, and warranty period exclusions. The loss leader simulation model, as seen in Figure 5.2, integrates set parameters with dynamic inputs by users/stakeholders to simulate various pricing and growth scenario assumptions to find break even years.

This model determines new building sales pricing with deferred profitability estimations, which justifies pricing curtailments. Also estimates cumulative revenues from spare parts and retrofits over a set period. And simulates using inputs like new build margin, yearly spare part growth, warranty exclusion periods, and projected vessel lifespan. It then visualizes the margin recovery timeline and evaluates the break-even year. By estimating the break-even year and lifetime value, this model provides long-term value demonstration, aiding in supporting loss-leader pricing implementation by encouraging cross-functional alignment between Sales, Finance, and Product teams.

The module is demonstrated to selected stakeholders in the aftermarket and sales teams. Having the ability to adjust margins and growth assumptions of spare part sales piqued stakeholders interest as profitability impacts became immediately visible. In particular, break-even year visualization was instrumental in supporting project return evaluation for new sales of new systems to the customers.

Potential for Further Development:

- Utilize system-specific installed base information to enable more precise estimations and forecasts.

- Incorporate replacement and upgrade retrofit cycles into the simulation.

- Facilitate parallel comparison between multiple vessel classes (e.g., fire-only and fire plus gas systems).

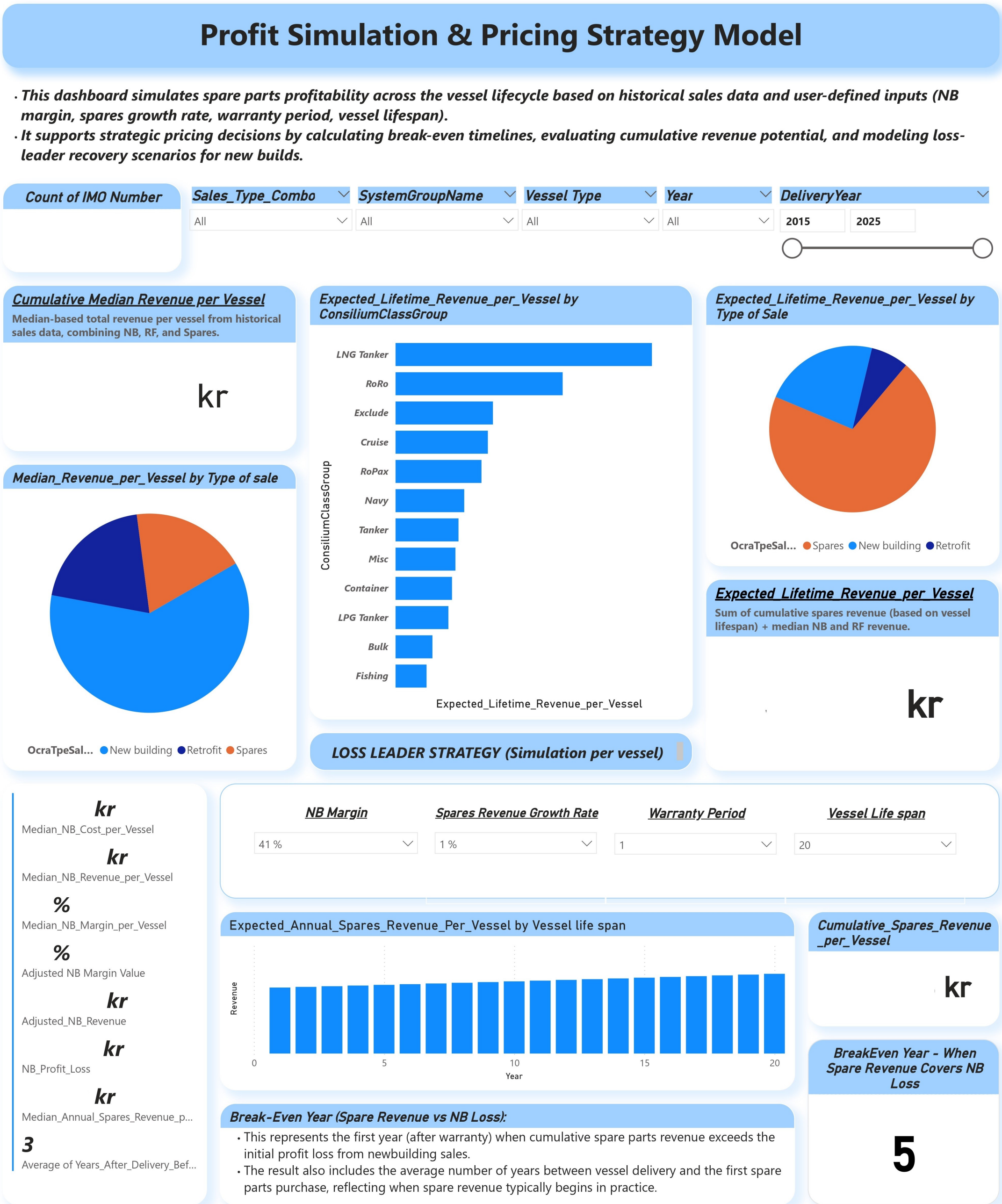

Figure 5.2: *Pricing & Life cycle Profit Simulation Module Dashboard overview*

This prototype enhances the case company's simulation capabilities to not only defend strategic pricing models but also simulate forward-looking life cycle profitability forecasting at vessel-product granularity. It also strengthens the explanation of the loss-leader pricing strategy talked about previously by showing how, with accurate planning and monitoring, deferred revenue recovery can be achieved.

5.3 Product Life cycle Status & EOL Risk Dashboard

Previously, product phase-out actions at the case company were made based on the purchase team's feedback from the suppliers and were entirely reliant on subjective evaluations. ERP terms like released or discontinued seldom align with actual market performance. This system generated a lot of ambiguity and complicated untangling products that were viable, were on a slow decline, or were completely obsolete. In an attempt to solve this problem, the Product Life Cycle Status & EOL Risk Dashboard was created. This tool assigns all released products into one of five life cycle stages: Active, Watch list, EOL Risk, Inactive, or New product.

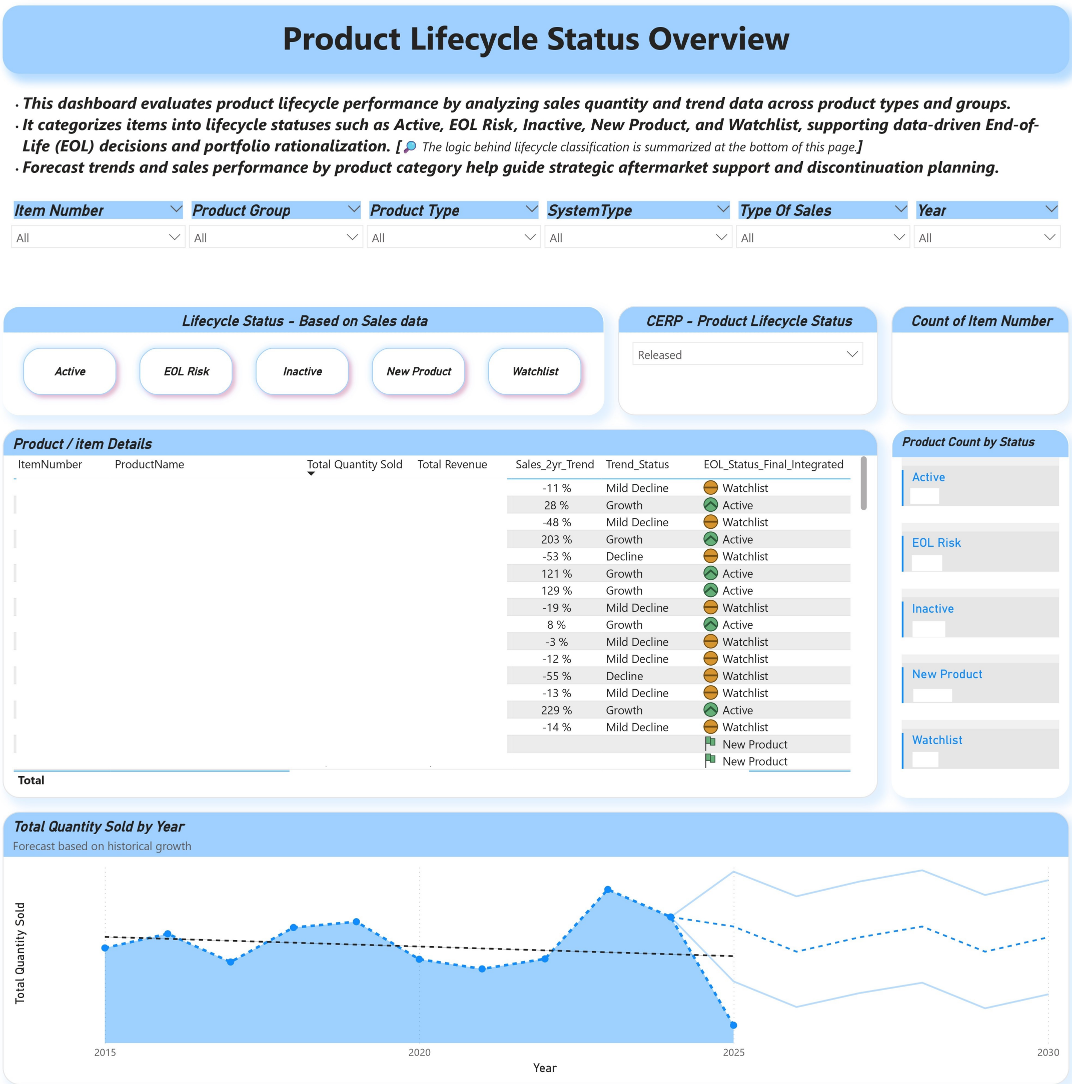

Figure 5.3: *Product Life Cycle Status Classification Tool overview*

The segmentation thresholds were established according to industry standards in the forecast of service-part obsolescence. As outlined by Jaarsveld and Dekker (2011), "demand-driven segmentation" considers elongated sales dormancy (e.g., 24 months with no sales) as definitive signs of obsolescence. This justifies the "Inactive" section of the dashboard, which ensures products with no recent market sales are flagged. Jennings et al. (2016) provides evidence that sharp, sustained sales declines (70% or greater over a 24-month window) crossing a threshold are reliable signs of obsolescence, while smaller declines are early warning. These directly support the "EOL Risk" and "Watchlist" designations, which are triggered by stable moderate declines prompting closer inspection, while drastic declines initiate retirement preparations.

The classification relies on dynamic sales performance logic instead of static system labels. The classification employs DAX-based business intelligence metrics on recent sales activity of the product, including rolling sales volume, the duration since the last sale, and the current directional movement of sales. With these calculated metrics, categorization in real-time becomes possible for every item within the portfolio. The dashboard displays data at various levels of aggregation, which enables stakeholders to track life cycle trends at the group, type, or even item level. Further refinement is possible with filters by vessel type, system category, and year of delivery.

Perhaps the most powerful visual feature of this dashboard is the forecasting chart outlining the anticipated sales trajectory and a summary view of product sales under each life cycle classification. Figure 5.3 provides an overview of the live life cycle status dashboard where stakeholders and other department people can explore item-level performance through interactive filters, observe trend classification (e.g., Growth, Decline, Mild Decline), and view the final integrated life cycle status based on sales data alongside the current ERP life cycle status. It also highlights the item count across each category and presents the total quantity sold, revenue, and recent trend data in a structured tabular format. These features make the dashboard an effective visual and analytical guide for product life cycle governance.

The dashboard's utility has already been demonstrated in internal meetings. On the other hand, some products marked as watch list performed better than expected, warranting a reassessment of their life cycle category. This capability will result in more precise and reliable life cycle planning, which has made it possible to better manage transitions into the end-of-life phase while safeguarding profitable product lines from withdrawal, labeled as a watch list.

The dashboard could be expanded to include integration with Supplier information and warehouse stock levels, which would enable real-time operational assessments of whether certain EOL transitions are operationally feasible. Other customer service indicators, like the frequency of service requests or customer complaints, might improve the precision of life cycle forecast accuracy as well. Lastly, EOL proposal triggers could be automate, which then would allow the process to be seamlessly incorporated, automating governance into ongoing product strategy and planning.

The complex nature of industrial portfolios demands integrated decision support systems. This dashboard demonstrates the shift towards a proactive approach to managing product life cycles driven by data.

5.4 Spare Parts Analytics Dashboard

While revenue generated from the sale of spare parts is essential to profitability, the case company did not have a clear understanding of the usage of spare parts across vessels and systems. From the available data, decision-makers could not ascertain which vessels were the biggest contributors to spare part revenue, the timing of customer purchases, or the historical performance of spares by product type. To fill this analysis gap, the Spare Parts Analytics Dashboard was created with a singular focus on spares sales.

Figure 5.4: *Spare parts analytics dashboard overview*

The Figure 5.4 shows the analytics/dashboard which synthesizes ERP transaction data and IHS vessel metadata, enabling users to analyze spare part sales at both the vessel and product levels with KPI's. Users can assess spare part metrics, including total units sold, average and median annual spare revenue per vessel, margin distribution across system types, and time to first purchase (consumption lag). Users are also able to filter by IMO number, vessel type, product category, system type (fire, gas, etc.), item number, and delivery year. Key performance indicators (KPIs) within the dashboard include year-to-date margins and projected forecast values, which are visually represented.

Equally important is the vessel-level segmentation that comprises age, the technical manager's company, the responsible commercial entity, and cumulative spare part behavior. This facilitates thorough benchmarking across cruise ships, tankers, and offshore vessels. During the internal assessments, stakeholders viewed the comparison of spare performance by vessel group as a robust enhancement during the internal evaluation, providing accurate vessel value identification and forecasting of spare demand.

The module aids in planning procurement frameworks, forecasting warranties, and intelligence on the installed base. Tracking aftermarket activities enables the business to monitor aftermarket vitality long after the initial system sale. Other predictive maintenance modeling, service visit log integrations, and the automatic flagging of vessels or products with low spare part usage cumulatively indicating life cycle decline or support issues concerning flagship products might be future directions of development.

6

Disucssion

This chapter focuses on the wider impact of the results captured in this thesis and links the findings to practical use and literature in the domain of life cycle revenue management and forecasting. It offers well-founded explanations of the research questions, explains theoretical and practical implications, analyzes the quality and limitations of the provided methodology, and evaluates the answers given. Furthermore, the chapter describes the original contributions of the study and notes how the case company, or comparable industrial contexts, could be developed or examined further.

6.1 Strategic Implications of Findings

In this section, the interpretation highlights the significance of the findings from a broader perspective and in relation to the research questions asked at the beginning of the thesis. Each sub-section that deals with a specific research question describes the conclusions that came from the results, models, and tools built.

6.1.1 Guiding Investment and Resource Allocation

Research Question 1 - **What is the effect of life cycle revenue analysis on resource allocation and investment decisions on aftermarket services and new product development?**

The revenue analysis made it clear that products and vessel classes do not perform the same over time. Spare parts tied to cruise and tanker, detectors emerged as steady earners, backing the case for deeper investment in those lines. For management, this evidence can guide not only sales focus but also where R&D energy and purchasing funds should go.

Rather than spreading cash evenly, the data calls for a targeted strategy that favors products with steady demand and strong life cycle margins in design and long-term support. In contrast, offerings that lose traction soon after installation may deserve reduced resources or phased-out status unless a clear strategic reason to keep them exists. Such discipline sharpens resource use and fits well with lean product-management principles.

Viewed through a systems-engineering lens, this line of thinking builds a life cycle-first product strategy that treats feedback from installed assets, real-world usage, and future design as daily input. It also strengthens life cycle-cost planning by ensuring early engineering choices are grounded in the commercial lessons that emerge once products enter the market.

Beyond charts and frameworks, the real lesson here is simple-spending your time where it counts is what moves the business forward. Anyone who works with competing product lines, and an endless stream of support tickets knows how easy it is to get overloaded. This framework slices through that clutter. It highlights the areas where one should lean in harder and flags the ones that may need a graceful exit. That kind of focus is genuinely valuable.

6.1.2 Data-Driven EOL Decision Criteria

Research Question 2 - **How can revenue trends from historical sales data be utilized to develop data-driven criteria for end-of-life (EOL) decisions on products?**

The end-of-life classifier is probably the most useful piece of this research. Its real payoff lies not in sending out warning bells for fading products, but in turning EOL choices from last-minute guesses to decisions backed by solid data. Since support costs, unsold stock, and customer confidence are all tangled together, a dashboard that spots items marked Watch list or Inactive early makes the whole process calmer and less driven by department silos.

More important, the model turns a fuzzy procedure into something concrete. Almost every business has a life cycle chart sitting in a drawer, but very few tie it to real-time, measurable signals that stakeholders can see every week. This study shows how to put that idea into practice by linking key metrics to clear visuals everyone across marketing, finance, and engineering can talk about. If we keep this model updated and weave it into everyday product rules within PLM software, a company can spend less time and money on EOL handovers and talk to customers more clearly and on time.

On a personal note, creating the model showed me that the nuts-and-bolts of phase-out can actually steer company strategy. No one enjoys yanking the cord on a product; it feels messy, and often heavy-hearted. Yet with solid data in front of us, one can do it not out of desire but simply because the numbers insist the moment has arrived.

6.1.3 Strategic Pricing through life cycle Revenue Models

Research Question 3 - **How can strategic pricing models from life cycle revenue analysis contribute for new marine safety products to enhance long-term profitability with effective strategic pricing?**

Pricing in many B2B situations goes well beyond a simple cost-plus formula and margins; it requires thinking across the entire product life cycle. The break-even simulation featured here puts that idea front and center. It shows how a new sale can start out with a deliberately low price point-even below its cost-if future sales of spare parts and upgrades more than make up the initial shortfall.

Although the approach is often described in strategy meetings, it usually lacks hard numbers to convince stakeholders. The model behind this page closes that gap. By calculating multiple break-even scenarios, yet displaying them in a clear dashboard, it connects upfront pricing with the revenue expected years later. For the company in this example, that insight opens several tactics: running trial pricing bands, monitoring the return of each system/products, and restoring margins at the portfolio level.

In practice, I believe the biggest benefit is the way the tool eases conversations between sales and finance. Salespeople naturally want to close deals at any price, while finance people rightly guard profitability. The break-even picture quantifies the tension so both sides can agree on terms and says, Yes, we can be aggressive now, because the model shows where the profit will come from later. That data-driven reassurance turns what feels like a risky discount into a planned investment.

6.1.4 Life cycle and Vessel-Based Revenue Patterns

Research Question 4 - **How do revenue generation patterns vary across different product life cycle stages and among various commercial vessel categories?**

The study found that revenue trends track more closely with the category of vessel than with the specific product in use. Tankers and cruise ships approach spare-part consumption in distinct ways, differing in timing, volume, and triggers. That variation is backed by the data, yet it also feels natural once the day-to-day operations and safety rules for each segment are laid out side by side.

For forecasters and planners, the takeaway is clear: vessel category deserves a front-row seat in any demand model. Life cycle initiatives-pricing revisions, service guarantees, retrofits-can then be matched to the customers that actually own each fleet class. Put simply, a one-size plan is almost certain to miss the mark; the strategy has to respect the quirks of every vessel.

The insight also clears a path to predictive segmentation. If vessels are grouped by behavior as well as type, everything from yearly spare-part cost to average replacement interval, the firm can craft sharper policies and more reliable forecasts. That level of granularity feeds into advanced analytics and might even power the digital twins being built for key high-value customers.

Personally, the observed divergence among vessel categories convinced me that segmentation is more than industry jargon; it is a strategic obligation. When two fleets respond in opposite ways, treating them identically wastes resources and squanders possible upside. The evidence in this set leaves little room for doubt on that point.

Taken together, these insights suggest that the thesis has delivered more than colorful graphs; it has crafted a decision-support framework ready to plug into the case company's strategic conversations. Every research question produced not only an answer but also a clear road map showing the stakeholders how to convert the insight into tangible action.

6.2 Reflections on the Methodology

This section looks back on the entire thesis process to understand how decisions were made and methods were applied beyond the specific technical tools. It examines the overall research flow, how easily new information have been adapted, and the bumps that arose during data collection, interviews, and fitting new insights into the everyday work of the case company. It also asks whether the chosen approach matched the research questions and imagines how the findings might look if a different angle had been taken.

6.2.1 Research Approach and Process Adaptation

The work opened with a tight brief on analyzing and forecasting revenue across the product life cycle, but conversations in meetings and interviews gradually widened the focus. Initially the thesis started with sales data only, then grew to include bigger topics like pricing model and end-of-life planning tools because real-life decisions proved far more interconnected than first thought. That insight demanded an agile, looped process rather than a neat, straight line of steps.

With those points in mind, an early project road map was sketched out, inspired by established practices in data analysis and product life cycle management. The plan underwent repeated updates because data arrived at different times, and priority areas shifted as new insights emerged. Regular weekly catch-ups with the supervisor and key business partners kept scope discussions live, enabling quick adjustments to outputs whenever fresh needs surfaced.

Pairing an overall road map with ongoing revision allowed work to traverse three broad domains: descriptive analytics, strategic modeling, and operational tooling. Each phase was layered on the last, moving logically from question exploration through prototype implementation. Still, the iterative nature meant some analyses had to be set aside and later revisited whenever additional data arrived or fresh stakeholder comments bubbled up.

Blending open-ended interviews with data-driven modeling proved a good fit for the research aims. Qualitative findings clarified why patterns emerged-for instance, how pricing rules or hesitation around end-of-life options shaped choices-while quantitative dashboards showed exactly what happened to sales and margin over time.

6.2.2 Methodological Challenges and Limitations

While the chosen approach generally fit the objectives, a handful of practical hurdles emerged during the process. In the initial data collection phase, historical datasets required frequent changes and updates due to ERP migration, limiting the richness of the early quantitative work. On the qualitative front, interviews with stakeholders yielded valuable information but remained narrow because of tight schedules and departmental availability. A few planned sessions were swapped for careful reviews of internal documents just to keep the timeline on track.

Forecasting, meanwhile, could not be cross-checked against finalized operational plans or actual customer-delivery data. The future work could close that gap by linking quotation-to-order lags or adding customer and installed-base, though doing so calls for system integration that lies beyond the present scope.

Had alternative techniques been employed-for instance, machine-learning forecasting or formal econometric models of price sensitivity-other, possibly deeper, insights could have appeared. Predictive precision might have increased, and finer links between vessel behavior and parts consumption could have surfaced. Yet those tools would also have layered complexity on the work, making it harder for front-line people to grasp what the model was doing and why. The present strategy, therefore, favoured simplicity and quick adoption over pure technical rigour.

In sum, the project stayed within a solid academic framework, but its real edge came from a flexible, on-the-spot process that let live business input steer updates. The chosen method matched the original research goals, yet later works could gain from adding advanced analytics and wider stakeholder voices, yielding an even richer view of the problem. This hybrid strategy of exploratory planning, agile execution, and stakeholder-driven validation was crucial in translating quantitative data into decision-support tools suitable for implementation within the case company.

7

Conclusion

This thesis has examined the use of life cycle revenue analysis aimed at enabling data-informed decision-making for marine safety systems with respect to aftermarket planning, pricing, and strategic long-term investments. The analysis integrates transactional sales data with vessel delivery metadata and product hierarchies, and as such, the analysis constructs a structured framework to evaluate product performance and identify End-of-Life (EOL) risks while simulating revenue forecasts using Power BI.

The work showcased that life cycle-based metrics not only serve to enhance investment prioritization but can also identify products and systems that have a greater long-term spares value. In order to facilitate aftermarket and discontinuation planning, a structured EOL classification model based on the product's recency of transactions, sales decline rates, and rolling-year volumes was developed. These dashboards and models were particularly beneficial in instances where explicit life cycle data was unavailable from PLM and ERP systems. The break-even pricing analysis also demonstrated that new builds with initially low margins can prove economically sustainable over time given robust spare part sales, and thus, supports bundling, loss leader pricing, and life cycle-based product differentiation strategies.

Lastly, the study carried out also noted important differences in revenue generation relative to product and vessel category. For example, gas detection systems outperformed fire systems in terms of operational revenue persistence. These findings are noteworthy to support segmentation for product life cycle management. As a whole, this study provides a replicable framework for employing life cycle revenue analytics in industrial settings. Strengthening forecast precision and decision relevance could be developed by integrating installed base information, refined cost detail, and signals from predictive maintenance.

Bibliography

Alrabghi, A., & Tiwari, A. (2015). State of the art in simulation-based optimisation for maintenance systems. *Computers & Industrial Engineering*, *82*, 167–182. https://doi.org/10.1016/j.cie.2014.12.022 (cit. on p. 19).

Balcan, M.-F., Blum, A., Chan, T.-H. H., & Hajiaghayi, M. (2007). A theory of loss-leaders: Making money by pricing below cost. *Proceedings of the 3rd International Workshop on Internet and Network Economics (WINE 2007)*, 293–299. https://doi.org/10.1007/978-3-540-77105-0_29 (cit. on p. 31).

Bazerghi, A., & Van Mieghem, J. A. (2024). Last time buys during product rollovers: Manufacturer & supplier equilibria. *Production and Operations Management*, *33*(3). https://doi.org/10.1177/10591478241231859 (cit. on p. 22).

Bryman, A., & Bell, E. (2011). *Business research methods* (3rd ed.). Oxford University Press. https://books.google.se/books?id=YnCcAQAAQBAJ&lpg=PP1&pg=PP1#v=onepage&q&f=false (cit. on pp. 7, 8).

Cavalieri, S., & Pezzotta, G. (2012). Productservice systems engineering: State of the art and research challenges. *Computers in Industry*, *64*, 278–288. https://doi.org/10.1016/j.compind.2012.02.006 (cit. on p. 23).

Doyle, K., Ijomah, W. L., & Antony, J. (2012). Identifying the end of life decision making factors. *Design for Innovative Value Towards a Sustainable Society*. https://doi.org/10.1007/978-94-007-3010-6_102 (cit. on p. 33).

Dubois, A., & Gadde, L.-E. (2002). Systematic combining: An abductive approach to case research. *Journal of Business Research*, *55*(7), 553–560. https://doi.org/10.1016/S0148-2963(00)00195-8 (cit. on pp. 7, 9).

Durugbo, C. M. (2020). After-sales services and aftermarket support: A systematic review, theory and future research directions. *International Journal of Production Research*, *58*(6), 1857–1892. https://doi.org/10.1080/00207543.2019.1693655 (cit. on p. 17).

Eggert, A., Hogreve, J., Ulaga, W., & Muenkhoff, E. (2014). Revenue and profit implications of industrial service strategies. *Journal of Service Research*, *17*(1), 23–39. https://doi.org/10.1177/1094670513485823 (cit. on pp. 15, 16, 31).

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review*, *14*(4), 532–550. https://doi.org/10.2307/258557 (cit. on p. 7).

Faramarzi, A., Worm, S., & Ulaga, W. (2024). Service strategys effect on firm performance: A meta-analysis of the servitization literature. *Journal of the*

Academy of Marketing Science, *52*(4), 1018–1044. https://doi.org/10.1007/s11747-023-00971-1 (cit. on p. 16).

Grubic, T., & Peppard, J. (2016). Servitized manufacturing firms competing through remote monitoring technology: An empirical analysis. *Journal of Information Technology*, *27*(2). https://doi.org/10.1108/JMTM-05-2014-0061 (cit. on pp. 17, 23).

Hasni, M., Aguir, M., Babai, M. Z., & Jemai, Z. (2019). Spare parts demand forecasting: A review on bootstrapping methods. *International Journal of Production Research*, *57*(15–16), 4791–4804. https://doi.org/10.1080/00207543.2018.1424375 (cit. on p. 20).

Hoyle, J., Jarratt, D., & Marlow, P. (2020). An exploration of sales forecasting practice. *Journal of Marketing Analytics*, *8*, 127–136. https://doi.org/10.1057/s41270-020-00082-8 (cit. on p. 19).

Hu, Q., Boylan, J. E., Chen, H., & Labib, A. (2018). Or in spare parts management: A review. *European Journal of Operational Research*, *266*(2), 395–414. https://doi.org/10.1016/j.ejor.2017.07.058 (cit. on pp. 17, 18).

Hunziker, S., & Blankenagel, M. (2024). *Research design in business and management*. Springer. https://doi.org/10.1007/978-3-658-42739-9 (cit. on p. 7).

Ifraz, M., Aktepe, A., Ersöz, S., & Çetinyoku, T. (2023). Demand forecasting of spare parts with regression and machine learning methods: Application in a bus fleet. *Journal of Engineering Research*, *11*(2), 100057. https://doi.org/10.1016/j.jer.2023.100057 (cit. on pp. 20, 21).

Jaarsveld, W. V., & Dekker, R. (2011). Estimating obsolescence risk from demand data to enhance inventory controla case study [Leading Edge of Inventory Research]. *International Journal of Production Economics*, *133*(1), 423–431. https://doi.org/10.1016/j.ijpe.2010.06.014 (cit. on p. 42).

Jennings, C., Wu, D., & Terpenny, J. (2016). Forecasting obsolescence risk and product life cycle with machine learning. *IEEE Transactions on Components, Packaging and Manufacturing Technology*, *6*(9), 1428–1439. https://doi.org/10.1109/TCPMT.2016.2589206 (cit. on p. 43).

Jungen, H., Specht, P., Ovens, J., & Lemper, B. (2021). The rise of ultra large container vessels: Implications for seaport systems and environmental considerations. In *Dynamics in logistics* (pp. 113–122). Springer. https://doi.org/10.1007/978-3-030-88662-2_12 (cit. on p. 1).

Kim, J.-D., Kim, T.-H., & Han, S. W. (2023). Demand forecasting of spare parts using artificial intelligence: A case study of k-x tanks. *Mathematics*, *11*(3), 501. https://doi.org/10.3390/math11030501 (cit. on p. 20).

Kowalkowski, C., Gebauer, H., & Oliva, R. (2017). Service growth in product firms: Past, present, and future. *Industrial Marketing Management*, *60*, 82–88. https://doi.org/10.1016/j.indmarman.2016.10.015 (cit. on p. 16).

Kus, W., & Zurakowska-Sawa, J. (2017). Phases in the lifecycle of a company and the profitability of industrial companies. *Management and Production Engineering Review*, *10*(4). https://doi.org/10.29316/ers-seir.2017.35 (cit. on p. 16).

Li, J., Tao, F., Cheng, Y., & Zhao, L. (2015). Big data in product lifecycle management. *International Journal of Advanced Manufacturing Technology*, *81*(1–4), 667–684. https://doi.org/10.1007/s00170-015-7151-x (cit. on pp. 22, 23).

Liang, Q., Knutsen, K. E., Vanem, E., Æsøy, V., & Zhang, H. (2024). A review of maritime equipment prognostics health management from a classification society perspective. *Ocean Engineering*, *301*, 117619. https://doi.org/https://doi.org/10.1016/j.oceaneng.2024.117619 (cit. on p. 1).

Linde, L., Frishammar, J., & Parida, V. (2021). Revenue models for digital servitization: A value capture framework for designing, developing, and scaling digital services. *IEEE Transactions on Engineering Management*, *70*(1), 82–97. https://doi.org/10.1109/TEM.2021.3053386 (cit. on p. 17).

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2020). The m4 competition: 100,000 time series and 61 forecasting methods. *International Journal of Forecasting*, *36*(1), 54–74. https://doi.org/10.1016/j.ijforecast.2019.04.014 (cit. on p. 20).

M.Z. Babai, J. B., M.M. Ali, & Syntetos, A. (2013). Forecasting and inventory performance in a two-stage supply chain with arima(0,1,1) demand. *International Journal of Production Economics*, *143*, 463–471. https://doi.org/10.1016/j.ijpe.2011.09.004 (cit. on pp. 16, 21).

Özyörük, E., Erkip, N. K., & Ararat, Ç. (2022). End-of-life inventory management problem: Results and insights. *International Journal of Production Economics*, *243*, 108313. https://doi.org/10.1016/j.ijpe.2021.108313 (cit. on pp. 21, 33).

Paterson, D. A., Ijomah, W. L., & Windmill, J. F. C. (2017). End-of-life decision tool with emphasis on remanufacturing. *Journal of Cleaner Production*, *148*, 653–664. https://doi.org/10.1016/j.jclepro.2017.02.011 (cit. on pp. 20, 21).

Pinçe, Ç., Turrini, L., & Meissner, J. (2021). Intermittent demand forecasting for spare parts: A critical review. *Omega*, *105*, 102513. https://doi.org/10.1016/j.omega.2021.102513 (cit. on p. 19).

Pourakbar, M., Frenk, H., & Dekker, R. (2012). End-of-life inventory decisions for consumer electronics service parts. *Production and Operations Management*, *21*(5), 889–906. https://doi.org/10.1111/j.1937-5956.2012.01340.x (cit. on p. 22).

R. Solomon, P. A. S., & Pecht, M. G. (2000). Electronic part life cycle concepts and obsolescence forecasting. *IEEE Transactions on Components and Packaging Technologies*, *23*(4), 707–717. https://doi.org/10.1109/6144.888857 (cit. on p. 22).

Ratnayake, A., & Ali, A. (2023). Demand forecasting of automobile spare parts after the end-of-production. *Institute of Industrial and Financial Management and Logistics*. https://gupea.ub.gu.se/bitstream/handle/2077/77645/LTM%202023-73.pdf?sequence=1 (cit. on pp. 20, 21).

Saccani, N., Visintin, F., & Rapaccini, M. (2014). Investigating the linkages between service types and supplier relationships in servitized environments. *International Journal of Production Economics*, *149*, 226–238. https://doi.org/10.1016/j.ijpe.2013.10.001 (cit. on p. 18).

Spiliotis, E. (2023). Time series forecasting with statistical, machine learning, and deep learning methods. *Palgrave Macmillan, Cham*, 49–75. https://doi.org/10.1007/978-3-031-35879-1_3 (cit. on pp. 19, 20).

Sreejesh, S., Mohapatra, S., & Anusree, M. R. (2014). *Business research methods: An applied orientation*. Springer. https://doi.org/10.1007/978-3-319-00539-3 (cit. on p. 8).

Sun, Y., Li, M., & Wang, J. (2024). Surge pricing strategies in lifecycle revenue management: A stochastic control approach. *Operations Research Letters*, *226*. https://doi.org/10.1016/j.matcom.2024.06.017 (cit. on p. 16).

Thai Young Kim, R. D., & Heij, C. (2017). Spare part demand forecasting for consumer goods using installed base information. *Computers & Industrial Engineering*, *103*, 201–215. https://doi.org/10.1016/j.cie.2016.11.014 (cit. on p. 20).

Ucar, A., Karakose, M., & Krmça, N. (2024). Artificial intelligence for predictive maintenance applications: Key components, trustworthiness, and future trends. *Applied Sciences*, *14*(2). https://doi.org/10.3390/app14020898 (cit. on p. 17).

Van der Auweraer, S., Boute, R. N., & Syntetos, A. A. (2019). Forecasting spare part demand with installed base information: A review. *International Journal of Forecasting*, *35*(1), 181–196. https://doi.org/10.1016/j.ijforecast.2018.09.002 (cit. on p. 19).

Visnjic, I., Neely, A., & Jovanovic, M. (2018). The path to outcome delivery: Interplay of service market strategy and open business models. *Technovation*, *72–73*, 46–59. https://doi.org/10.1016/j.technovation.2018.02.003 (cit. on p. 22).

Vorst, P., & Yohn, T. L. (2018). Life cycle models and forecasting growth and profitability. *Accounting Review*. https://doi.org/10.2308/accr-52091 (cit. on p. 16).

Wiesner, S., Freitag, M., Westphal, I., & Thoben, K.-D. (2015). Interactions between service and product lifecycle management. *Procedia CIRP*, *30*, 36–41. https://doi.org/10.1016/j.procir.2015.02.018 (cit. on p. 22).

Zhang, S., Huang, K., & Yuan, Y. (2021). Spare parts inventory management: A literature review. *Sustainability*, *13*(5), 2460. https://doi.org/10.3390/su13052460 (cit. on pp. 17, 18, 31).

A

Appendix

A.1 Search String Review Matrix

Theme	Search Terms	Hits	Relevant Papers
Lifecycle Revenue Management	"lifecycle revenue", "aftermarket revenue B2B", "servitization manufacturing"	150	15
Spare Parts	"spare parts strategy", "aftermarket B2B logistics", "service parts planning"	120	20
Forecasting	"spare parts forecasting", "intermittent demand", "machine learning forecast"	200	25
End-of-Life (EOL)	"EOL planning", "last time buy decision", "product phase-out strategy"	80	12
Strategic Aftermarket / PLM	"aftermarket planning PLM", "service lifecycle integration"	130	18

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