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Doctoral School IAEM Lorraine

Integrated Optimisation Informed by Predictive Models in a Sustainable, Carbon-Conscious Supply Chain with Reverse Logistics

DISSERTATION

Publicly presented and defended on **12/12/2025**

For the degree of

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(Automation, Signal and Image Processing, Computer Engineering)

By

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lgipm Laboratoire de Génie Informatique, de Production et de Maintenance

LGIPM - Laboratoire de Génie Informatique, de Production et de Maintenance

Dedication

To my parents, brothers, and sister, whose unwavering love and sacrifices have shaped the person I have become.

To my husband, son, and daughters, for their constant encouragement and steadfast support throughout this journey.

To my mentors, who believed in me even when I faltered in self-belief.

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Table of Contents

General Introduction **8**

Chapter 1: State of the Art and Thesis Problem Statement **12**

1.1 Introduction **13**

1.2 Supply Chain **13**

1.2.1 Supply chain: State of art 13

1.2.2 Reverse Supply Chain 14

1.2.3 Manufacturing-Remanufacturing Supply Chain (MRSC) 15

1.2.4 Supply Chain Optimisation 16

1.3 Transportation in the Supply Chain **17**

1.3.1 Transportation: Role and Importance 17

1.3.2 Transportation Strategies in the Supply Chain 17

1.3.3 Transportation Planning and Optimisation 17

1.4 Inventory Management in the Supply Chain **18**

1.4.1 Inventory Management: State of the Art 18

1.4.2 Types of Inventory Stocks in the Supply Chain 19

1.4.3 Inventory Planning and Optimisation 19

1.5 Procurement in a Supply Chain **20**

1.5.1 Raw Material Procurement: State of the Art 20

1.5.2 Raw Material Procurement Strategies 20

1.5.3 Procurement Planning in a Supply Chain 21

1.6 Sustainability in a Supply Chain: Environmental Impact **22**

1.6.1 Sustainable and Carbon-conscious Supply Chain 22

1.6.2 Low-Carbon Manufacturing Remanufacturing Supply Chain 23

1.6.3 Carbon Emission Policies in a Supply Chain 23

1.6.4 Integrating Carbon into Supply Chain Optimisation 24

1.7 Maintenance Concept in a Supply Chain **26**

1.7.1 Maintenance: Generalities 26
1.7.2 Types of Maintenance 26
1.7.3 Maintenance Policies 28
1.7.4 Degradation Models 29
1.7.5 Maintenance and Transport Coupling Optimisation 30
1.8 Machine Learning: Prediction and Data-Driven Optimisation 32
1.8.1 Machine Learning in a Supply Chain 32
1.8.2 Predictive Models for Forecasting in the Supply Chain 32
1.8.3 Data-Driven Optimisation in the Supply Chain 34
1.9 Integrated Optimisation Models in a Supply Chain 35
1.10 Scientific Positioning 35
1.11 General Objective and Thesis Problem Statement 38
1.12 Conclusion 38
Chapter 2: Integrated Multi-Period Planning of Acquisition, Manufacturing, Remanufacturing, and Transport in a Supply Chain with Reverse Logistics 40
2.1 Introduction 41
2.2 Problem Description and Working Assumptions 42
2.2.1 System Description 42
2.2.2 Notations 44
2.2.3 Working Assumptions 47
2.3 Analytical Study 48
2.3.1 Model Formulation Under Simplified Acquisition Strategy 48
2.3.2 Model Formulation Under Contract-Based Acquisition Strategy 60
2.4 Numerical Studies 64
2.4.1 Input Parameters 64
2.4.2 Obtained Results 67
2.5 Conclusion 73
Chapter 3: Integrated Multi-Period Planning of Acquisition, Manufacturing, Remanufacturing, and Transport in a Carbon-Conscious Supply Chain with Reverse Logistics 75
3.1 Introduction 76

3.2 Problem Description and Working Assumptions 77
3.2.1 System Description 77
3.2.2 Notations 79
3.2.3 Working Assumptions 80
3.3 Analytical Study 81
3.3.1 Mathematical Formulation of Profit Under Carbon Tax Strategy 81
3.3.2 Mathematical Formulation of Profit Under Carbon Cap-and-Trade Strategy 83
3.3.3 Mathematical Formulation of Profit Under Carbon Limit-and-Subsidy Strategy 83
3.4 Numerical Studies 85
3.4.1 Input Parameters 85
3.4.2 Obtained Results 86
3.5 Conclusion 93
Chapter 4: Integrated Optimisation of Vehicle Maintenance and Transport within a Supply Chain with Reverse Logistics 96
4.1 Introduction and Literature Review 97
4.2 System Description and Modelling Assumptions 98
4.2.1 Vehicle Problem Description 99
4.2.2 Notations and Definitions 100
4.2.3 Modelling Assumptions 101
4.3 Analytical Study 101
4.3.1 Mathematical Formulation of the Total Cost of Maintenance Actions 102
4.3.2 Average Number of Failures During Maintenance Cycle 102
4.3.3 Average Failures Between Last Preventive Maintenance and End of Horizon 103
4.4 Numerical Results 104
4.4.1 Input Parameters 104
4.4.2 Obtained Results 105
4.5 Theoretical and Managerial Implications of the Model 109
4.6 Conclusion 110
Chapter 5: Data-Driven Predictive Modelling and Integrated Optimisation for Multi-Period Planning in a Carbon-Conscious Supply Chain with Reverse logistics 112

5.1 Introduction 113
5.2 Problem Description and Working Assumptions 114
5.3 Analytical Model 116
5.3.1 Notations and Decisions Variables 116
5.3.2 Total Expected Profit Formulation 117
5.4 Prediction and Optimisation Approach 122
5.4.1 Two-Stage Framework Approach 122
5.4.2 Case Study and Prediction Results 123
5.5 Numerical Studies 132
5.5.1 Input Parameters 132
5.5.2 Obtained Results 132
5.6 Conclusion 139
General Conclusion 141
References 143

List of Tables

Table 1.1. Carbon emissions policies and agreements in carbon-conscious supply chains 25
Table 1.2. Integrated maintenance-transport optimisation techniques 33
Table 1.3. Frequent forecasting methods in recent studies 34
Table 1.4. Classification dimensions of integrated optimisation models 36
Table 1.5. Scientific positioning 37
Table 2.1. Demands and returns data ($Z = 24$) 66
Table 2.2. Necessary data for coding 66
Table 2.3. Initials values 66
Table 2.4. Optimal plans under Simplified Acquisition Strategy ($Z = 24$) 68
Table 2.5. Additional results under Simplified Acquisition Strategy ($Z = 24$) 68
Table 2.6. Optimal plans with Fixed Lot Procurement ($Z = 24$) 70
Table 2.7. Additional results with Fixed Lot Procurement ($Z = 24$) 71
Table 2.8. Optimal plans under Hybrid Procurement Agreement ($Z = 24$) 72
Table 2.9. Additional results under Hybrid Procurement Agreement ($Z = 24$) 72
Table 3.1. Environmental impact input parameters 86
Table 3.2. Optimal plans with *ucp*=0.1 ($Z = 24$) 88
Table 3.3. Additional results with *ucp*=0.1 ($Z = 24$) 88
Table 3.4. Optimal plans with *cct=2* and *cap*=110000 units ($Z = 24$) 89
Table 3.5. Additional results with *cct*=2 and *cap*=110000 units ($Z = 24$) 89
Table 3.6. Optimal plans with *LIMC* =95000 and *S* =30000 ($Z = 24$) 91
Table 3.7. Additional results with *LIMC* =95000 and *S* =30000 ($Z = 24$) 91
Table 3.8. Regulated versus Non-Regulated Scenarios 94
Table 4.1. Input parameters (Initial Setup) 104
Table 4.2. Numerical results for n from 1 to 60 months 106
Table 4.3. Effect of varying preventive maintenance cost (*PM*) 109
Table 4.4. Effect of varying corrective maintenance cost (*CM*) 110
Table 5.1. Collected data during 60 periods 125
Table 5.2. Comparison of metrics results 131
Table 5.3. Predicted demand and returned products 131
Table 5.4. Input parameters for coding 133
Table 5.5. Initials values for coding 133
Table 5.6. Optimal plans with *ucp*=0 (Z=24) 134
Table 5.7. Additional results with *ucp*=0 ($Z = 24$) 134
Table 5.8. Trade-off among carbon emission reduction, economic performance, and service levels 138

List of Figures

Figure 1.1. Forward and reverse supply chain 15
Figure 1.2. Thematic analysis through strategic map 24
Figure 1.3. Weibull hazard function for different β values 27
Figure 1.4. Evolution of failure rate over time by maintenance type 28
Figure 1.5. Discrete degradation model/continuous degradation model 30
Figure 1.6. Balance between corrective and preventive maintenance 31
Figure 2.1. Integrated manufacturing–remanufacturing system with logistics and reverse flow 43
Figure 3.1. Carbon-conscious supply chain with reverse logistics 79
Figure 4.1. The evolution of the vehicle's failure rate 100
Figure 4.2. Evolution of the total average cost *TMC* according to *n* 108
Figure 4.3. Evolution of the expected number of failures according to *n* 108
Figure 5.1. Comprehensive carbon-conscious supply chain 115
Figure 5.2. Prediction and optimisation approach 122
Figure 5.3. Prediction process 124
Figure 5.4. Time-series plot for *dnp*(*k*), *drp*(*k*), and *rup*(*k*) 124
Figure 5.5. VAR prediction 127
Figure 5.6. SARIMA prediction 128
Figure 5.7. SARIMA–VAR prediction 128
Figure 5.8. LSTM prediction 129
Figure 5.9. HWES prediction 130
Figure 5.10. Impact of carbon tax pricing on total carbon footprint and profit 135
Figure 5.11. Impact of emission targets on profitability 137
Figure 5.12. Effect of carbon constraints on service level and demand fulfilment 137

General Introduction

In the context of a rapidly changing industrial landscape, supply chains have evolved from linear, functionally isolated structures to highly dynamic, interconnected networks (Xu et al., 2024). This shift has been influenced by a number of factors, including technological advancement, environmental pressures (Gryparis et al., 2025), globalisation, and the increased focus on sustainability and circularity (Rahaman et al., 2024). Traditional approaches that prioritised cost-effectiveness and delivery speed have steadily proven insufficient for the complex issues of modern production systems (Ni et al., 2025). Rather, it is now crucial to have a thorough understanding of how procurement, manufacturing, remanufacturing, transportation, inventory, maintenance, and sustainability are all interdependent. The current dissertation discusses the need for integrated, data-driven, and environmentally responsible models that can guide strategic decision-making in complex supply-chain environments within this framework.

The study's theoretical and conceptual foundations are laid out in the first chapter, which also examines the development of supply-chain management from linear to circular and networked models that incorporate reverse logistics. It highlights how operations are increasingly incorporating resilience, sustainability, and digital transformation. Although optimisation techniques are frequently used in production, inventory, transportation, and procurement, they are frequently researched separately. The absence of an integrated framework that integrates operational reliability, environmental responsibility, and economic performance is identified as a major research gap in this chapter. It suggests creating and validating a comprehensive optimisation model that facilitates multifunctional and sustainability-focused decision-making in order to close this gap.

A comprehensive multi-period optimisation model that collaboratively plans manufacturing, remanufacturing, acquisition, and transportation within a supply chain with reverse logistics network is presented in the second chapter. The model, which was created as a Mixed-Integer Linear Programming (MILP) framework, seeks to maximise total profit while satisfying resource, demand, and operational constraints. The analysis also looks at the effects of different procurement strategies on system flexibility and profitability, including fixed-lot and hybrid agreements. The

findings highlight the advantages of coordinated decision-making by illustrating how coordinating logistics and acquisition planning can reduce expenses, enhance service quality, and maximise resource utilisation. Therefore, this chapter offers a strong methodological foundation for expanding the framework to incorporate sustainability goals in later sections.

Chapter three adds environmental factors, particularly carbon emissions, to the optimisation framework. It recognises that in addition to financial performance, modern supply chains must now be assessed on environmental compliance and carbon reduction goals. The model examines three types of policies: the Carbon Tax, Cap-and-Trade, and Limit-and-Subsidy, that take production, transportation, and inventory emissions into consideration. Through comparative numerical analysis, the chapter demonstrates how carbon policies improve operational efficiency and sustainability over time, even though they may slightly reduce short-term profits. Cap-and-trade is the approach that best balances economic and environmental objectives. Consequently, this chapter advances the concept of carbon-conscious optimisation and provides useful data to practitioners and policymakers who seek to strike a balance between competitiveness and regulatory responsibility.

Chapter Four furthers the research by integrating maintenance planning into the broader framework of supply-chain optimisation. Beyond earlier models that assumed perfect vehicle availability, it acknowledges the realities of deterioration, malfunctions, and variable reliability in transportation systems. By incorporating both preventive and corrective maintenance strategies, the model increases realism and examines their effects on operational stability and cost-effectiveness. The findings demonstrate that maintenance is more than just a technical necessity. It is a strategic decision that affects sustainability and overall performance. Effective preventive maintenance reduces emissions, extends equipment life, and boosts efficiency. In order to achieve long-term sustainability, this chapter highlights the importance of treating maintenance and transportation as interconnected parts of an integrated logistics strategy and the need for proactive, data-driven system reliability management.

In the last chapter, these developments are synthesised in a comprehensive, data-driven optimisation framework for a carbon-conscious reverse supply chain. It extends the analytical models to forecast demand and return flows using predictive forecasting techniques, specifically hybrid SARIMA–VAR models. When forecasted data is directly integrated into the optimisation

process, the system becomes adaptive to uncertainty, improving planning accuracy and responsiveness. The integration of contract-based transport operations, capacity-limited facilities, and urban collection centres demonstrates a realistic alignment with real-world logistics environments. Furthermore, the model assesses how global policy frameworks impact supply-chain decisions by incorporating carbon-tax mechanisms and international environmental commitments like the Paris Agreement. By showing how data-driven optimisation can support the sustainable and profitable operation of complex logistics networks, the methodological and analytical developments discussed in this chapter highlight the dissertation's contribution to closing the gap between theoretical modelling and operational practice.

All things considered, this dissertation makes theoretical and practical advances in supply-chain management and operational research. It develops several multi-period integrated optimisation models that integrate economic, environmental, and maintenance considerations into a unified decision-making framework. The study demonstrates that supply chains can achieve a balance between sustainability and profitability when they are guided by coordinated, model-based decision-making supported by accurate forecasting. The analytical results provide useful information for industry practitioners and emphasise the benefits of integrating maintenance schedules, carbon management, and reverse logistics into long-term planning. From an academic perspective, the dissertation expands on existing optimisation theory by adding multi-dimensional and data-driven components to traditional models, thereby deepening our understanding of sustainable and circular supply-chain systems.

In summary, the overall goal of this research is to support the creation of reliable, flexible, and ecologically conscious optimisation tools that satisfy the demands of today’s industrial systems. In order to support the continuous transformation of global supply chains towards sustainability, circularity, and long-term competitiveness, the work presented in this dissertation integrates operational resilience, economic performance, and responsible environmental management. Lastly, this manuscript will conclude with a general conclusion and perspectives. Two international conferences (ICNSC 2023 and MIMAR 2025) have discussed the work presented in this thesis, and on February 23, 2025, a review paper was published in Supply Chain Forum: An International Journal, and on June 5, 2025, a research paper was published on Sustainability.

Chapter 1: State of the Art and Thesis Problem Statement

Abstract

An overview of the fundamental concepts and current developments that serve as the foundation for this study is provided in this chapter. It begins by introducing modern supply chains and detailing how they have developed into complex, interconnected systems. With a focus on the optimisation methods used for each, the discussion examines significant aspects of supply-chain design and operation, such as procurement management, inventory management, transportation, manufacturing-remanufacturing interactions, and reverse logistics. Sustainability is analysed from an economic and environmental perspective, showing how optimisation methods may achieve a balance between accountability and performance. The chapter also examines strategies for reducing carbon emissions and how supply-chain optimisation frameworks incorporate them. Predictive models and machine learning are becoming more and more important because of their capacity to enhance real-time decision-making, and forecasting. Maintenance strategies and how they enhance system performance are also discussed. It then presents a synthesis of integrated optimisation approaches, categorizing them based on scope, objectives, and solution methods. The chapter concludes with the formulation of the research problem, the general objective, and the scientific positioning of the thesis.

1.1 Introduction

In the quickly evolving industrial landscape of today, supply chains are dynamic systems composed of numerous interdependent components rather than being linear or isolated. To effectively manage them, one must consider factors other than price or speed. It necessitates a more thorough comprehension of the relationships and effects between procurement, production, transportation, inventory, maintenance, and sustainability. This chapter takes a step back to examine the broader picture, previous work in the field, ongoing difficulties, and the relevance of this research. Starting with a general overview of supply chains, we examine their evolution from conventional models to more circular systems that incorporate remanufacturing and reverse logistics (Rouhani et al., 2025).

Next, we focus on the logistics aspect, where inventory and transportation are essential to maintaining order (Ke et al., 2025). Not only are these chain components functional, but they also serve as decision-making points that impact the overall system's performance. Another important issue is sustainability. Today's supply chains have to reduce their negative effects on the environment while maintaining their financial viability (Salame, 2020). Models that balance costs, emissions, and service quality have been proposed by researchers (Nweje and Taiwo, 2025). Frequently neglected, maintenance also contributes strategically to this balance by extending asset life, decreasing downtime, and promoting resource efficiency (Thomas et al., 2022). The need for integrated approaches that take into account several functions at once and optimise them all at once is growing as supply chains get more complicated (Syofra et al., 2025). Before outlining the scientific positioning of the research, its overall goal, and the specific problem this thesis seeks to address, this chapter examines the most recent work on that front.

1.2 Supply Chain

1.2.1 Supply chain: State of art

A supply chain is the entire network that connects manufacturers, suppliers, transporters, warehouses, and consumers via an ongoing transfer of products, data, and services (Ivanov and Dolgui, 2020). Procurement is the first step, followed by production and distribution, and customer delivery and service at the end. In order to make supply chains more sustainable and in line with

the objectives of the circular economy, reverse logistics, such as managing returns, recycling used products, and remanufacturing components, are now crucial (Aguirre Rodríguez et al., 2024). The focus of supply chain research has changed from separate activities like transportation or inventory to more comprehensive, system-wide approaches. It is now crucial to coordinate smoothly at every stage as global networks grow more complex (Jing and Fan, 2024). Recent focus areas, include system reliability and risk management , especially post Covid-19 pandemic, where flexible sourcing and contingency strategies have become priorities (Guo et al., 2024).

Growing regulatory pressure and consumer expectations to reduce emissions and use resources more responsibly have made sustainability a major theme in supply chain management. In this context, green supply chain practices, such as energy-efficient operations, eco-friendly sourcing, and circular product design, are now essential for improving a business's environmental performance (Michael Adekunle et al., 2025). Planning and operations are also changing as a result of data-driven decision-making, which incorporates analytics, AI, and predictive models (Iseri et al., 2025). However, there are still issues with growing logistics costs, regulatory demands, and striking a balance between sustainability, speed, and cost. Most decisions still involve trade-offs. By providing out a combined optimisation framework that incorporates procurement, production, inventory, maintenance, transportation, operational performance, and sustainability, this dissertation addresses these changing demands.

1.2.2 Reverse Supply Chain

Traditional supply chains moved straight from raw materials to manufacturers and then to consumers, paying little attention to end-of-life (Chirumalla et al., 2024) responsibilities. In order to facilitate circular economy strategies and measurable sustainability gains, reverse logistics now manages the backward flow of used products for repair, refurbishment, recycling, remanufacturing, or safe disposal (see Figure 1) (Abassi et al., 2023). This paradigm shift comes after stricter environmental regulations and expectations (Butt et al., 2023). It is commonly defined as the planning, implementation, and management of efficient, cost-effective return flows and information from use back to origin in order to recover value or ensure proper disposal (Namweseza et al., 2025). Reverse chains, especially in the electronics, automotive, and pharmaceutical sectors, operationally collect, sort, and inspect EOL items before directing them towards reuse, remanufacturing, or disposal in accordance with quality and regulatory standards

(Che Hassan, 2025). Unlike forward flows, returns can occur in an unpredictable quantity, timing, and condition, which increases the variability of processing and design decisions (Ji-Hyland et al., 2025). Leading businesses incorporate reverse activities with core operations to minimise reliance on virgin materials and the associated consequences. This ensures that returns quickly feed recycling and remanufacturing (Li et al., 2025a).

Strategic reverse logistics is a crucial part of sustainable supply-chain design because it reduces waste and costs, encourages compliance, and can differentiate market offerings despite problems with infrastructure, processing costs, and stochastic returns (Salas-Navarro et al., 2024).

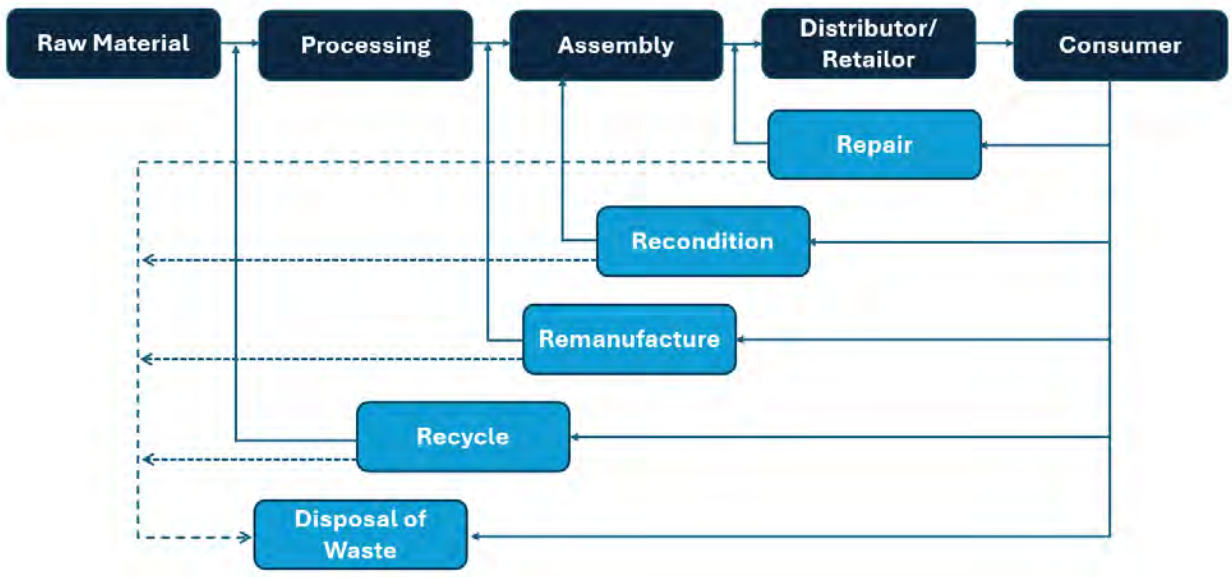

Figure 1.1. Forward and reverse supply chain

1.2.3 Manufacturing-Remanufacturing Supply Chain (MRSC)

Used products are gathered, examined, and remanufactured by the MRSC, which combines forward production with structured return flows. The system frames end-of-life as a renewed production opportunity rather than a terminal one, preserving economic value while recovering materials and embedded value, reducing primary inputs, and minimising the impact on the environment. Strong cross-functional coordination is essential for effective MRSCs. Remanufacturing teams must deal with irregular quantities, variable quality, and technically challenging restoration; manufacturers require visibility into return timing and composition. Although consumer acceptance and supportive take-back regulations continue to be crucial

enablers, early adoption has been strongest in the automotive, electronics, and heavy equipment industries where remanufactured units (such as engines) can match new-product performance at lower cost and footprint (Alam et al., 2025).

From a logistics perspective, reverse flows complicate planning, inventory, and capacity. However, when paired with procurement and production, remanufacturing replaces virgin inputs with recovered components, improving responsiveness, relieving pressure on limited resources, and decreasing costs (Yu et al., 2021). As resource limitations grow and carbon regulations become more stringent, MRSCs are not only environmentally responsible architectures but also strategically robust ways for reliable, cost-effective operations.

1.2.4 Supply Chain Optimisation

Supply chain optimisation is no longer a goal, but a necessity. Businesses must coordinate procurement, production, inventory, and logistics as one interdependent system in the face of growing costs, more stringent environmental regulations, and fluctuating demand. Each node's decisions affect the others (Ivanov and Dolgui, 2020). Cost minimisation is no longer the only goal; a balanced frontier of cost, speed, flexibility, and sustainability is now the goal.

The field employs stochastic, multi-objective, and mixed-integer linear programming models to navigate real trade-offs, such as service levels versus emissions or inventory buffers versus disruption risk, in order to create implementable, system-wide policies (Seifbarghy et al., 2024). Machine learning and predictive modelling bring about yet another step-change: LSTM (Long Short-Term Memory) networks, random forests, and associated tools enhance demand forecasting, risk identification, and dynamic re-planning, allowing for prompt modifications to production, inventory, and transportation without requiring continual manual intervention (Wilson et al., 2024).

Sustainability is used as a parallel design criterion these days. By combining carbon, energy, and waste metrics with financial performance, green optimisation facilitates choices like less packaging, cleaner routing, circular flows, and recovery options (Hasan et al., 2024). All things considered, effective supply chains are open and flexible, capable of making adjustments in real time, and able to strike a balance between operational resilience, environmental responsibility, and competitive cost control.

1.3 Transportation in the Supply Chain

1.3.1 Transportation: Role and Importance

Transportation plays a critical role in modern supply chains, facilitating a smooth transfer of materials and products from suppliers to end users. It connects all stages, including production, distribution, returns, and procurement, and it directly affects sustainability, dependability, and cost effectiveness (Badakhshan et al., 2024). Any disruption in transport can have a negative impact on the entire system, delaying production and increasing costs, even though efficient transport management can give an advantage over competitors (Karmaker et al., 2021). Nowadays, environmental responsibility is given more weight when discussing transportation. Businesses are employing green logistics techniques, like reducing down on unnecessary travel, using vehicles with reduced emissions, and optimising their routes (Hsu and Lo, 2026). The design of the supply chain is influenced by strategic transport planning, which also affects sourcing and warehouse placement choices (Pinheiro et al., 2025). As a result, transportation is no longer a passive function, it is now a strategic pillar of operational and environmental performance.

1.3.2 Transportation Strategies in the Supply Chain

When choosing a transportation plan, it is important to carefully consider cost, speed, reliability, and environmental impact. Road freight still dominates short- to medium-distance transportation because of its flexibility and true door-to-door reach, but it also has externalities like emissions and congestion that need to be actively managed (Varghese and Pradhan, 2025). Both chronic undercapacity and excess capacity increase fuel consumption, unit costs, and variability, while compromising service quality; fleet size and load utilisation are important levers (Omidkar et al., 2025, Bahamazava, 2025). Based on market conditions, asset intensity, demand trends, and risk tolerance, businesses strategically evaluate contract carriage, private fleets, and third-party logistics (3PL) (Hsu and Lo, 2026). By cutting waste, lowering total landed costs, and increasing responsiveness, an efficient transport strategy turns logistics from a cost centre into a source of sustained competitive advantage (Wang et al., 2025b, Zheng and Wang, 2025).

1.3.3 Transportation Planning and Optimisation

Through transportation planning, logistics operations are synchronised with cost, service, and environmental goals. Decisions regarding carrier selection, load distribution, and vehicle

routing must be made in order to transport goods efficiently while reducing emissions (Arisoy et al., 2025). Poor planning results in fuel waste and delays, but route optimisation improve punctuality and reduce total travel time (Das et al., 2024).

By integrating inventory and demand forecasting with transport planning, businesses can reduce emergency shipments and anticipate needs (Qian et al., 2022, Ngoc Anh Nguyen et al., 2026). Furthermore, load consolidation increases capacity utilisation, which lowers carbon emissions per shipment (Rajabzadeh and Mousavi, 2023). In the end, well-optimised transportation systems enhance supply chains that are robust, sustainable, and profitable.

1.4 Inventory Management in the Supply Chain

1.4.1 Inventory Management: State of the Art

These days, inventory is a strategic lever that links production, distribution, sourcing, and customer service across unstable, eco-friendly supply networks, acting as more than just a buffer. The difficulty lies in keeping a sufficient supply of raw materials, components, finished products, and spare parts to ensure service and continuity while minimising overall expenses and environmental impact (Palanivel et al., 2025). Nowadays, timing and placement, the right stock, in the right place, with the right responsiveness, are more crucial than quantity alone.

Modern practice uses multi-echelon optimisation and real-time visibility, to balance variability and synchronise upstream and downstream plans across geographies (Zabraoui et al., 2025, Zhang and Meng, 2025). Dynamic policies now strive for a feasible middle ground in accordance with service commitments and carbon targets, as excess stock ties up capital and increases obsolescence and waste, while shortages reduce revenue and dependability (Wu et al., 2024). Reverse inventories, returns, items for repair, remanufacturing cores, and recyclables are all included in the inventory scope in circular settings in order to recover value and reduce disposal (Shin et al., 2025). All things considered, contemporary inventory management combines efficiency, resilience, and sustainability, making it a crucial element of supply-chain performance that is competitive and low-impact.

1.4.2 Types of Inventory Stocks in the Supply Chain

In a supply chain with reverse logistics, inventory is present at several stages to ensure availability, maintain flow, and reduce costs. Raw material inventory guarantees production continuity, while work-in-process (WIP) stock reduces production delays and congestion (Orlando et al., 2022). On-time customer deliveries are made easier by completed goods inventory, and urban warehouse stocks situated close to customers enable faster response times and lower emissions associated with transportation.

In reverse logistics, returned products inventory handles products that are pending inspection, repair, or disposal, whereas repairable inventory maintains items undergoing remanufacturing procedures to recover value. Remanufactured product inventory, which links forward logistics and circular operations, is the final stage before redistribution (Motla et al., 2023). Coordinating these inventories across both forward and reverse flows ensures efficient resource use, reduced waste, and improved service reliability which are all crucial elements of sustainable manufacturing and supply-chain performance.

1.4.3 Inventory Planning and Optimisation

Inventory planning determines what, where, and when to stock items in order to efficiently meet demand. It incorporates forecasting, stock allocation, and order scheduling to balance service levels and expenses (Reyana and Kautish, 2024). Modern optimisation tools employ network-level strategies, such as multi-echelon models, to reduce overall inventory levels while maintaining responsiveness at every supply-chain level (Charaf et al., 2024).

Sustainability considerations are increasingly being incorporated since maintaining excess inventory raises not only financial costs but also has an adverse effect on the environment due to waste and energy use. Companies now include carbon metrics and circular principles in their optimisation models (de Souza et al., 2025). Reverse inventory planning, which covers returned, repaired, and remanufactured goods, is equally important for supply chains with reverse logistics (Turki et al., 2025). As a result, inventory optimisation is now both an operational and environmental requirement and enhances agility, cost effectiveness, and resilience in modern supply networks.

1.5 Procurement in a Supply Chain

1.5.1 Raw Material Procurement: State of the Art

Raw material procurement in supply chains is a foundational process involving cost management, supplier selection, sustainability, risk mitigation, and strategic integration which directly impacting operational efficiency, cost control and competitiveness (Luo et al., 2025). Multiple references confirm that procurement is the supply chain's front line, protecting the resources that production, inventory, and logistics depend on and establishing the benchmark for cost control, service reliability, and sustainability (Tubis and Werbinska-Wojciechowska, 2025a, Hafish et al., 2024).

It performs two purposes. Raw material procurement strategically defines sourcing strategies, qualifies suppliers, and balancing single and multiple sourcing to combine resilience to disruption with collaboration on critical items (Luo et al., 2025). Operationally, it aligns capacity, cash flow, and material availability by coordinating purchases with inbound transportation, safety stocks, and production plans (Ghanbari et al., 2025).

These days, operations and the unstable input markets are coordinated through the procurement of raw materials. It employs multi-tier traceability to determine what is bought and from whom, resilient contracting to guarantee supply assurance, and circularity metrics to demonstrate sustainable performance (Riemens et al., 2023, Deka et al., 2025, Zhou and Xu, 2024).

1.5.2 Raw Material Procurement Strategies

Modern procurement integrates strategic sourcing choices with cautious purchasing guidelines to balance cost, reliability, and sustainability in the face of volatility. Businesses employ either single or multiple sourcing in terms of structure; the former allows for close technical collaboration on important items, while the latter protects against the risk of disruption (Yousefi et al., 2025). While resilience building adds real-time visibility and data-driven re-planning to absorb shocks from demand, price, or supply, green sourcing connects supplier selection with emissions, certification, and circularity goals (Chotia et al., 2026).

Day-to-day operations are based on three complementary policy families: hybrid strategies that secure a base load under fixed agreements and add flexible "top-ups" from secondary or

alternative sources to manage spikes, quality variability, or sustainability targets; fixed lot-size strategies that provide price and schedule stability for predictable items; and flexible strategies that vary quantities, timing, and pricing through the use of options, capacity reservations, indexed contracts, dual sourcing, and dynamic lot-sizing. Together, these strategies turn procurement into a well-coordinated system that fulfils environmental commitments, reduces overall costs, and safeguards service and continuity.

1.5.3 Procurement Planning in a Supply Chain

Procurement planning is the operational cornerstone that transforms strategic sourcing decisions into feasible, time-sensitive supply programs. It involves determining what materials are required, when they are required, and which suppliers will supply them in order to guarantee a consistent flow of resources to support production and distribution activities. (Reyana and Kautish, 2024). By coordinating purchases with production schedules, inventory regulations, and transportation limitations, an effective procurement plan increases cost effectiveness and service dependability (Jubiz-Diaz et al., 2025). The state-of-the-art in supply chain planning for raw material procurement is characterised by integrated, financially informed, and technologically enabled approaches (Mohammadi and Tosarkani, 2026, Yuan and Wang, 2025). Together, these strategies increase supply chain resilience, efficiency, and competitiveness in an increasingly complex and unstable global marketplace.

Businesses can now evaluate the environmental impact of sourcing decisions in addition to cost and lead-time metrics thanks to the growing incorporation of sustainability considerations into procurement planning models (Nwobi et al., 2025). Planning the procurement process is crucial to achieving operational resilience and sustainability in this context (Tan et al., 2025a). As industries deal with growing regulatory pressures and uncertainty, integrated procurement planning, which links forecasting, inventory, and supplier management, has become crucial for maintaining competitive advantage in modern supply networks (Alvarez et al., 2022).

1.6 Sustainability in a Supply Chain: Environmental Impact

1.6.1 Sustainable and Carbon-conscious Supply Chain

Sustainability evolved from compliance to a crucial strategy in supply-chain management. Businesses are now incorporating environmental goals into their production, logistics, and procurement processes to reduce their impact and boost resilience and efficiency (Sharifpour Arabi et al., 2025). Recent literature and industry reports confirm that the carbon-conscious supply chain, sometimes referred to as green or sustainable, focusses on quantifiable carbon dioxide equivalent CO_2e performance across all three GHG Protocol scopes. Scope 1 represent the direct on-site/process emissions, Scope 2 represent the emissions from purchased electricity and heat, and the Scope 3 represent the upstream/downstream value-chain emissions (Mubarik, 2023).

Recent work highlights three imperatives: integration (aligning sourcing, network design, operations, and reverse flows with carbon targets), transparency (supplier data, product footprints, and verifiable reporting), and innovation (digital monitoring and multi-objective optimisation to balance cost, service, and emissions). These trends are strongly supported by recent research and industry practices, which highlight the importance of integration, transparency, and innovation in modern sustainable supply chain management (Belhadi et al., 2024) (Ouassou et al., 2024) (Lindbergh et al., 2024).

Businesses are rethinking transportation and facilities, optimising loads and routes, switching to fuels and modes that produce fewer emissions, and integrating renewable energy into their operations, according to (Liu et al., 2025c), (Tan et al., 2025b) and (Kimuli et al., 2025). Market mechanisms that incentivise verified reductions, such as emissions trading systems, and policy tools that price emissions, such as carbon taxes, support these changes.

Sustainability enhances brand credibility, increases access to carbon-conscious markets, and lowers regulatory exposure as carbon metrics are incorporated into supplier selection and site selection choices (Shaik et al., 2025). All things considered, supply chains that are carbon-conscious connect long-term financial and operational performance with environmental responsibility.

1.6.2 Low-Carbon Manufacturing Remanufacturing Supply Chain

The implementation of low-carbon manufacturing–remanufacturing supply chains, or MRSCs, is one of the most promising paths to carbon neutrality. By incorporating remanufacturing into production loops, companies can recover value from used products, save materials, and significantly decrease emissions (Zhu et al., 2026, Zhou et al., 2024). Recent studies show that remanufacturing, particularly in the electronics and automotive sectors, can cut emissions by up to 80% when compared to traditional manufacturing (Bai and Luo, 2025). Carbon pricing mechanisms like cap-and-trade and carbon taxes promote these circular strategies by increasing the cost of carbon-intensive operations (Dimic et al., 2024). Effective MRSCs depend on IoT-enabled tracking (Internet of Things) and emissions monitoring systems, which let companies decide when local remanufacturing is more ecologically friendly than global production (Vishwakarma et al., 2025).

In the literature many recent studies also claim that low-carbon MRSCs support economic and environmental objectives by aligning with the Paris Agreement targets and the circular economy principles, thereby facilitating the transition to climate-resilient and resource-efficient operations (Kundu and Goh, 2024) (Mohsin et al., 2024). According to the figure 1.2 from our study published in Supply Chain Forum: An International Journal (Abassi et al.) supply chain optimisation research under carbon constraints is based on decisions about remanufacturing and reverse logistics. While reliability-aware optimisation is a new trend, the mainstream consists of models that are coupled with policies (carbon taxes and market mechanisms) and circular economy formulations.

1.6.3 Carbon Emission Policies in a Supply Chain

Researchers focus on managing carbon emissions in supply chain networks under five major policies: carbon taxes, carbon cap-and-trade, carbon subsidies, carbon offsetting and carbon constraints. The table 1.1 summarise and synthesise the main carbon emissions policies and agreements relevant to carbon-conscious supply chains, focusing on pricing, limits, and subsidies, and their alignment with the Paris Agreement.

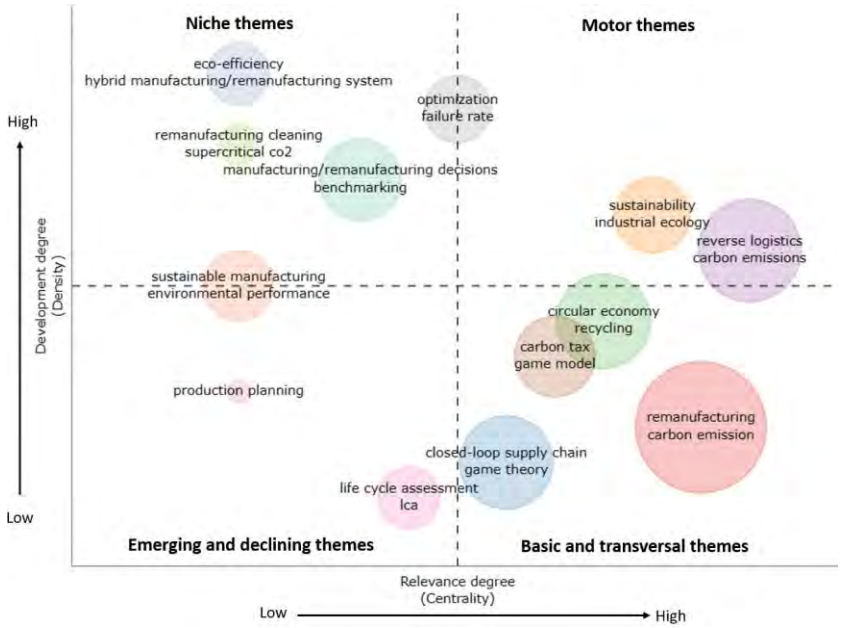

Figure 1.2. Thematic analysis through strategic map

1.6.4 Integrating Carbon into Supply Chain Optimisation

As sustainability gains strategic importance, supply-chain design now prioritises environmental optimisation along with cost and service performance. Businesses are using multi-objective optimisation frameworks to decrease emissions, waste, and energy use while maintaining profitability (Dalal et al., 2024). According to recent references (Yuniarti et al., 2025) (Lyu and Liu, 2025), incorporating carbon into supply-chain optimisation through advanced optimisation models and carbon policies is a well-established and growing field, with a range of approaches. It demonstrated impacts on economic and environmental outcomes.

Key practices, like multi-objective optimisation models, are used to analyse trade-offs between carbon emissions and operating costs in order to support decision-making that is consistent with both economic and environmental goals. In this context, (Lyu and Liu, 2025) addressed the necessity to find a balance between economic efficiency and environmental benefits as the effects of climate change worsen. In order to achieve equitable profit distribution and carbon emissions reduction responsibilities among supply chain participants, the study focusses on integrating the carbon cap-and-trade policy and the carbon cap-sharing mechanism.

Ultimately, carbon integration transforms sustainability from a reactive goal into a fundamental operational principle that encourages innovation, efficiency, and accountability across the supply chain (Bag et al., 2024).

Table 1.1. Carbon emissions policies and agreements in carbon-conscious supply chains

Policy/ Mechanism	Pricing Mechanism	Limits/Regulation	Subsidies/Incentives	Paris Agreement Link	References
Carbon Tax	Direct tax on emissions; affects wholesale pricing and order decisions.	No explicit cap, but cost pressure reduces emissions.	It can be combined with government incentives for green tech.	Supports Paris goals by reducing emissions.	(Xin et al., 2025) , (Liu et al., 2025b) (Jauhari et al., 2025) (Jiang et al., 2025) (Wang et al., 2024)
Cap-and-Trade	Permit price determined by market; trading allows cost optimisation.	Strict cap on total emissions; flexible compliance via trading.	Revenue from permit sales can be reinvested in green tech.	Aligns with Paris targets for emission reduction.	(Xin et al., 2025) (Liu et al., 2025b) (Jauhari et al., 2025) (Jiang et al., 2025) (Wang et al., 2024)
Carbon Subsidies	Reduces effective cost of green investments; can affect product pricing.	No direct emission cap, but incentives lower emissions.	Direct government subsidies for emission reduction activities.	Encourages innovation to meet Paris goals.	(Xin et al., 2025) (Liu et al., 2025b) (Jauhari et al., 2025)
Carbon Offsetting	Cost of offsets factored into supply chain decisions.	No direct cap but offset ratio can be regulated.	Sometimes incentivised by policy.	Supports net-zero ambitions of Paris Agreement.	(Liu et al., 2025b)
Carbon Constraints	May indirectly affect pricing by limiting production/recycling.	Strict operational limits on emissions.	Not typically subsidy based.	Contributes to Paris-aligned emissions reductions.	(Liu et al., 2025b)

1.7 Maintenance Concept in a Supply Chain

1.7.1 Maintenance: Generalities

These days, maintenance is a key factor influencing supply-chain performance, influencing throughput, reliability, and overall cost. In line with NF EN 13306 (2010), it comprises the technical, administrative, and managerial actions taken across an asset's life cycle to retain or restore required function, embedding maintenance within production and logistics rather than treating it as after-the-fact repair. Its three organising principles, maintain, restore, and assure condition, map to system-level, preventive, and corrective procedures that support service continuity and resilience.

Recent studies have shown that well-designed programs lower life-cycle costs and unplanned downtime while fostering agility and sustainability (Boujarif et al., 2025), (Fošner et al., 2024). The field has been able to move from reactive fixes to proactive asset management thanks to condition monitoring and data-driven planning. Operators trust and decision quality are further enhanced by new explainable predictive-maintenance techniques (Alqaryuti et al., 2025). To sum up, maintenance management has developed into a strategic, technology-enabled role that balances performance across global supply networks, sustainability, and organisational effectiveness.

1.7.2 Types of Maintenance

Preventive and corrective maintenance are selected from the most wideley recognised and implemented maintenance strategies across industries (Sanzana et al., 2024). Both strategies aim to achieve different operational goals. Preventive maintenance (PM) employs planned or condition-based interventions to try to avoid failures, whereas corrective maintenance (CM) restores function after failure (Hamzaoui et al., 2023). The four main subcategories of PM are predictive, condition-based (Tran et al., 2025), scheduled, and systematic maintenance, and each is increasingly supported by intelligent technologies (Chakroun et al., 2023) . According to a recent study by (Saeed et al., 2024), predictive maintenance can increase asset lifespan by up to 20%, decrease maintenance costs by 10% to 40%, and reduce equipment downtime by 50%.

An essential analytical tool for PM is the Weibull distribution, which models failure behaviour over time. Its probability density function (PDF) is as follows:

$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right], t \geq 0$ and its hazard (failure rate) function by:

$$\lambda(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1}$$

where β (shape parameter) defines how failure rates evolve, decreasing (β < 1), constant (β = 1), or increasing (β > 1), and η (scale parameter) represents the characteristic life, when about 63.2% of items have failed.

Maintenance engineers can balance cost and risk by using the Weibull model to determine the optimal intervals for inspections or replacements through data-driven decision-making. Figure 1.3 below shows the Weibull Hazard function for different β values.

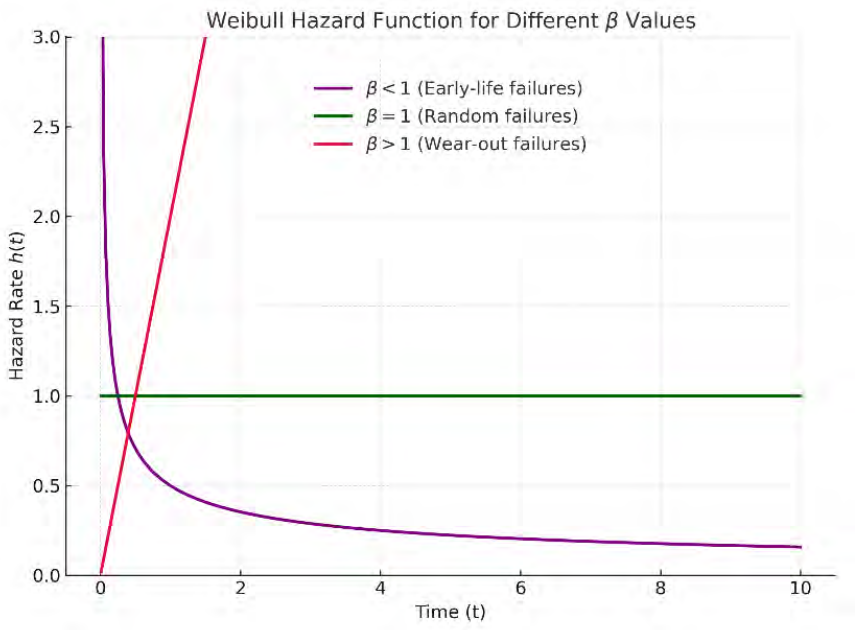

Figure 1.3. Weibull hazard function for different β values

Corrective maintenance, on the other hand, can be carried out right away or delayed based on operational urgency. Three post-maintenance states, perfect ("as good as new"), minimal ("as bad as old"), and imperfect ("as bad as old"), describe varying degrees of restoration (Syamsundar

et al., 2021). Figure 1.4 shows how the failure rate changes over time depending on the type of maintenance action applied. Each maintenance procedure returns the system to "as good as new" condition, bringing the failure rate back to zero in the case of perfect maintenance (blue line). The failure rate drops but does not reach its starting point because the system is only partially restored by the imperfect maintenance (orange dashed line). Lastly, the system's condition is not improved by the minimal maintenance (green dotted line); rather, it only slows down additional deterioration, and the failure rate keeps increasing over time.

Frequent minor repairs may degrade long-term dependability, necessitating planned preventive replacements (Cai and Zhao, 2025). Modern maintenance integrates PM and CM within adaptable frameworks to maximise system resilience and resource utilisation across the supply chain.

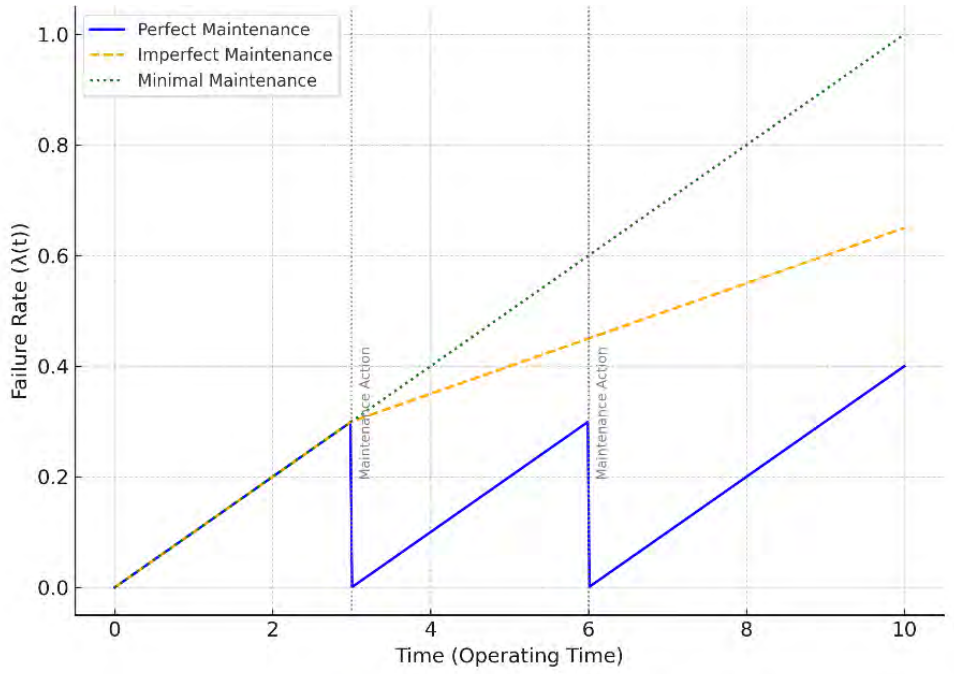

Figure 1.4. Evolution of failure rate over time by maintenance type

1.7.3 Maintenance Policies

Maintenance policies provide organised frameworks for determining when equipment needs to be replaced or repaired in order to ensure dependability and cost effectiveness. The k-out-of-n replacement policy applies to systems consisting of multiple components, meaning that the system

will continue to operate as long as at least k of n of its components are functional. Only small adjustments are made following each failure until the kth one calls for a total replacement. Recent optimisation studies have improved this policy by showing how the proper k value can lower costs and downtime (Zhao et al., 2023).

Combining the number of failures and operating time, the k–T policy suggests minimal repairs for early failures and total replacement if a certain operating threshold T is exceeded (Sheu et al., 2019). By striking a balance between cost and reliability, this hybrid approach increases decision flexibility. Likewise, the age-based replacement policy suggests preventive replacement when a system reaches a certain age, with repairs for failures prior to that (Chien and Zhang, 2024). The ideal replacement age is now dynamically determined by modern analytical techniques using historical data.

The block replacement policy, on the other hand, guarantees predictable maintenance cycles by scheduling replacements at predefined intervals, regardless of condition, but occasionally results in unnecessary expense increases (Chin et al., 2020). Recent studies that incorporated economic factors like inflation into block replacement decision models have improved long-term cost efficiency (Hosamo et al., 2024).

More sophisticated hybrid models, like the combined age-block policy with imperfect repairs, account for partial restorations after maintenance (Hamdan et al., 2021). By combining stochastic and reliability-based modelling, such as point process methods, these techniques more closely resemble real-world operating conditions. All things considered, these evolving regulations demonstrate how maintenance planning is becoming a proactive, data-driven field thanks to digital analytics and mathematical optimisation.

1.7.4 Degradation Models

Degradation is the gradual degradation of an asset's ability to function as a result of use, ageing, or environmental stress. Degradation is defined by AFNOR (2010) as a negative change in an asset's state over time that directly affects system availability, maintenance planning, and lifecycle management. If proper maintenance is not performed, degradation leads to performance loss, unplanned downtime, and a reduction in service quality. There are two primary model types that describe this process. The discrete degradation model depicts degradation as a sequence of

sudden alterations or shocks. Each shift in condition indicates a phase of degradation that approaches equipment failure. These models are particularly useful for systems exposed to irregular stresses or events, like transport or mechanical shocks, and are often represented using stochastic or Markov-based frameworks (Shen et al., 2025).

The continuous degradation model, on the other hand, depicts wear as a slow, quantifiable process that occurs over time. These models enable the prediction of future conditions and remaining useful life by monitoring degradation increments and applying probabilistic laws (Liang et al., 2023). Engineers can more accurately forecast failures and schedule interventions before critical degradation levels are reached by integrating these models into predictive maintenance frameworks (Gouiaa-Mtibaa et al., 2018). Because of this, degradation modelling has become an essential part of reliability-centered maintenance, which enables companies to switch from reactive repairs to condition-based management.

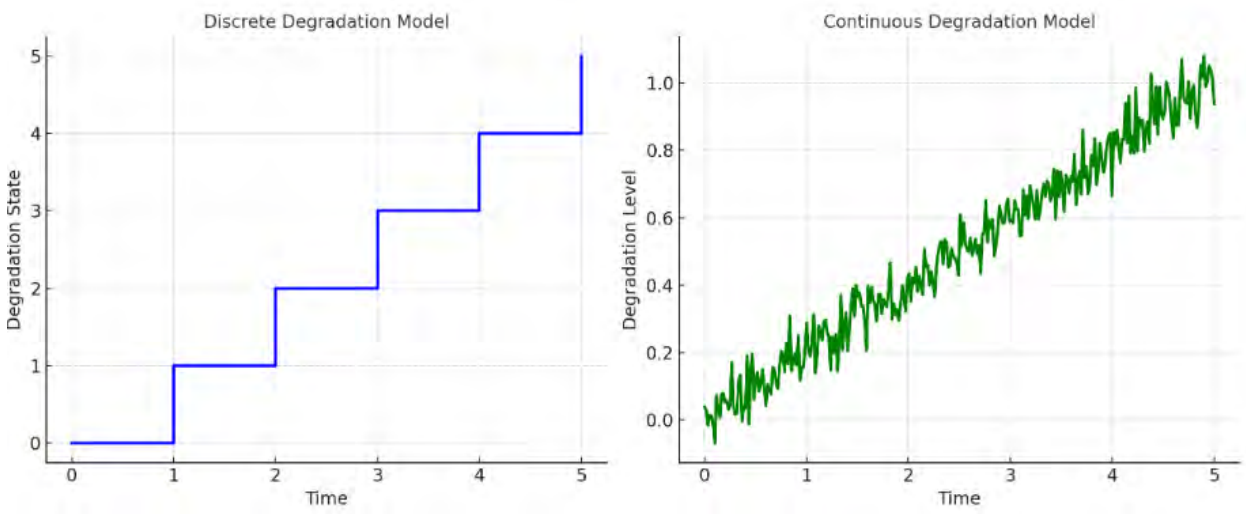

Figure 1.5. Discrete degradation model/continuous degradation model

1.7.5 Maintenance and Transport Coupling Optimisation

In contemporary supply chains, maintenance and transportation planning can no longer operate separately. Their integration is crucial for ensuring operational effectiveness, cost reduction, and service dependability (Chaves Franz et al., 2024). Finding a balance between preventive maintenance (PM), which avoids failures but raises service costs, and corrective maintenance (CM), which occurs after a failure and frequently results in costly downtime, is the aim of

maintenance optimisation. As a result, effective scheduling must minimise overall maintenance expenses while maintaining service continuity. Figure 1.6 shows the balance between corrective and preventive maintenance.

In logistics operations, vehicle maintenance directly affects delivery performance, route planning, and customer satisfaction. For fleets engaged in last-mile or temperature-sensitive deliveries, improper scheduling of maintenance tasks can lead to missed deadlines or product loss. Aligning maintenance windows with transportation schedules has been shown to improve fleet availability and route efficiency (Yang et al., 2024b).

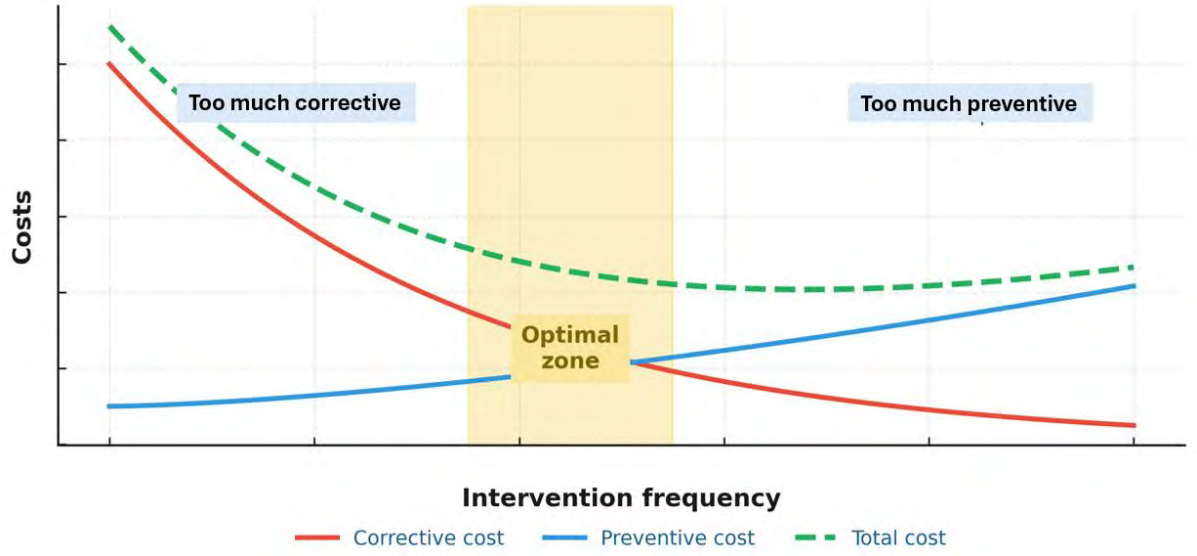

Figure 1.6. Balance between corrective and preventive maintenance

Advanced optimisation techniques such as multi-objective heuristic algorithms and Mixed-Integer Linear Programming (MILP), which account for resource limitations, demand variability, and equipment condition, are now used to jointly plan maintenance and transport operations. Recent studies used advanced optimisation techniques for joint maintenance and transport operations (see Table 1.2). Additionally, when early degradation indicators are identified, data-driven modifications to transport schedules are made possible by predictive maintenance technologies backed by IoT sensors. By cutting emissions and increasing asset utilisation, this proactive strategy lowers unscheduled breakdowns and advances sustainability goals (Pourrahmani et al., 2025). Coordination of maintenance with transport planning is particularly important in reverse logistics systems, where vehicle availability impacts the success of product

returns and remanufacturing cycles. Therefore, integrating these two functions results in improved environmental performance, efficiency, and resilience for both forward and reverse supply chains.

1.8 Machine Learning: Prediction and Data-Driven Optimisation

1.8.1 Machine Learning in a Supply Chain

Machine Learning (ML) has emerged as a crucial element of supply-chain operations due to its ability to provide accurate forecasting, anomaly detection, and real-time decision support across forward and reverse flows (Bhuiyan et al., 2025, Alrashdi et al., 2025). Machine Learning, as opposed to automating rules, learns from both historical and current data, exposing patterns that increase planning precision, reduce waste, and support circular economy initiatives. Machine learning helps with demand forecasting, inventory optimisation, production scheduling, and dynamic transport routing in operations; it also evaluates product condition, forecasts return volumes, and recommends repair, reuse, or recycling routes to increase recovery returns in remanufacturing and reverse logistics (Tubis and Werbinska-Wojciechowska, 2025b).

A practical toolkit is now available. Supervised models such as Random Forest, XGBoost, and Support Vector Machines handle tasks related to demand, lead times, and quality risk prediction. Deep architectures, especially LSTM networks, capture long-range dependencies in demand and returns for temporal signals (Hosseini et al., 2025). Clustering and anomaly detection are examples of unsupervised techniques that support fraud screening, early warning, and supplier segmentation. Crucially, data-driven optimisation is integrated with these projections to ensure that "what will happen" informs "what to do." For instance, risk scores guide sourcing, forecasts guide capacity and inventory decisions, and real-time signals start load consolidation and routing. The outcome is a smart, adaptable supply chain that balances efficiency, responsiveness, and environmental performance.

1.8.2 Predictive Models for Forecasting in the Supply Chain

Forecasting plays a major role in supply chain performance. With the exponential growth of global networks and data, predictive models are crucial for converting uncertainty into actionable insights. The following forecasting methods, shown in Table 1.3, are the most frequently employed in recent studies.

Each of the models in table 1.3 provides distinct advantages based on the characteristics of the data. While VAR and SARIMA are valued for their interpretability, LSTM and hybrid models excel in non-linear, non-stationary scenarios. HWES and RRM remain valuable for short-term operational forecasting. The optimal predictive model must be selected based on the data structure, time horizon, and decision context in order to strike a balance between forecast accuracy and computational complexity.

Table 1.2. Integrated maintenance-transport optimisation techniques

Reference	Optimisation Techniques Used	Considered Aspects	Application Context
(Wang et al., 2019)	Mixed-Integer Linear Programming (MILP), Hybrid Ant Colony Optimisation (ACO), Greedy Heuristic	Resource limitations, multi-item/multi-location systems, waiting-time constraints	Maintenance resource planning, emergency transportation
(Liu et al., 2023)	Mixed-Integer Programming, Genetic Algorithm (GA), Differential Evolution (DE), Simulated Annealing (SA), Ant Colony Optimisation (ACO)	Multi-objective optimisation, equipment condition, system-scale decision making	Maintenance planning and scheduling, joint optimisation in series-parallel systems
(Jafar-Zanjani et al., 2022)	Bi-objective optimisation, Simulated Annealing, Cooperative Genetic Algorithm	Reliability maximisation, disruption cost minimisation, production time uncertainty, equipment condition	Joint maintenance planning and workers routing, preventive maintenance scheduling

Table 1.3. Frequent forecasting methods in recent studies

Reference	Method Name	Definition /Description
(Yang et al., 2024a)	Vector AutoRegression (VAR)	is useful for predicting demand for several products or geographical areas since it captures multivariate relationships between interdependent time-series variables.
(Waqas et al., 2025)	Seasonal AutoRegressive Integrated Moving Average (SARIMA)	models seasonality and trends in time-series data to generate precise baseline forecasts for cyclic industries.
(Rad et al., 2023)	Long Short-Term Memory (LSTM)	A deep learning model capable of preserving long-term dependencies and capturing complex demand fluctuations.
(Sun et al., 2025)	SARIMA–VAR Hybrid Model	combines the univariate strengths of SARIMA with the multivariate forecasting power of VAR to improve robustness in volatile environments.
(Shahidian et al., 2025)	Holt–Winters Exponential Smoothing (HWES)	models trend and seasonality using adaptive smoothing coefficients to produce accurate short-term forecasting
(Chen et al., 2026)	Ridge Regression Model (RRM)	A regularised linear regression model that minimises multicollinearity and performs well with high-dimensional data

1.8.3 Data-Driven Optimisation in the Supply Chain

Data-driven optimisation turns forecasts into actionable decisions, even though forecasting only makes predictions about future behaviour. Combining machine learning (ML) forecasts with optimisation frameworks such as genetic algorithms, Mixed Integer Linear Programming (MILP), and simulation-based models can help businesses identify the best solutions for logistics planning, production scheduling, and resource allocation (Razmi et al., 2025). Remanufacturing and reverse

logistics employ data-driven optimisation to determine the best processing paths for returned goods, including which ones need to be recycled, refurbished, or disassembled (Teixeira et al., 2022). Classification models evaluate the condition of returned goods, whereas predictive analytics determines return volumes and processing times. This integration enhances material recovery and supports closed-loop supply-chain performance. Together, predictive analytics and prescriptive optimisation create an intelligent feedback system that continuously learns, anticipates, and acts. These systems strengthen the supply chain's resilience to disruptions and environmental changes while enhancing responsiveness and efficiency.

1.9 Integrated Optimisation Models in a Supply Chain

Research on integrated optimisation, where production, inventory, transportation, procurement, and reverse flows are coordinated within a single model rather than handled separately, has accelerated due to growing network complexity and sustainability pressures. To place the thesis and highlight the gaps it addresses, this section arranges the literature according to integration scope, objective functions, modelling approaches, and solution techniques. Table 1.4 provides an overview of the current classification and methodology used in the literature for integrated optimisation models in supply chains. Integration scope, objective function, modelling approach, and solution technique are among the classifications.

1.10 Scientific Positioning

For several decades, numerous research studies have examined the integrated stages of supply chains, with particular emphasis on sustainability and data-driven optimisation. To position the present work within this body of literature, a comparative analysis has been conducted based on specific criteria, including the integration of procurement, manufacturing, remanufacturing, inventory management, transportation, maintenance, machine-learning-based prediction, and environmental impact. The outcomes of this comparison are summarised in Table 1. 5. From this review, it becomes evident that no existing study has addressed all these dimensions simultaneously within a single optimisation framework. The joint consideration of these interrelated aspects, balancing economic performance with environmental responsibility, constitutes the central originality of the research problem investigated in this dissertation. A more detailed definition and formulation of this research problem are presented in the following section.

Table 1.4. Classification dimensions of integrated optimisation models

Classification Dimension	Current Approaches/Types	References
Integration Scope	- Production-distribution integration - Procurement-production-distribution integration - Closed-loop/forward-reverse integration - Supply chain design, production planning and scheduling, inventory control, transportation and logistics management - LIR (location-inventory-routing) and LPR (location-production-routing)	(Garside et al., 2025) (Wang, 2024) (Jauhari et al., 2021) (Bootaki and Zhang, 2024)
Objective Function	- Single-objective (e.g., cost minimisation, profit maximisation) - Multi-objective (e.g., balancing economic, environmental, and operational objectives; maximising customer service level and minimising costs, and emissions) - Trade-offs among multiple performance metrics are considered, especially in sustainability contexts	(Momeni et al., 2025) (Bamufleh et al., 2025) (Liao and Hsu, 2025)
Modelling Approach	- Mathematical optimisation models (deterministic and stochastic) - Simulation-based models - Hybrid simulation-optimisation models - Information-technology driven models (real-time integration of big data) - Economic game theory-based models - Models can be further classified as continuous time, discrete time, discrete event simulations, and operations research (OR) based models	(Mai et al., 2023) (Madani et al., 2024) (Cavagnini et al., 2024) (Badakhshan et al., 2024)
Solution Technique	- Exact-based methods (mathematical techniques) - Heuristic and metaheuristic algorithms - Hybrid approaches (combining exact and heuristic/metaheuristic methods) - Simulation - The choice of technique depends on problem complexity and computational requirements	(Bootaki and Zhang, 2024) (Alcaraz, 2024)

Table 1.5. Scientific positioning

Reference	Procurement	Manufacturing/ Remanufacturing	Inventory	Transportation	Maintenance	ML/ Prediction	Environmental Impact
(Dalal et al., 2024)	✓ (supplier relationships, procurement)	✓ (manufacturing, production)	✓ (inventory management)	✓ (transportation, route optimisation)	✕	✓ (ML for forecasting, risk mitigation, supplier collaboration, transportation)	✓ (ML for reducing environmental impact in transportation)
(Leung, 2025)	✕	✓ (production scheduling)	✓ (inventory management)	✓ (vehicle routing, shipment consolidation)	✕	✕	✕
(Li et al., 2025b)	✕	✓ (production, manufacturing)	✓ (inventory)	✓ (distribution, delivery)	✕	✕	✕
(Zarejeddi et al., 2025)	✓ (supplier selection)	✓ (production)	✓	✓ (transportation model)	✕	✕	✓ (carbon emissions, trading)
(Ait El Cadi et al., 2024)	✕	✓ (production)	✕	✕	✓ (predictive maintenance)	✓ (ML for real-time adaptation)	✓ (sustainability metrics in production/ maintenance)
(Rahmanipe rchkolaei et al., 2024)	✓ (supplier relationship)	✓ (production planning)	✓ (inventory management)	✓ (distribution network design, transportation)	✕	✓ (data analytics, forecasting)	✓ (sustainable practices, environmental impact)
(Rane et al., 2021)	✕	✓ (production effectiveness, scheduling)	✕	✕	✓ (maintenance, time-to-repair)	✕	✕
(Khedr and S, 2024)	✓ (supplier collaboration, supplier selection with ML)	✓ (production systems supported by ML/DL)	✓ (inventory demand forecasting applications)	✓ (transportation & logistics optimisation with ML)	✕ (no maintenance-focused content)	✓ (ML & DL for SCM optimisation, forecasting, decision-making)	✕
Present work in this dissertation	✓ (Simplified, Fixed Lot size, Hybrid procurement)	✓ (manufacturing-remanufacturing plan)	✓ (inventory management)	✓ (transport plan, contract carriers)	✓ (vehicle problem, preventive and corrective maintenance)	✓ (ML prediction for forecasting demands and returns)	✓ (Reduction Carbon emissions Strategies)

1.11 General Objective and Thesis Problem Statement

The research problem addressed in this thesis is one of the major optimisation challenges within supply-chain management. It concerns the developpement of an integrated, multi-period optimisation framework that jointly addresses the principal stages of a supply chain incorporating reverse logistics. More precisely, the study seeks to determine optimal plans of the procurement of raw materials, manufacturing and remanufacturing activities, transportation, inventory management, and maintenance, while considering economic, operational, and environmental constraints. The central problem lies in the lack of comprehensive models capable of simultaneously optimising these interdependent processes within a unified, data-driven framework. Much of existing studies tend to analyse each stage separately, neglecting their interactions and the trade-offs between cost efficiency, service reliability, and sustainability performance. In order to close this gap, this thesis develops a set of mathematical models presented in the different chapters which integrate procurement strategies, multi-vehicle transport planning, carbon-emission policies, and predictive forecasting methods into the multi-period optimisation problem.The aim is to establish a practical and adaptive decision-support framework that enhances both strategic and operational planning within circular, carbon-conscious supply-chain environments.

1.12 Conclusion

The main theories and advancements supporting the study were reviewed in this chapter. It followed the development of supply chains from linear systems to dynamic, networked systems that depend on cross-functional cooperation and adaptability. The discussion focused on how, in addition to cost and efficiency, contemporary supply-chain management now incorporates sustainability, resilience, and technological innovation. Reverse logistics, manufacturing, remanufacturing, transportation, inventory, and procurement were among the fundamental areas of supply-chain optimisation that were investigated. The review also emphasised the importance of maintenance planning in guaranteeing dependability and resource efficiency, as well as the growing significance of sustainability and predictive technologies like machine learning.

By synthesising existing optimisation techniques, the chapter demonstrated the need for comprehensive, adaptable models that can manage interdependent operations. It concluded that

the primary research goal was to create an integrated multi-period optimisation framework that balances economic and environmental goals across production, inventory, transportation, procurement, and maintenance.

Chapter 2: Integrated Multi-Period Planning of Acquisition, Manufacturing, Remanufacturing, and Transport in a Supply Chain with Reverse Logistics

Abstract

This chapter develops a multi-period supply chain planning integrated optimisation framework for coordinating procurement, manufacturing, remanufacturing, and transportation within a supply system with a reverse logistics. The Mixed-Integer Linear Programming (MILP) model maximises overall profit by optimising production, procurement, inventory, and logistics decisions under operational constraints. The framework enables dynamic production and transportation adjustments while guaranteeing full demand satisfaction by synchronising forward and reverse flows. It evaluates various procurement strategies and shows that contract-based agreements, such as fixed-lot and hybrid policies, enhance flexibility and cost-effectiveness when compared to simpler acquisition techniques. The study extends classical production-inventory theory by integrating capacity constraints, reverse logistics, and temporal dependencies into a unified, decision-synchronised formulation. All things considered, the model offers a helpful tool for making decisions that strike a balance between sustainability, adaptability, and cost, setting the stage for additional research on environmentally and carbon-conscious supply chain.

2.1 Introduction

With the need to efficiently satisfy consumer demand while simultaneously adjusting to growing demands related to sustainability, operational risks, and resource constraints, supply chains have grown in complexity in recent years. One of the main challenges facing modern manufacturers is combining manufacturing and remanufacturing activities into a single, coherent planning framework. This integration becomes even more significant when considering transportation, as it connects production sites, warehouses, and markets over a range of time periods. Remanufacturing has emerged as a key supply chain management strategy in the modern era because of its advantages for the economy and the environment. Lowering operating costs and conserving resources are two benefits of restoring used products to a high-quality and functional state (Abassi et al., 2025). However, by distinctly separating remanufactured products from new ones in terms of quality and market value, this study offers a more accurate representation of industrial practice. This distinction reflects the real-world challenges faced by companies that must balance cost-effectiveness, service quality, and sustainability objectives (Wang et al., 2025a).

The goal of this chapter is to develop an analytical model for the optimal coordination of an integrated supply chain's manufacturing, remanufacturing, acquisition, and transportation processes. The mathematical model developed aims to maximise overall profit by accounting for all major operational expenses, production, remanufacturing, transportation, inventory management, shortages, and raw material acquisition, as well as the dynamic nature of demand, returns, and capacity constraints. Unlike static or single-period formulations, Multi-period Mixed-Integer Linear Programming (MILP) captures decision interdependencies over time, increasing planning flexibility and realism.

The framework also incorporates practical constraints such as limited warehouse capacity, finite transportation resources, and bounded production capability. The model can be used in sectors that manufacture both new and remanufactured goods, such as consumer electronics, automotive parts, and home appliances, where value recovery and the concepts of the circular economy are essential to long-term competitiveness. The incorporation of acquisition strategy analysis into the optimisation framework is one of this chapter's distinctive contributions. A Hybrid Procurement Agreement, two variations of Fixed Lot Procurement, and a Simplified Acquisition Strategy are the three procurement configurations that are analysed. A comprehensive evaluation

of the effects of contractual flexibility, lot sizing, and penalty structures on the overall stability, responsiveness, and profitability of the system is made possible by this comparison.

Overall, the chapter promotes supply chain optimisation and integrated production–remanufacturing by providing a rigorous, realistic, and profit-driven decision-support model. It demonstrates how synchronised coordination between production, acquisition, and logistics decisions can boost efficiency, reduce waste, and enhance responsiveness. Building on the knowledge gained, the following chapter extends the framework to incorporate environmental and carbon-emission goals, bringing supply chain management closer to sustainability and carbon-consciousness.

This chapter's remaining sections are arranged as follows. Section 2.2 outlines the assumptions used in the system design and modelling. The objective function is formulated analytically in Section 2.3. Section 2.4 presents and discusses the numerical results based on real operational data, highlighting the model's capacity to effectively coordinate decisions pertaining to production, acquisition, and reverse logistics. Section 2.5 provides the conclusion, which enumerates the key findings and theoretical implications of the study. Developing efficient, sustainable, and carbon-conscious supply chain systems requires the knowledge gathered from this analysis.

2.2 Problem Description and Working Assumptions

2.2.1 System Description

This section presents and explains the structure of the proposed system (see Figure 2.1), which integrates both manufacturing and remanufacturing operations within a comprehensive and sustainable supply chain framework. The system operates through two parallel production streams. The first, represented by the manufacturing machine (*MM*), transforms raw materials into new products, while the second, represented by the remanufacturing machine (*MR*), processes collected end-of-life items to produce remanufactured products. Each production stream serves a distinct market segment: newly manufactured products are supplied to the primary market (*P-Market*), whereas remanufactured items are distributed to the secondary market (*S-Market*).

The forward flow begins with the raw materials warehouse (*WRM*), which provides the manufacturing process with the required quantity, denoted by $wrm(k)$. The manufacturing unit

(*MM*) produces *mn*(*k*) units, which are then stored in the warehouse of new products (*WNP*) before being dispatched to the logistics and distribution system. In parallel, returned products collected from customers are gathered at the collection centre and stored in the warehouse of used products (*WUP*). This stock supplies the remanufacturing process through *wup*(*k*), enabling the remanufacturing unit (*MR*) to produce *rm*(*k*) units, subsequently stored in the warehouse of remanufactured products (*WRP*). From these two storage points, quantities *trn*(*k*) and *trr*(*k*) are transported, respectively, towards the city through the logistics and distribution network.

Within the city, two sales inventories, *INP* for newly manufactured products and *IRP* for remanufactured ones, regulate product availability and ensure demand satisfaction at each period *k*. The demand for new products, *dnp*(*k*), is fulfilled by the sales *vnp*(*k*) in the primary market, while the demand for remanufactured products, *drp*(*k*), is met by *vrp*(*k*) in the secondary market. On the reverse side, used products returned by customers generate the flow *rup*(*k*), representing a key decision point in the system. These items returned are transported back to the collection centre (*WUP*), where they are stored and later reused by the remanufacturing unit (MR), thus completing a closed-loop cycle that links consumption, collection, and reuse.

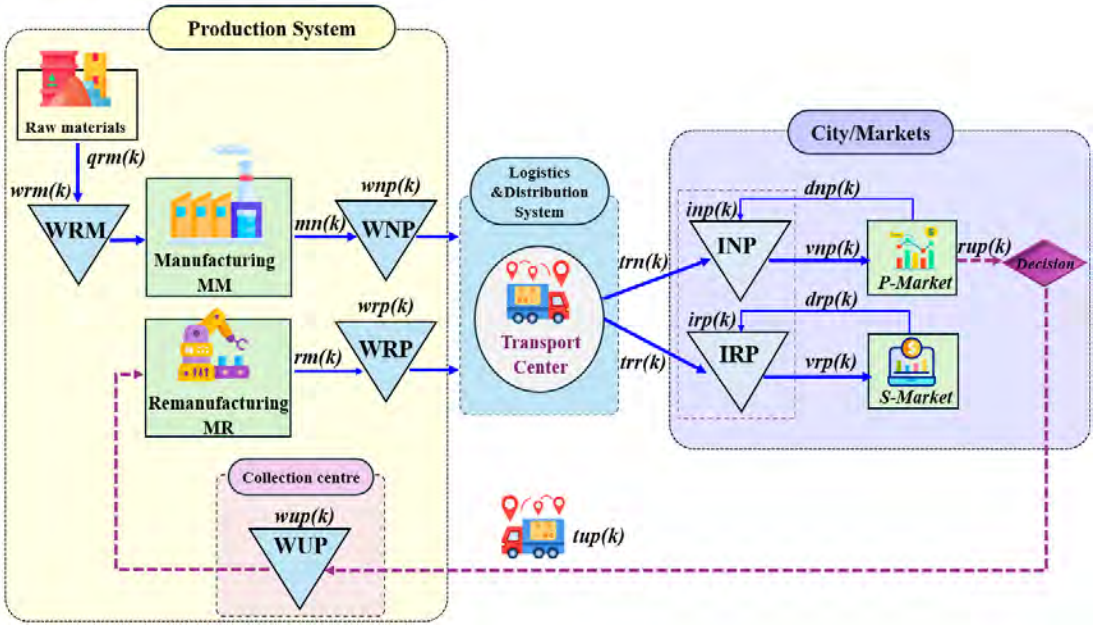

Figure 2.1. Integrated manufacturing–remanufacturing system with logistics and reverse flow

We assume that the production planning horizon is divided into equal-length periods, within which operational decisions are scheduled. The objective of the proposed problem consists in maximising a total profit, defined as the total revenue obtained from both markets minus the aggregate costs of production, remanufacturing, inventory holding, shortages, transportation, raw material acquisition, and the recovery of used products. By incorporating capacity constraints across inventories, warehouses, and vehicles, as well as managing both forward and reverse flows, the model captures the complexity and realism of an integrated and sustainable supply chain that jointly optimises acquisition, manufacturing, remanufacturing and transport activities. The total profit is maximised according to the decision variables, which include the raw material ordering plan, the production schedules of both machines (MM and MR), and the transportation plans for new, remanufactured, and recovered used products. To ensure clarity and coherence in the mathematical formulation that follows, the next section introduces the notations and symbols used to represent the different parameters and variables of the system. For notational simplicity, we set $\lambda = 1$ (length of the production period) throughout the formulation.

2.2.2 Notations

The parameters and decision variables that are used in order to define the mathematical model and illustrate the problem are listed below:

λ	Length of the production period
Z	Number of production periods in the planning horizon
$Z.\ \lambda$	Length of the finite planning horizon
$PR(Z)$	Total profit over $Z.\ \lambda$
k	Period indices in $Z.\ \lambda$
$qrm(k)$	Quantity of raw materials to order during period k
$qrm0$	Quantity of raw materials to order at the start of period 1
$mn(k)$	Produced quantity of machine *MM* during period k
$mn0$	Produced quantity of machine *MM* at the start of period 1
$rm(k)$	Produced quantity of machine *MR* during period k
$rm0$	Produced quantity of machine *MR* at the start of period 1
$trn(k)$	Transported quantities of new products at period k
$trn0$	Transported quantities of new products at the start of period 1

trr(*k*)	Transported quantities of remanufactured products at period *k*
*trr*0	Transported quantities of remanufactured products at the start of period 1
tup(*k*)	Quantity of recovered used products transported to the collection centre.
*tup*0	Quantity of recovered used products at the start of period 1
rup(*k*)	Quantity of collected used products from the primary market at period *k*
wrm(*k*)	Warehouse level of raw materials at the end of period *k*
*wrm*0	Warehouse level of raw materials at the start of period 1
wnp(*k*)	Warehouse level of new products at the end of period *k*
*wnp*0	Warehouse level of new products at the start of period 1
wrp(*k*)	Warehouse level of remanufactured products at the end of period *k*
*wrp*0	Warehouse level of remanufactured products at the start of period 1
wup(*k*)	Warehouse level of used products at the end of period *k*
*wup*0	Warehouse level of used products at the start of period 1
inp(*k*)	Sales inventory level of new products at the end of period *k*
*inp*0	Sales inventory level of new products at the start of period 1
irp(*k*)	Sales inventory level of remanufactured products at the end of period *k*
*irp*0	Sales inventory level of remanufactured products at the start of period 1
dnp(*k*)	Demand in the primary market (new product) at the period *k*
drp(*k*)	Demand in the secondary market (remanufactured product) at the period *k*
rup(*k*)	Quantity of available used products returned by customers in the city
lnp(*k*)	Unsatisfied demand quantity of new products at the period *k*
lrp(*k*)	Unsatisfied demand quantity of remanufactured products at the period *k*
x	Acquisition cost per unit of raw materials per period
a	Production cost per unit of new products per period
b	Production cost per unit of remanufactured products per period (b<a)
y	Cost per unit of recovered product per period
wx	Warehousing cost per unit of raw materials per period in *WRM*
wa	Warehousing cost per unit of new products per period in *WNP*
wb	Warehousing cost per unit of remanufactured products per period in *WRP*
wc	Warehousing cost per unit of recovered products per period in *WUP*
ct	Transport cost per unit of new, remanufactured or recovered products per period

ca	Inventory holding cost per unit of new products per period in *INP*
cb	Inventory holding cost per unit of remanufactured products per period in *IRP*
sn	Shortage cost per unit of new products per period
sr	Shortage cost per unit of remanufactured products per period
FT	Fixed round trip cost for the vehicle *V*
vnp(*k*)	Quantity of new products sold at period *k*
*vnp*0	Quantity of new products sold at the start of period 1
vrp(*k*)	Quantity of remanufactured products sold at period *k*
*vrp*0	Quantity of remanufactured products sold at the start of period 1
pn	Unit selling price for a new product
pr	Unit selling price for remanufactured product
RM	Maximum capacity of *WRM*
NP	Maximum capacity of *WNP*
RP	Maximum capacity of *WRP*
N	Maximum capacity of *INP*
R	Maximum capacity of *IRP*
WP	Maximum capacity of *WUP*
TRV	Capacity of the transport vehicle
α(k)	Round trip variable occurrence
BN	Big number for the linearisation
GM	Maximum quantity produced by *MM* during period *k*
GR	Maximum quantity produced by *MR* during period *k*
MC(*Z*)	Manufacturing cost over *Z*. λ
RC(*Z*)	Remanufacturing cost over *Z*. λ
NSC(*Z*)	Shortage cost of new products over horizon *Z*. λ
RSC(*Z*)	Shortage cost of remanufactured products over horizon *Z*. λ
HRM(*Z*)	Inventory holding cost of raw material stock over horizon *Z*. λ
HNP(*Z*)	Inventory holding cost of new products stock over horizon *Z*. λ
HRP(*Z*)	Inventory holding cost of remanufactured products stock over horizon *Z*. λ
HUP(*Z*)	Inventory holding cost of recovered products stock over horizon *Z*. λ
HIN(*Z*)	Inventory holding cost of the sales stock of new products over horizon *Z*. λ

HIR(*Z*)	Inventory holding cost of the sales stock of remanufactured products over horizon *Z.* λ
TC(*Z*)	Transportation cost over horizon *Z.* λ
ARM(*Z*)	Acquisition of raw material cost over horizon *Z.* λ
RPC(*Z*)	Recovered products cost over horizon *Z.* λ
R(*Z*)	Revenue over the horizon *Z.* λ

Let the following decision plans be defined over the discrete planning horizon $Z.\lambda$, where k = 1, 2,…Z :

$QRM = \{ qrm(k) \mid k = 1,2, \dots, Z \}$: Raw materials ordering plan

$MN = \{ mn(k) \mid k = 1,2, \dots, Z \}$: Manufacturing plan of the machine *MM*

$RM = \{ rm(k) \mid k = 1,2, \dots, Z \}$: Remanufacturing plan of the machine *MR*

$TRN = \{ trn(k) \mid k = 1,2, \dots, Z \}$: Transport plan of new products

$TRR = \{ trr(k) \mid k = 1,2, \dots, Z \}$: Transport plan of remanufactured products

$TUP = \{ tup(k) \mid k = 1,2, \dots, Z \}$: Transport plan of recovered used products from the primary market

In order to maximise the total profit *PR*(*Z*), we determine the optimum values of the decision variables *QRM**, *MN**, *RM**, *TRN**, *TRR**, and *TUP** in this study. As a result, the maximum (optimal) value of *PR*(*Z*) is equal to the value of *PR**(*Z*). The problem of MILP corresponds to the profit model that must be developed under constraints related to production, acquisition, inventory and transport.

2.2.3 Working Assumptions

We consider the following assumptions in the section that follows:

- We noted that the acquisition strategy is simplified by assuming that the supplier does not offer alternative supply options and that no formal supply agreements exist. All raw material procurement is therefore conducted under a single, standardised supply mode.
- We assume that after their useful lives are over, the remanufactured products sold in *S-Market* will be destroyed.

- It is assumed that the producer can determine the number of recovered products ($tup(k)$) from those available in the *P-Market* ($rup(k)$).
- To meet the demands $dnp(k)$ and $drp(k)$, the quantities $mn(k)$ and $rm(k)$ produced during period k are added to the stock at the end of the period.
- There are no backorders, and a shortage cost is incurred because the units are lost.
- Considering that the remanufactured products were the same size as the new ones but were of lower quality and price.
- It is assumed that stocks *WRM*, *WNP*, *WRP*, *WUP, INP*, and *IRP* have limited capacities.
- We consider the period of time between placing an order and receiving the raw materials. It means that the decided quantity of raw materials is ordered at period k and received at time $k+1$ in order to have a realistic approach to our system.
- We consider that the quantity of transported new, remanufactured, and returned products should be done in one period. It means that we can cancel the trip if there are no new, remanufactured, or returned products.

This section first develops the optimisation model under a simplified acquisition strategy, where supply is obtained without the need for contractual agreements or alternative sourcing options. After that, it is expanded to incorporate a more flexible framework for procurement that covers a range of supply options governed by distinct contractual agreements. This two-phase approach allows for a comparative evaluation of system performance while highlighting the operational and financial impacts of supplier flexibility.

2.3 Analytical Study

2.3.1 Model Formulation Under Simplified Acquisition Strategy

2.3.1.1 Objective Function and Constraints

Before presenting the constraints and the equations in this section, it is essential to introduce a binary variable to indicate whether the vehicle performs a round trip during a given period. We define and represent below a round-trip variable:

$$\alpha(k)=\begin{cases}1 \text{ if the vehicle made a round trip}\\ 0 \text{ otherwise}\end{cases}$$

This binary indicator is essential for controlling and tracking transportation activities within the supply chain. By explicitly modelling vehicle availability through this variable, the system ensures that logistical constraints are respected, especially in cases where transport capacity and cost, must be factored into the decision-making process. This also allows the model to reflect the real-world scheduling of the vehicle more accurately within the broader optimisation framework. Based on the assumptions and notations outlined above, a mathematical equation (2.1) is formulated to maximise the total expected profit $PR(Z)$. This equation serves as an objective function aimed at maximising the overall profit over the planning horizon, by capturing the difference between total sales revenues and the sum of various associated costs namely the production costs, the shortage costs, the inventory holding costs, the transportation costs, the acquisition costs, and the recovered products cost.

$$\text{Maximise } PR(Z) = \sum_{k=1}^{z}(R(Z) - (MC(Z) + RC(Z) + NSC(Z) + RSC(Z) + HRM(Z) + HNP(Z) + HRP(Z) + HUP(Z) + HIN(Z) + HIR(Z) + TC(Z) + ARM(Z) + RPC(Z) + (FT \times \alpha(k))) \quad (2.1)$$

Under the following constraints:

- ✓ Production capacity:

$$0 \leq mn(k) \leq GM \quad (2.2)$$

$$0 \leq rm(k) \leq GR \quad (2.3)$$

To ensure production remains within feasible operational limits, the model incorporates upper and lower bounds on the quantities produced by each machine during the planning horizon. Specifically, for each production period $k = 1, \ldots, Z$, the quantity produced by machine *MM*, denoted $mn(k)$, is restricted by the constraint (2.2) above where *GM* represents the maximum production capacity of machine *MM* in a given period. Similarly, the output from machine *MR*, represented by $rm(k)$, is restricted by the constraint (2.3) above, with *GR* denoting its maximum production capacity per period. These constraints reflect practical limitations in terms of machine throughput and available resources, and they ensure that the production schedules generated by the model remain realistic and implementable across all *Z* periods in the planning horizon.

- ✓ Transportation capacity and warehouse inventory compliance:

$$trn(k) + trr(k) \leq TRV \tag{2.4}$$

$$trn(k) \leq wnp(k) \tag{2.5}$$

$$trr(k) \leq wrp(k) \tag{2.6}$$

$$tup(k) \leq TRV \tag{2.7}$$

$$trn(k) \leq (\min (wnp(k-1), N - vnp(k-1)) \tag{2.8}$$

$$trr(k) \leq (\min (wrp(k-1), R - vrp(k-1)) \tag{2.9}$$

To ensure feasibility in the distribution phase of the supply chain, transportation constraints are imposed on the movement of finished products. Specifically, the total quantity of products transported during period *k*, which includes both new products *trn*(*k*) and remanufactured products *trr*(*k*), must not exceed the carrying capacity of the designated transport vehicle *V*, represented by *TRV* (see constraint (2.4) above). Additionally, the quantities transported cannot surpass the available inventory levels in the warehouses. That is, *trn*(*k*) must remain less than or equal to the warehouse level of new products *wnp*(*k*), and *trr*(*k*) must not exceed the warehouse stock of remanufactured products *wrp*(*k*) (see constraints (2.5) and (2.6) above). In addition, constraint (2.7) ensures that the transported of recovered products, denoted by *tup*(*k*), also respects the same vehicle capacity *TRV*. This condition guarantees that the collection of used items from customers does not exceed the physical transportation limits, thereby aligning reverse logistics with forward operations. The last two constraints (2.8) and (2.9) above limit the quantity of products that can be shipped. They ensure that the transported quantities of new and remanufactured products do not exceed the available stock from the previous period, nor do they have the remaining space in the new and remanufactured products' sales inventories. These conditions ensure balanced inventory management by preventing stock shortages and excessive accumulation at the points of sale. Together, these constraints ensure that transportation operations are not only within vehicle limits but also grounded in the actual availability of stock, thereby maintaining consistency between logistics planning and inventory status.

✓ Linearisation constraints:

$$trn(k) + trr(k) \leq TRV + (BN \times (1 - \alpha(k))) \quad (2.10)$$

$$trn(k) + trr(k) \leq BN \times \alpha(k) \quad (2.11)$$

In the context of optimisation, and more specifically in MILP, nonlinear constraints frequently arise when modelling real-world systems. However, most commercial solvers such as CPLEX are designed to handle linear models efficiently. To ensure compatibility with these solvers and maintain computational tractability, it becomes necessary to transform nonlinear relationships into an equivalent set of linear constraints, a process commonly referred to as linearisation. This group of constraints ensures that the transportation of products during each period is both feasible in terms of inventory levels and logically tied to the activation of transport vehicle. The above constraints (2.10) and (2.11) govern the logic of vehicle usage. Constraint (2.10) ensures that if the vehicle *V* will do the round trip ($\alpha(k)= 1$), transported quantity cannot exceed its capacity *TRV*. Conversely, if the vehicle is not used ($\alpha(k)= 0$), the inequality becomes non-restrictive due to the inclusion of the large number *BN*. Constraint (2.11) ensures that no transport takes place unless the transport decision is activated. Together, these constraints establish a consistent, inventory-aware, and decision-driven structure for managing vehicle use and product dispatching across the planning horizon.

✓ Warehouses and inventories capacities constraints

$$wnp(k) \leq NP \quad (2.12)$$

$$wrp(k) \leq RP \quad (2.13)$$

$$wrm(k) \leq RM \quad (2.14)$$

$$wup(k) \leq WP \quad (2.15)$$

$$inp(k) \leq N \quad (2.16)$$

$$irp(k) \leq R \quad (2.17)$$

$$qrm(k) \leq RM - wrm(k) \quad (2.18)$$

To ensure the model remains grounded in realistic operational limits, several constraints are introduced to cap inventory levels within their respective storage capacities. Specifically, the warehouse levels of new products, remanufactured products, raw materials and collected returned products at the end of each period represented by $wnp(k)$, $wrp(k)$, $wrm(k)$, and $wup(k)$ respectively, are each constrained by their corresponding maximum capacities, *NP*, *RP*, *RM and WP* (see constraints (2.12–2.15) above). These limits reflect the physical boundaries of warehouse infrastructure and prevent infeasible storage scenarios. Similarly, the sales inventory levels for both new and remanufactured products at the end of each period, denoted $inp(k)$ and *irp(k)*, are subject to upper bounds *N* and *R*, which represent the maximum permissible stock at distribution or sales points (see constraints (2.16–2.17) above).

Constraint (2.18) above establishes a capacity limitation on the ordering of raw materials within the planning horizon. It ensures that the quantity of raw materials ordered during period *k*, denoted as $qrm(k)$, does not exceed the available storage capacity in the raw materials warehouse (*WRM*). Specifically, the total quantity ordered must be less than or equal to the remaining capacity of the warehouse.

Together, these constraints ensure that procurement and storage activities operate within practical capacity limits, reflecting the physical realities of warehouse management. They contribute to maintaining inventory balance, avoiding unnecessary accumulation of materials, and reducing excessive holding costs. In doing so, the optimisation model remains both operationally feasible and economically efficient, providing a realistic representation of supply chain behaviour under bounded storage conditions. To begin, we formulated equations governing inventory balance, along with the quantities of new and remanufactured products sold at each period. These expressions formed the foundation for calculating the total cost over the full planning horizon.

- ✓ <u>Balance inventory</u>

Equations (2.19) and (2.20) describe the evolution of new product inventory in the warehouse over time. Specifically, Equation (2.19) models the inventory balance at the end of each period $k+1$, denoted as $wnp(k+1)$, based on three elements: the remaining inventory from the previous period $wnp(k)$, the number of newly produced units $mn(k+1)$, and the quantity transported out for sales or distribution $trn(k+1)$. This relationship ensures that the warehouse inventory reflects actual operational activity: what is produced adds to the stock, and what is shipped reduces

it. Equation (2.20) defines the initial condition at period 1. Here, the starting warehouse level *wnp* (*1*) is determined by the initial inventory *wnp0*, the quantity produced *mn*(*1*), and the transported quantity *trn*(*1*). These equations are essential for maintaining an accurate flow of inventory throughout the system, ensuring that warehouse levels remain consistent with production outputs and logistics operations over the entire planning horizon.

$$wnp(k+1) = wnp(k) + mn(k+1) - (trn(k+1) \times \alpha(k))$$
$$\forall\ k = 0,\ldots, Z-1 \tag{2.19}$$

$$wnp(1) = wnp0 + mn(1) - (trn(1) \times \alpha(k)) \tag{2.20}$$

Equations (2.21) and (2.22) describe how the remanufactured product inventory in the warehouse evolves over time. In Equation (2.21), the inventory level at the end of each period $k + 1$, denoted $wrp(k+1)$, is determined by the inventory carried over from the previous period $wrp(k)$, the quantity of remanufactured products produced during the current period $rm(k+1)$, and the quantity transported out for distribution or sales $trr(k+1)$. This formulation captures the fundamental inventory balance: what is produced adds to stock, while what is shipped out reduces it. Equation (2.22) sets the initial warehouse level for remanufactured products at the end of period 1. It combines the initial stock *wrp0*, the production volume *rm*(*1*), and the transported amount *trr*(*1*) to determine the available inventory at that point. Together, these equations allow the model to track the flow of remanufactured products across the planning horizon, ensuring consistency between production, storage, and outbound logistics in the reverse side of the supply chain.

$$wrp(k+1) = wrp(k) + rm(k+1) - (trr(k+1) \times \alpha(k))$$
$$\forall\ k = 0,\ldots, Z-1 \tag{2.21}$$

$$wrp(1) = wrp0 + rm(1) - (trr(1) \times \alpha(k)) \tag{2.22}$$

Equations (2.23) and (2.24) describe the inventory flow of used products stored in the warehouse across periods. Equation (2.23) updates the warehouse level at the end of each period *k+1* by taking the previous stock *wup*(*k*), adding the newly recovered used products *tup*(*k+1*), and subtracting the remanufactured quantity *rm*(*k+1*). Equation (2.24) sets the initial balance, where the stock of used products equals the starting level *wup0*, plus the first recovered used products, less the remanufactured quantity in period 1. These relations ensure that warehouse levels consistently reflect both incoming and outgoing flows throughout the planning horizon.

$$wup\,(k+1) = wup(k) + tup\,(k+1) - rm\,(k+1) \quad \forall\ k = 0,\ldots, Z-1 \tag{2.23}$$

$$wup(k) = wup0 + tup(1) - rm\,(1) \tag{2.24}$$

As previously discussed in the section on working assumptions, we choose to place our raw material order at time k, and we anticipate receiving it in the subsequent period $k + 1$, once it reaches stock *WRM*, which has a limited capacity. Equations (2.25) and (2.26) describe the evolution of raw material inventory in the warehouse over the planning horizon. Specifically, Equation (2.25) calculates the stock level of raw materials at the end of each period $k + 1$ based on three factors: the stock remaining from the previous period $wrm(k)$, the quantity of raw materials ordered during the current period $qrm(k)$, and the quantity consumed by the production process $mn(k + 1)$. This equation ensures that material usage for manufacturing is properly reflected in the inventory update, capturing the flow of resources within each cycle.

Equation (2.26) defines the initial condition for this inventory stream, where the warehouse level at the end of period 1 is determined by the starting stock *wrm0*, the quantity ordered at the beginning $qrm(0)$, and the materials used by the machine $mn(1)$. Together, these equations provide a straightforward yet essential mechanism for tracking raw material availability across all periods $k = 0, \ldots, Z - 1$, ensuring that production decisions remain feasible and aligned with procurement planning. They also establish a clear connection between procurement schedules and production demands, which is crucial for maintaining operational continuity in the system.

$$wrm\,(k+1) = wrm(k) + qrm(\mathrm{k}) - mn\,(k+1) \quad \forall\ k = 0,\ldots, Z-1 \tag{2.25}$$

$$wrm\,(1) = wrm0 + qrm(0) - mn\,(1) \tag{2.26}$$

Within the structure of the supply chain, *INP* refers specifically to the inventory location for new products, while *IRP* holds remanufactured products, each serving the primary and secondary markets, respectively. By clearly separating these two sales inventory streams, the model reflects the practical dynamics of dual-market supply strategies and supports more accurate inventory planning. Equation (2.27) below governs the inventory flow of new products in the primary sales market, represented by the inventory variable $inp(k+1)$. This equation ensures that the sales inventory at the end of period $k + 1$ accounts for three essential elements: the stock carried over

from the previous period $inp(k)$, the quantity of new products transported to the sales point during the current period $trn(k+1)$, and the quantity sold in the same period $vnp(k+1)$. In essence, the available inventory grows with incoming stock and decreases as sales are fulfilled. This formulation is applied across all planning periods $k = 0, \ldots, Z - 1$, and allows the model to continuously update and monitor inventory levels in response to supply and demand variations.

$$inp(k+1) = inp(k) + (trn(k+1) \times \alpha(k)) - vnp(k+1) \quad \forall\, k = 0, \ldots, Z-1 \tag{2.27}$$

Equation (2.28) below describes the inventory dynamics of remanufactured products in the secondary sales market. Specifically, $irp(k+1)$ represents the inventory level at the end of period $k+1$, and it is calculated by adding the incoming remanufactured products $trr(k+1)$ to the existing inventory $irp(k)$, then subtracting the quantity sold during that period $vrp(k+1)$. This simple yet essential balance ensures that the remanufactured stock is accurately updated across each time step based on actual inflows and outflows. This relationship holds for all periods $k = 0, \ldots, Z - 1$, and is fundamental to maintaining a reliable supply of remanufactured products in the secondary market.

$$irp(k+1) = irp(k) + (trr(k+1) \times \alpha(k)) - vrp(k) \quad \forall\, k = 0, \ldots, Z-1 \tag{2.28}$$

- ✓ Quantities sold of new and remanufactured products at period k

Equations (2.29) and (2.30) determine the actual sales quantities of new and remanufactured products in each period by accounting for both customer demand and inventory availability. In Equation (2.29), the quantity of new products sold in period k, denoted as $vnp(k)$, is defined as the minimum between the demand in the primary market $dnp(k)$ and the available inventory from the previous period $inp(k-1)$. This formulation ensures that sales do not exceed what is physically available in stock, and thus respects inventory constraints. Similarly, Equation (2.30) defines the sales of remanufactured products $vrp(k)$ as the minimum of the demand in the secondary market $drp(k)$ and the remanufactured inventory carried over from the previous period $irp(k-1)$. Again, this guarantees that only the quantity available in inventory can be sold. Together, these two equations reflect a realistic sales mechanism in both the primary and secondary markets, where product availability may limit fulfilment even when demand exists. By capturing this dependency,

the model ensures a more accurate representation of how inventory levels impact service performance across planning periods.

$$vnp\,(k) = \min\,(dnp\,(k), inp(k-1)) \tag{2.29}$$

$$vrp(k) = \min\,(drp(k), irp(k-1)) \tag{2.30}$$

We now present the total sales revenue along with the various costs that appear in the objective function.

2.3.1.2. Total Sales Revenue

$$R(Z) = pn \times \sum_{k=1}^{Z} vnp(k) + pr \times \sum_{k=1}^{Z} vrp(k) \tag{2.31}$$

Equation (2.31) above defines the total revenue generated over the planning horizon $Z.\ \lambda$, accounting for all streams of product sales within the system. The revenue is calculated as the sum of three components. The first term represents the revenue from selling new products, where $vnp(k)$ is the quantity sold in period k, and pn is the unit selling price. The second term captures revenue from remanufactured products, with $vrp(k)$ being the quantity sold and pr the corresponding unit price. By aggregating all sales income over all periods, this equation offers a comprehensive measure of system-level revenue, supporting the evaluation of both financial performance and market effectiveness in a closed-loop supply chain.

2.3.1.3. Manufacturing and Remanufacturing Costs

$$MC(Z) = a \times \sum_{k=1}^{Z} mn(k) \tag{2.32}$$

$$RC(Z) = b \times \sum_{k=1}^{Z} rm(k) \tag{2.33}$$

Equations (2.32) and (2.33) above define the cumulative manufacturing and remanufacturing costs over the planning horizon Z. In Equation (2.32), $MC(Z)$ represents the total manufacturing cost of new products, calculated as the product of the unit production cost a and the sum of all new product quantities $mn(k)$ produced over each period $k = 1, \ldots, Z$. Similarly, Equation (2.33) defines $RC(Z)$, the total remanufacturing cost, as the unit cost b multiplied by the total volume of remanufactured products $rm(k)$ produced across the same horizon. These two

expressions quantify the direct production-related expenses for both product streams, new and remanufactured, and form a key component of the overall cost structure in the supply chain model.

2.3.1.4. Shortages Costs

$$lnp\ (k) = \ dnp(k) - vnp(k) \tag{2.34}$$

$$lrp\ (k) = \ drp(k) - vrp(\mathrm{k}) \tag{2.35}$$

$$NSC(Z) = sn\ \times \sum_{\mathrm{t=1}}^{\mathrm{Z}} lnp(k) \tag{2.36}$$

$$RSC(Z) = sr \times \ \sum_{\mathrm{k=1}}^{\mathrm{Z}} \ lrp(k) \tag{2.37}$$

Equations (2.34) -(2.37) above quantify the shortage costs associated with unmet demand for both new and remanufactured products over the planning horizon *Z. λ*. Equation (2.34) defines *lnp*(*k*), the unsatisfied demand for new products at period *k*, as the difference between the actual demand *dnp*(*k*) and the quantity fulfilled *vnp*(*k*). Similarly, Equation (2.35) computes the unsatisfied demand for remanufactured products *lrp*(*k*), as the gap between demand *drp*(*k*) and the sold quantity *vrp*(*k*). These shortages carry financial consequences, captured in Equations (2.36) and (2.37). Equation (2.36) calculates the total shortage cost for new products, *NSC*(*Z*), as the product of the per-unit shortage cost *sn* and the total accumulated shortfall across all *Z* periods. In the same way, Equation (2.37) computes the shortage cost for remanufactured products, *RSC*(*Z*), using the unit shortage penalty *sr* applied to the total unmet demand *lrp*(*k*) over the same horizon. Together, these expressions ensure that the cost of lost sales due to insufficient inventory is fully accounted for in the objective function, reinforcing the importance of balancing supply with market demand in both the primary and secondary channels.

2.3.1.5. Inventory Holding Costs

$$HRM(Z) = \ wx\ \times \ \sum_{\mathrm{k=1}}^{\mathrm{Z}} wrm(k) \tag{2.38}$$

$$HNP(Z) = \ wa\ \times \sum_{\mathrm{k=1}}^{\mathrm{Z}} wnp(k) \tag{2.39}$$

$$HRP(Z) = wb \times \sum_{k=1}^{Z} wrp(k) \quad (2.40)$$

$$HUP(Z) = wc \times \sum_{k=1}^{Z} wup(k) \quad (2.41)$$

$$HIN(Z) = ca \times \sum_{k=1}^{Z} inp(k) \quad (2.42)$$

$$HIR(Z) = cb \times \sum_{k=1}^{Z} irp(k) \quad (2.43)$$

Equations (2.38) to (2.43) define the total inventory holding costs associated with various stages and types of products across the supply chain over the planning horizon *Z*. λ. These costs are essential components in the total cost structure, reflecting the financial impact of storing materials and products throughout the system.

Equation (2.38), *HRM*(*Z*), calculates the inventory holding cost for raw materials based on the per-unit warehousing cost *wx* and the cumulative stock *wrm*(*k*) over all periods. Similarly, Equation (2.39), *HNP*(*Z*), represents the holding cost of new products in the production warehouse *WNP*, using the unit cost *wa*. Equation (2.40), *HRP*(*Z*), accounts for the inventory cost of remanufactured products stored in *WRP* with unit warehousing cost *wb*. Equation (2.41), *HUP*(*Z*), reflects the cost of storing returned used products in *WUP* multiplied by the corresponding unit cost *wc*. On the sales side, Equation (2.42), *HIN*(*Z*), captures the inventory holding cost of new products stored in the primary market sales inventory *INP* using a per-unit cost *ca*. Finally, equation (2.43), *HIR*(*Z*), does the same for remanufactured products held in the secondary market inventory *IRP* with cost *cb*. Altogether, these expressions provide a detailed and structured view of inventory-related expenses throughout the supply chain from raw material input to returned product handling ensuring that storage decisions are appropriately weighted in the optimisation model.

2.3.1.6. Transportation Cost

$$TC(Z) = ct \times \sum_{k=1}^{Z} \left(\left(trn(k) + trr(k) + tup(k) \right) \times \alpha(k) \right) \quad (2.44)$$

Equation (2.44) represents the total transportation cost, denoted as *TC*(*Z*), accumulated over the entire planning horizon *Z. λ*. This cost accounts for all transport activities within the supply chain, including the movement of new products *trn*(*k*), remanufactured products *trr*(*k*), and used products recovered from the primary market, represented by *tup*(*k*). Each of these transported quantities is summed over all periods and multiplied by the unit transportation cost *ct*, which is assumed here to be uniform across product types for simplicity. By incorporating all flows, forward and reverse, this expression ensures that the full cost impact of logistical operations is reflected in the overall model. This is particularly important in closed-loop supply chains, where managing both delivery and return logistics plays a critical role in cost optimisation and system efficiency.

2.3.1.7. Raw Material Acquisition Cost

$$ARM(Z) = x \times \sum_{k=1}^{Z} qrm(k) \tag{2.45}$$

Equation (2.45) calculates the total acquisition cost of raw materials, denoted as *ARM*(*Z*), over the planning horizon *Z. λ*. This cost is determined by summing the quantities of raw materials ordered in each period *qrm*(*k*), and multiplying the total by *x*, which represents the unit cost of acquiring one unit of raw material. The expression captures the cumulative financial commitment associated with material procurement and ensures that raw material ordering decisions are fully integrated into the overall cost structure of the supply chain. Since raw materials are the foundation of both manufacturing and remanufacturing processes, accurately accounting for their cost is essential for evaluating profitability and resource planning across all production stages.

2.3.1.8. Recovered Products Cost

$$RPC(Z) = \ y \times \sum_{k=1}^{Z} tup(k) \tag{2.46}$$

Equation (2.46) represents the total cost associated with handling recovered used products, denoted as *RPC*(*Z*), over the planning horizon. This cost is computed by summing up the quantity of used products collected from the primary market in each period, *tup*(*k*), and multiplying the total by *y*, the unit cost of managing a recovered used product. The above expression accounts for the

operational effort involved in receiving, inspecting, and processing returned items, which forms an important part of reverse logistics in a closed-loop supply chain. By including $RPC(Z)$ in the overall cost model, the formulation ensures that the economic impact of product returns is fully considered in evaluating system performance and sustainability.

2.3.2 Model Formulation Under Contract-Based Acquisition Strategy

In this formulation, the acquisition strategy is extended to incorporate contractual relationships between the supplier and the manufacturer. It is assumed that the supplier provides two alternative options for the procurement of raw materials, each representing a distinct type of supply agreement. These contractual options are introduced to reflect realistic procurement practices observed in industrial settings, where variations in lot size, cost structure, and commitment levels influence purchasing decisions.

2.3.2.1 Fixed Lot Size Procurement

This procurement strategy introduces contractual arrangements based on fixed-lot size supply agreements between the supplier and the manufacturer. Within this framework, the manufacturer operates under predefined lot sizes that determine both the procurement costs and the contractual penalties incurred in cases of non-ordering. Two variants of the fixed-lot strategy are examined, each representing a distinct purchasing policy and cost structure. The arrangement spans from a moderate to a more binding contractual commitment, ensuring a consistent flow of raw materials while potentially generating economies of scale through sustained production continuity.

To integrate these contractual options into the optimisation model, corresponding modifications have been applied to the acquisition component of the mathematical formulation. The following parameters and decision variables are introduced:

- qlz: lot size of raw materials;
- clz: cost associated with one lot of raw materials;
- pol: penalty incurred for not placing an order;
- $\beta(k)$: lot order state in period k, where $\beta(\mathrm{k}) = 0$ if no order is placed, and $\beta(k) = 1$ if an order is placed;

- $qlrm(k)$: acquisition quantity of raw materials following the lot-based strategy;
- $ALRM(Z)$: total acquisition cost of raw materials under the lot-based procurement policy.

The mathematical formulation of the objective function is revised in this section to incorporate the contractual acquisition framework introduced under the fixed-lot procurement strategy. Specifically, the original acquisition cost term, $ARM(Z)$, defined in the simplified acquisition model, is replaced by $ALRM(Z)$, which reflects the lot-based cost structure and the associated contractual penalties. The modified objective function, therefore, becomes:

$$\begin{aligned} \text{Maximise } PR(Z) = \textstyle\sum_{k=1}^{Z}(R(Z) - (MC(Z) + RC(Z) + NSC(Z) + RSC(Z) + \\ HRM(Z) + HNP(Z) + HRP(Z) + HUP(Z) + HIN(Z) + HIR(Z) + TC(Z) + \\ ALRM(Z) + RPC(Z) + (FT \times \alpha(k))) \end{aligned} \quad (2.47)$$

Equations (2.48) and (2.49) establish the mathematical formulation of the acquisition cost and procurement quantity under the fixed-lot policy. Equation (2.48) defines *ALRM(Z)* as the total acquisition cost of raw materials over the planning horizon, incorporating both ordering expenses and penalties for inactivity. The first term represents the cumulative cost of placing orders across all periods, while the second accounts for penalties incurred during periods without procurement. Together, these components capture the trade-off between maintaining supply regularity and avoiding the financial consequences of missed orders, thereby reflecting the economic implications of contractual procurement commitments.

$$ALRM(Z) = clz \times \sum_{k=1}^{Z} \beta(k) + pol \times \sum_{k=1}^{Z} (1 - \beta(k)) \quad (2.48)$$

Equation (2.49) establishes the link between the binary order decision and the actual procurement quantity. The relationship $qlrm(k) = \beta(k) \times qlz$ specifies that raw materials are acquired in fixed batches of size qlz only when $\beta(k) = 1$, i.e., when an order is placed. If no order is made ($\beta(k) = 0$), the acquisition quantity for that period is zero. This discrete formulation enforces the fixed-lot nature of the procurement agreement, aligning the model with the practical realities of contract-based supply systems, where ordering decisions are typically made in predetermined batch sizes rather than continuous quantities.

$$qlrm(k) = \beta(k) \times qlz \tag{2.49}$$

This formulation captures the discrete nature of procurement decisions within a contractual framework, where the manufacturer must decide in each period whether to place a lot order or incur the corresponding non-order penalty.

2.3.2.2 Hybrid Procurement Agreement

This procurement configuration introduces a more flexible contractual arrangement, enabling the manufacturer to adapt procurement decisions dynamically to production needs and market conditions. Under this agreement, the manufacturer may, in each planning period, select a fixed lot procurement, or place no order at all. When no order is made, a higher penalty is imposed, reflecting the contractual cost of inactivity. This hybrid formulation thus combines the advantages of flexibility and structured commitment, allowing the manufacturer to balance cost efficiency, responsiveness, and operational continuity across varying production scenarios.

To incorporate this flexible procurement structure into the optimisation model, additional parameters and decision variables have been defined to represent the hybrid decision logic. These elements enable the model to distinguish between the different lot types, their associated costs, and the penalties arising from non-ordering behaviour. The following parameters and decision variables are introduced:

- qlz_1: lot size of raw materials for option 1;
- qlz_2: lot size of raw materials for option 2;
- cl_1: cost associated with one lot of raw materials for option 1;
- cl_2: cost associated with one lot of raw materials for option 2;
- pol: penalty incurred when no order is placed for either option;
- $\beta_0(k)$: no-order state in period k, where $\beta_0(k) = 1$ if no order is placed and $\beta_0(k) = 0$ otherwise;
- $\beta_1(k)$: order state for lot 1 in period k, where $\beta_1(k) = 1$ if a lot 1 order is placed and $\beta_1(k) = 0$ otherwise;

- $\beta_2(k)$: order state for lot 2 in period k, where $\beta_2(k) = 1$ if a lot 2 order is placed and $\beta_2(k) = 0$ otherwise;
- $qhrm(k)$: acquisition quantity of raw materials under the hybrid lot strategy;
- $AHRM(Z)$: total acquisition cost of raw materials under the hybrid procurement policy.

This formulation enhances the adaptability of the acquisition process within the optimisation framework, capturing the trade-off between flexibility, cost, and supply assurance that characterises hybrid contractual strategies. The mathematical formulation of the objective function is further revised in this section to integrate the contractual acquisition framework associated with the hybrid procurement strategy. In this context, the acquisition cost term used in the simplified model, $ARM(Z)$, which was previously replaced by $ALRM(Z)$ under the fixed-lot procurement approach, is now substituted with $AHRM(Z)$. This new term represents the total acquisition cost of raw materials under the hybrid procurement policy, capturing the flexibility of ordering between different lot sizes and the penalties incurred for inactivity. The modified objective function therefore becomes:

$$\begin{aligned}\text{Maximise } PR(Z) = \textstyle\sum_{k=1}^{z}(R(Z) - (MC(Z) + RC(Z) + NSC(Z) + RSC(Z) + \\ HRM(Z) + HNP(Z) + HRP(Z) + HUP(Z) + HIN(Z) + HIR(Z) + TC(Z) + \\ AHRM(Z) + RPC(Z) + (FT \times \alpha(k)))\end{aligned} \quad (2.50)$$

The hybrid acquisition cost function is formulated to account for the different contractual options available to the manufacturer within each planning period. As shown in Equation (2.51), $AHRM(Z)$ represents the total acquisition cost of raw materials over the planning horizon, incorporating the costs of both lot types and the penalties incurred for non-ordering. The first two terms correspond to the total expenditure resulting from orders of lot 1 and lot 2, weighted by their respective unit costs (cl_1 and cl_2). The third term captures the cumulative penalty associated with periods in which no order is placed ($\beta_0(k)$), thereby ensuring that contractual inactivity is appropriately penalised within the optimisation process.

$$ALRM(Z) = cl_1 \times \sum_{k=1}^{z} \beta_1(k) + cl_2 \times \sum_{k=1}^{z} \beta_2(k) + pol \times \sum_{k=1}^{z} \beta_0(k) \quad (2.51)$$

Equation (2.52) enforces the logical exclusivity between the three decision states in each period, ensuring that only one action, ordering lot 1, ordering lot 2, or placing no order, can occur at one time. This constraint preserves the integrity of the procurement decision structure and prevents overlapping contractual commitments.

$$\beta_1(k)+\beta_2(k)+\beta_0(k)=1 \tag{2.52}$$

Finally, Equation (2.53) defines $qhrm(k)$ as the total quantity of raw materials acquired in each period under the hybrid policy. This expression links the acquisition quantity directly to the binary decision variables ($\beta_1(k)$ and $\beta_2(k)$) and their respective lot sizes (qlz_1 and qlz_2), thereby integrating the hybrid ordering logic into the broader optimisation framework.

$$qhrm(k)= \beta_1(k) \times qlz_1+\beta_2(k) \times qlz_2 \tag{2.53}$$

2.4 Numerical Studies

In this section, we illustrate the developed model using a case study of a manufacturing-remanufacturing supply chain that integrates the production and sale of both new and remanufactured microwaves. To support our analysis, we contacted a home appliance sales company and obtained relevant information regarding prices, costs, and demand for microwaves. We found that the obtained data are significant and can be used to conduct a study that closely reflects a real system case. Let us recall that our objective in this section is to simultaneously optimise the quantity ordered for raw materials, manufacturing, remanufacturing, transport, and the returned quantity of used products. Using the solver CPLEX 22.1.1, we experimented by solving the suggested MILP on a laptop equipped with an Intel(R) Core (TM) i3-6006U CPU @2.00 GHz and 3,87 Gb of usable RAM. In fact, we chose to use CPLEX to solve our MILP because it is known as a very robust and reliable solver that includes sophisticated features such as sensitivity analysis. At its core, CPLEX is a set of algorithms used to make decisions. Moreover, it provides good-quality solutions at moderate computational time.

2.4.1 Input Parameters

The input parameters used in the suggested optimisation model are described in this section. It includes demand for new, remanufactured, and returned products (Table 2.1), and numerical data like unit costs, storage capacities, selling prices, vehicle capacity, production limits, and fixed

transportation costs (Table 2.2). The optimisation analysis in Section 2.4.2 is based on the initial values of the decision variables, which are listed in Table 2.3.

Table 2.1. Demands and returns data ($Z = 24$)

k	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
dnp(k)	29	20	5	30	35	31	35	41	13	20	69	24	2	54	25	61	50	41	33	27	30	8	62	25
drp(k)	17	18	4	25	25	23	5	16	2	2	21	35	18	10	61	16	17	40	25	18	35	31	51	12
rup(k)	25	20	16	13	10	30	13	19	23	30	40	32	41	30	64	11	23	22	24	32	30	29	12	1

Table 2.2. Necessary data for coding

x	***a***	***b***	***y***	***wx***	***wa***	***wb***	***wc***	***ct***	***ca***	***cb***	***sn***	***sr***
10	40	9	2	0.1	0.5	0.4	0.1	1	1.5	1.2	250	180
FT	***pn***	***pr***	***RM***	***NP***	***RP***	***N***	***R***	***WP***	***TRV***	***BN***	***GM***	***GR***
600	145	105	150	220	200	160	110	250	170	10000	80	60

Table 2.3. Initials values

qrm0	***mn0***	***rm0***	***trn0***	***trr0***	***wrm0***	***wnp0***	***wrp0***	***wup0***	***inp0***	***irp0***	***tup0***	***vnp0***	***vrp0***
0	20	30	30	20	30	30	20	30	35	25	10	30	20

2.4.2 Obtained Results

2.4.2.1 The System's Performance Under Simplified Acquisition Strategy

This section presented the optimisation results from the integrated model, which jointly makes decisions about acquisition, manufacturing, remanufacturing, and transportation over a 24-period horizon. The analysis's primary focus was the Simplified Acquisition Strategy, which buys raw materials from a single, standardised source with no contractual flexibility. The results, which are summarised in Tables 2.4 and 2.5, demonstrate how effectively the model can meet capacity and operational requirements while managing each stage of the manufacturing–remanufacturing supply chain.

Procurement quantities are dynamically adjusted to production demands and storage capacity to prevent shortages and overstock. Manufacturing and remanufacturing operations respond to changes in demand in complementary ways to preserve balanced forward and reverse flows. Complete service levels are maintained throughout, and there is no unmet demand for either new or remanufactured products. Transportation options closely follow production and sales trends by using selective round trips to lower fuel consumption and costs. The model's ability to coordinate production, logistics, and procurement decisions is demonstrated by the overall profit of 111,091 mu that the optimisation produces. By effectively adjusting to changes in demand and return, the system guarantees operational efficiency and sustainable resource utilisation within an integrated supply-chain framework.

2.4.2.2 The System's Performance Under Contract-Based Acquisition Strategy

Optimal plans under Fixed Lot Size Procurement

This section examined two contractual arrangements under the Fixed-Lot Procurement strategy to assess their impact on supply-chain coordination and profitability. Orders of 40 units with lower costs and penalties were used in Option 1, while orders of 60 units with higher costs and penalties were used in Option 2. Within the integrated optimisation model, these parameters allowed for the evaluation of the effects of lot size and contract design on procurement behaviour, production scheduling, and logistics performance.

Table 2.4. Optimal plans under Simplified Acquisition Strategy (Z = 24)

k	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
$mn(k)$	0	29	35	40	80	0	0	20	69	24	2	54	25	61	50	41	60	0	38	7	80	0	0	0
$rm(k)$	0	9	25	23	23	0	0	2	21	35	18	11	60	16	17	40	43	6	60	3	60	0	0	0
$qrm(k)$	34	40	80	0	0	20	69	24	2	54	25	61	50	41	60	0	38	7	80	0	0	0	0	0
$trn(k)$	14	5	30	35	31	89	0	0	20	69	24	2	54	25	61	50	41	60	0	38	0	87	0	0
$trr(k)$	10	4	25	25	23	23	0	0	2	21	35	18	10	61	16	17	40	43	0	66	0	63	0	0
$tup(k)$	25	20	16	13	10	30	0	0	23	30	40	32	41	30	64	11	23	22	0	32	0	0	0	0

Table 2.5. Additional results under Simplified Acquisition Strategy (Z = 24)

k	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
$vnp(k)$	29	20	5	30	35	31	35	41	13	20	69	24	2	54	25	61	50	41	33	27	30	8	62	25
$vrp(k)$	17	18	4	25	25	23	5	16	2	2	21	35	18	10	61	16	17	40	25	18	35	31	51	12
$\alpha(k)$	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0
$lnp(k)$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$lrp(k)$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Tables 2.6 and 2.7 show that both options achieve balanced manufacturing–remanufacturing flows, complete demand satisfaction, and efficient transportation scheduling. Consistent operations and a total profit of 112,070 mu are guaranteed by regular ordering under Option 1. Because Option 2 employs larger but less frequent orders, economies of scale and reduced penalty exposure lead to a slightly higher profit of 112,224 mu. On the other hand, the larger-lot arrangement provides a marginal economic advantage, while the smaller-lot approach offers greater flexibility and continuity. Both configurations demonstrate that fixed-lot procurement can remain profitable and operationally stable under a variety of contractual conditions, thereby validating the model's resilience.

Optimal plans under Hybrid Procurement Agreement

This section looked at the Hybrid Procurement Agreement, a flexible contractual approach that allows the manufacturer to choose between two lot sizes, 40 or 60 units, or to place no orders for a predetermined amount of time and incur an inactivity penalty. If no order is placed during a period, a penalty of 120 mu is imposed. The results in Tables 2.8 and 2.9 show how this flexibility allows for adaptive coordination of transportation, procurement, remanufacturing, and production activities.

Depending on production demand and inventory levels, the acquisition plan dynamically alternates between the two lot sizes, while the binary variables $\beta_1(k)$, $\beta_2(k)$, and $\beta_0(k)$ represent ordering or non-ordering periods. A responsive procurement policy that minimises excess inventory and maximises storage utilisation is demonstrated by this behaviour. Both product types satisfy all demands during the planning horizon, and the amounts of production and remanufacturing remain balanced. On-time delivery and continuous reverse flows free of unnecessary trips are ensured by efficient scheduling of transport operations. From an economic perspective, the hybrid setup generates a total profit of 111,878 mu, which is slightly less than that of the fixed-lot strategies. The results demonstrate a clear trade-off between flexibility and cost effectiveness: hybrid procurement boosts responsiveness and adaptability but also raises management complexity and exposure to penalties.

Table 2.6. Optimal plans with Fixed Lot Procurement ($Z = 24$)

k	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Option 1 (*qlz*: 40, *clz*: 300 mu, *pol*: 60 mu)																								
***mn*(*k*)**	0	29	35	31	35	54	0	20	69	24	23	40	49	80	0	41	60	0	38	7	80	0	0	0
***rm*(*k*)**	0	9	25	23	5	18	0	2	21	35	18	11	60	33	0	40	43	6	60	3	60	0	0	0
***qlrm*(*k*)**	40	40	40	40	40	40	40	40	40	40	40	40	0	40	40	40	40	40	40	0	0	0	0	0
***trn*(*k*)**	14	5	30	35	31	35	54	0	20	69	24	2	54	25	111	0	41	60	0	38	0	87	0	0
***trr*(*k*)**	10	4	25	25	23	5	18	0	2	21	35	18	10	61	33	0	40	43	0	66	0	63	0	0
tup(k)	23	20	16	13	10	30	13	0	23	30	40	32	41	30	64	0	23	22	0	32	0	0	0	0
Option 2 (*qlz*: 60, *clz*: 390 mu, *pol*: 80 mu)																								
***mn*(*k*)**	0	29	35	40	80	0	0	20	69	24	2	54	25	61	50	41	60	0	38	7	80	0	0	0
***rm*(*k*)**	0	9	25	23	23	0	0	2	21	35	18	11	60	16	17	40	43	6	60	3	60	0	0	0
***qlrm*(*k*)**	60	60	60	0	0	60	60	0	0	60	0	60	60	60	60	0	0	60	60	0	0	0	0	0
***trn*(*k*)**	14	5	30	35	31	89	0	0	20	69	24	2	54	25	61	50	41	60	0	38	0	87	0	0
***trr*(*k*)**	10	4	25	25	23	23	0	0	2	21	35	18	10	61	16	17	40	43	0	66	0	63	0	0
tup(k)	25	20	16	13	10	30	0	0	23	30	40	32	41	30	64	11	23	22	0	32	0	0	0	0

Table 2.7. Additional results with Fixed Lot Procurement (Z = 24)

k	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Option 1 (*qlz*: 40 , *clz*: 300 mu, *pol*: 60 mu)																								
***vnp*(*k*)**	29	20	5	30	35	31	35	41	13	20	69	24	2	54	25	61	50	41	33	27	30	8	62	25
***vrp*(*k*)**	17	18	4	25	25	23	5	16	2	2	21	35	18	10	61	16	17	40	25	18	35	31	51	12
***β*(*k*)**	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0	0	0	0
α*(k)*	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0
***lnp*(*k*)**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
***lrp*(*k*)**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Option 2 (*qlz*: 60 , *clz*: 390 mu, *pol*: 80 mu)																								
***vnp*(*k*)**	29	20	5	30	35	31	35	41	13	20	69	24	2	54	25	61	50	41	33	27	30	8	62	25
***vrp*(*k*)**	17	18	4	25	25	23	5	16	2	2	21	35	18	10	61	16	17	40	25	18	35	31	51	12
***β*(*k*)**	1	1	1	0	0	1	1	0	0	1	0	1	1	1	1	0	0	1	1	0	0	0	0	0
α*(k)*	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0
***lnp*(*k*)**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
***lrp*(*k*)**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 2.8. Optimal plans under Hybrid Procurement Agreement ($Z = 24$)

k	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
$mn(k)$	0	29	35	40	80	0	0	20	69	24	2	54	25	61	50	41	60	0	38	7	80	0	0	0
$rm(k)$	0	9	25	23	23	0	0	2	21	35	18	11	60	16	17	40	43	6	60	3	60	0	0	0
$qlrm(k)$	40	60	60	0	0	40	60	40	0	40	40	40	40	40	60	0	40	40	60	0	0	0	0	0
$trn(k)$	14	5	30	35	31	89	0	0	20	69	24	2	54	25	61	50	41	60	0	38	0	87	0	0
$trr(k)$	10	4	25	25	23	23	0	0	2	21	35	18	10	61	16	17	40	43	0	66	0	63	0	0
$tup(k)$	25	20	16	13	10	30	0	0	23	30	40	32	41	30	64	11	23	22	0	32	0	0	0	0

Table 2.9. Additional results under Hybrid Procurement Agreement ($Z = 24$)

k	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
$vnp(k)$	29	20	5	30	35	31	35	41	13	20	69	24	2	54	25	61	50	41	33	27	30	8	62	25
$vrp(k)$	17	18	4	25	25	23	5	16	2	2	21	35	18	10	61	16	17	40	25	18	35	31	51	12
$\beta 0(k)$	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1
$\beta 1(k)$	1	0	0	0	0	1	0	1	0	1	1	1	1	1	0	0	1	1	0	0	0	0	0	0
$\beta 2(k)$	0	1	1	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0
$\alpha(k)$	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	0
$lnp(k)$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$lrp(k)$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

In the context of the integrated supply chain, the hybrid approach enhances operational agility overall. All contract-based procurement structures are more profitable than the Simplified Acquisition Strategy because they have lower unit acquisition costs (7.5 and 6.5 mu for fixed-lot options versus 10 mu for the simplified case). This illustrates how contractual procurement mechanisms provide observable strategic and financial advantages in complex, multi-period supply-chain settings.

2.4.2.3 Theoretical and Managerial Implications of the Model

The findings theoretically support the importance of multi-period integrated optimisation in coordinating interdependent supply chain operations. The model optimises acquisition, manufacturing, remanufacturing, and transportation activities simultaneously, integrating traditional production-inventory theory into a unified, decision-synchronised framework. It also improves comprehension of circular supply chains by demonstrating the effects of different procurement structures, simplified, fixed lot, and hybrid, on overall system dynamics and performance. From a managerial standpoint, the findings demonstrate that by managing forward and reverse flows in a coordinated manner, full-service levels can be preserved while profit is maximised. Larger lots under Fixed-Lot Procurement boost cost efficiency through economies of scale, while smaller lots provide more operational flexibility. Flexibility is further increased by responsive ordering, which is made possible by the Hybrid Procurement Agreement, though at a minor cost to profitability. All things considered, the model is a useful tool for decision-making that helps strike a balance between sustainability, flexibility, and cost. It demonstrates how integrated, data-driven coordination can simultaneously make supply-chain operations more resilient, profitable, and environmentally conscious.

2.5 Conclusion

This chapter introduced an integrated optimisation framework for multi-period planning of transportation, production, remanufacturing, and procurement within a coordinated supply chain. Using MILP formulation, the model simultaneously optimises decisions related to production, inventory, logistics, and procurement in order to maximise overall profit under operational and capacity constraints. Numerical analysis over a 24-period horizon shows that the framework effectively synchronises forward and reverse flows, leading to cost-effective scheduling and

responsive procurement strategies. A comparison of these strategies shows that contract-based agreements, such as fixed-lot and hybrid strategies, enhance flexibility and cost-effectiveness when compared to simplified acquisition strategies. The study contributes both theoretically and practically by incorporating dynamic decision linkages and reverse logistics into traditional production-inventory models. It offers a logical decision-support tool that enhances overall performance, dependability, and resource utilisation. These results set the stage for the following chapter, which discusses environmental considerations and carbon-emission regulations to guide sustainable supply-chain optimisation.

Chapter 3: Integrated Multi-Period Planning of Acquisition, Manufacturing, Remanufacturing, and Transport in a Carbon-Conscious Supply Chain with Reverse Logistics

Abstract

This chapter builds on the optimisation framework developed in Chapter 2 by incorporating carbon emission considerations into multi-period planning for acquisition, manufacturing, remanufacturing, and transportation within an integrated supply chain. Three regulatory approaches are examined: The Carbon Tax Strategy, the Carbon Cap-and-Trade Strategy, and the Carbon Limit-and-Subsidy Strategy. A mixed-integer linear programming (MILP) model is created to maximise total profit while accounting for production, logistics, and inventory emissions. Numerical experiments based on real data are used to evaluate the system's performance under each strategy. The results show that carbon taxes provide strict emission control, the Cap-and-Trade mechanism allows for greater flexibility and cost effectiveness, and the Limit-and-Subsidy approach, which incentivises low-emission performance, promotes proactive environmental management. To assist decision-makers in carbon-conscious supply chains, the chapter offers an analytical framework that combines operational and financial performance with environmental responsibility.

3.1 Introduction

The importance of climate change and the tightening of environmental regulations have put carbon management at the forefront of supply chain research. Manufacturers today must look beyond cost-effectiveness and service quality to reduce emissions in production, distribution, and reverse logistics. As a result of this shift, supply chain optimisation is now a comprehensive approach that strikes a balance between economic performance and environmental responsibility. Recent studies show that carbon-conscious planning and green logistics can effectively cut emissions without compromising operational efficacy (Koh et al., 2023, Lee and Hussain, 2024).

Building on the framework established in Chapter 2, this chapter extends the multi-period optimisation model by integrating carbon emission considerations into the planning process. The system monitors acquisition, production, remanufacturing, and transportation activities while specifically accounting for emissions generated at each stage. Quantified carbon footprints from material procurement, manufacturing, transportation, and inventory management are all included in the optimisation model. This approach responds to the growing need for supply chains that balance sustainability objectives with profitability and are conscious of carbon emissions (Hasan et al., 2024). In the same context, a recent study showed that corporate carbon regulation promotes green innovation and strategic transformation under regulatory pressure (Qi et al., 2025). Another study examined how capital-constrained manufacturers modify production and pricing in response to cap-and-trade schemes (Kong and Yuan, 2025). Moreover, (Ren et al., 2025) highlight the positive impacts of government subsidies on green investment and service performance, while (Turki et al., 2025) propose an optimal control framework for manufacturing and remanufacturing systems under subsidy and penalty mechanisms. Despite these developments, little research has been done on the combined operational and economic impacts of different regulatory frameworks within integrated, multi-period supply chains.

To address this research gap, the current study looks at three regulatory mechanisms: The Carbon Tax strategy, the Carbon Cap-and-Trade strategy, and the Carbon Limit-and-subsidy strategy. The first mechanism, which uses financial penalties to encourage reduction, imposes a tax on businesses based on their emissions. By setting an overall emission cap and permitting the trading of emission allowances, the second offers flexibility in achieving compliance. The third introduces financial incentives for companies that operate below a certain emission threshold,

which promotes reduction and rewards proactive environmental performance. Together, these systems support the shift to cleaner production methods and more sustainable industrial practices.

The analytical model is developed as a MILP formulation to maximise overall profit while meeting operational and environmental constraints. It includes all of the cost components discussed in Chapter 2, such as production, remanufacturing, transportation, inventory, and raw material acquisition, in addition to newly added carbon-related costs and incentives. This integration enables a realistic assessment of how various carbon regulation policies affect procurement, production scheduling, remanufacturing levels, and transport coordination over multiple planning periods.

Reverse logistics supply chains and the trade-offs between sustainability and profitability are also examined in the study. Although they may reduce profit margins, strict regulatory measures like carbon taxes or emission caps promote cleaner production, more efficient use of resources, and increased environmental compliance. However, flexible mechanisms like Cap-and-Trade and Limit-and-Subsidy encourage flexible and sustainable business practices by allowing companies to pursue economic optimisation through incentive-based schemes and emission trading. From this perspective, the proposed model functions as both an optimisation framework and a tool to help make environmentally conscious supply chain management decisions.

This chapter's remaining sections are arranged as follows. Section 3.2 presents the emission-related parameters and notations introduced in the extended model, as well as the system description and underlying assumptions. Section 3.3 develops the models for maximising profits under the three carbon regulation strategies. Section 3.4 provides a description of the numerical experiments, input parameters, and results analysis. After that, a comparison between carbon-regulated and non-regulated systems is covered. Section 3.5 concludes the chapter by outlining the implications of integrating carbon-conscious planning into sustainable supply chain management, providing theoretical and managerial insights.

3.2 Problem Description and Working Assumptions

3.2.1 System Description

This section builds upon the integrated framework introduced in Chapter 2 by incorporating environmental considerations into the decision-making process. The proposed model illustrates a

carbon-conscious supply chain with emissions from production, remanufacturing, storage, transportation, and procurement specifically measured and evaluated to reflect sustainability-focused industrial practices. As shown in Figure 3.1, the system is composed of three interconnected subsystems: the production system, the logistics and distribution system, and the city/markets zone. The forward flow handles the acquisition, manufacturing, and distribution of raw materials, whereas the reverse flow keeps track of product returns and recoveries. In this enlarged version, every activity contributes to the system's overall carbon footprint, striking a balance between environmental impact and economic performance. The procurement and storage of raw materials, production and remanufacturing activities, warehousing, city-level inventories, and transportation are all considered as sources of emissions. Since all inter-facility movements are handled by a single vehicle, which produces both variable and fixed emissions, transport is the activity with the highest emissions. The system's cumulative carbon footprint ($CF(Z)$) over the planning horizon is determined by the sum of these sources.

The model incorporates three regulatory mechanisms:

1. Carbon Tax Strategy: applies a unit tax ucp on total emissions, generating a carbon tax cost $TCX(Z)$ and affecting profit $PRCX(Z)$.
2. Carbon Cap-and-Trade Strategy: allows for price-based emission trading while imposing a carbon limit *cap*, yielding profit $PRCT(Z)$ that depends on the system's performance relative to the cap.
3. Carbon Limit-and-Subsidy Strategy: provides a subsidy in addition to setting a maximum emission limit $LIMC$. When emissions remain below this threshold, profit $PRCS(Z)$ is generated.

The extended model seeks to maximise overall profit while accounting for carbon-related costs and regulatory constraints in order to balance economic and environmental objectives. This framework for sustainable optimisation supports strategic decision-making when it comes to striking a balance between profitability and carbon accountability. The following sections provide mathematical formulation and numerical analysis for each regulatory strategy.

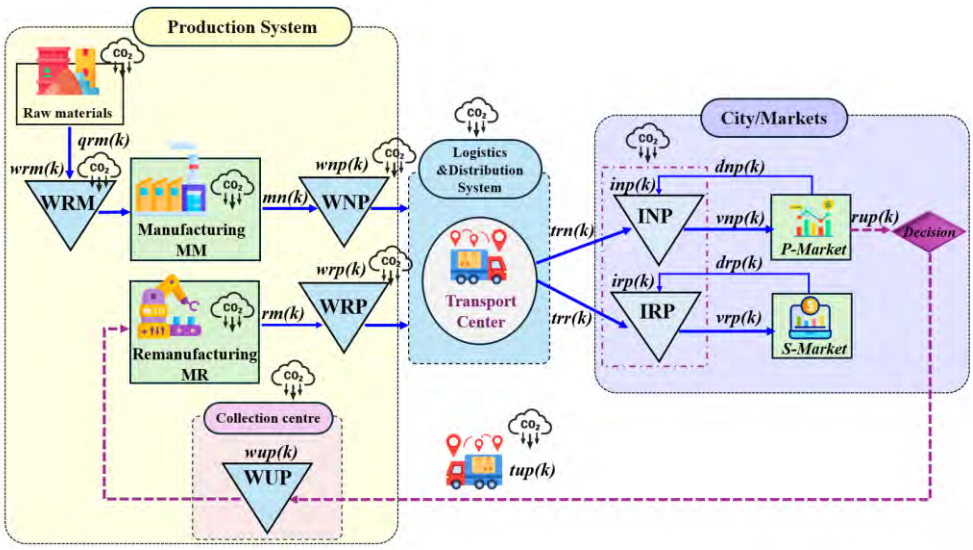

Figure 3.1. Carbon-conscious supply chain with reverse logistics

3.2.2 Notations

The essential parameters and decision variables underpinning the model formulation are introduced below to provide a clear basis for the subsequent mathematical development.

$PRCX(Z)$	Total profit considering Carbon Tax strategy
$PRCT(Z)$	Total profit considering Carbon Cap-and-Trade strategy
$PRCS(Z)$	Total profit considering Carbon Limit-and-Subidy strategy
$TCX(Z)$	Total carbon tax cost over the horizon $Z.\lambda$
$TCT(Z)$	Total carbon trade over the horizon $Z.\lambda$
ucp	Unit carbon tax price
cct	Unit carbon trading price
cap	Carbon cap
$LIMC$	Maximum permitted cumulative carbon emissions during the planning horizon $Z.\lambda$
S	Subsidy amount awarded when total emissions are maintained below $LIMC$.
$SUB(Z)$	Subsidy value over the planning horizon $Z.\lambda$
$CF(Z)$	Carbon footprint over the horizon $Z.\lambda$
$CF0$	Carbon footprint at the start of period 1
em	Unit carbon emissions from acquisition of raw materials

en	Unit carbon emissions from manufacturing new product
er	Unit carbon emissions from remanufacturing product
erm	Unit carbon emissions from holding raw materials in *WRM*
ewn	Unit carbon emissions from holding new product in *WNP*
ewr	Unit carbon emissions from holding remanufactured in *WRP*
ecu	Unit carbon emissions from holding one used product in *WUP*
enp	Unit carbon emissions from holding new product in *INP*
erp	Unit carbon emissions from holding remanufactured products in *IRP*
etr	Unit carbon emissions from transporting new, remanufactured, or returned products
efrt	Fixed quantity of carbon emitted by vehicle *V*

The decision structure in this chapter follows the same framework that was developed in Chapter 2 to ensure uniformity across all models. Under the Carbon Tax Strategy, the objective is to determine the optimal values of the decision variables, QRM^* MN^*, RM^*, TRN^*, TRR^*, and TUP^* that maximise total profit $PRCX(Z)$, yielding the optimal profit $PRCX^*(Z)$. The MILP formulation includes production, procurement, inventory, and transportation constraints, together with carbon taxation parameters. The Carbon Cap-and-Trade Strategy maximises profit *PRCT*(*Z*) by optimising the same decision variables, resulting in the best *PRCT** (*Z*) outcome. Finally, the Carbon Limit-and-Subsidy Strategy generates an optimal profit *PRCS** (*Z*) using an analogous formulation. This version includes an incentive mechanism that rewards emission levels below a predefined limit while keeping the same operational constraints in order to align economic performance with sustainability goals.

3.2.3 Working Assumptions

By following the working assumptions listed in Chapter 2, this study preserves the methodological consistency between the two modelling frameworks. Other assumptions are made in order to take into consideration the environmental impact of carbon emissions:

- The basic assumptions underlying acquisition, production, remanufacturing, and transportation activities preserve coherence in the system structure.

- Carbon emissions from all major supply chain operations contribute to the overall carbon footprint, or $CF(Z)$, which is determined by specific unit emission rates.
- From an initial value of $CF_0=0$, the cumulative footprint progressively increases over the planning horizon as operations continue.
- Emissions from the transportation of new, remanufactured, and returned products are treated as equivalent, simplifying the analysis by treating all transport-related emissions equally.

All things considered, these additional assumptions incorporate environmental responsibility into the operational model and offer a rational basis for assessing economic and ecological trade-offs in a supply chain framework that takes carbon emissions into account.

3.3 Analytical Study

In this section, an analytical development of the extended optimisation model for a carbon-conscious supply chain is made. The economic impact of emissions produced by acquisition, production, remanufacturing, storage, and transportation activities is taken into account when the model is reformulated to incorporate environmental considerations. This expands on the structure outlined in Chapter 2. The formulation has two main applications. It first establishes the mathematical framework of the profit function under the three regulatory strategies, the Carbon Tax, Carbon Cap-and-Trade, and Carbon Limit-and-Subsidy mechanisms, to ensure that all carbon-related costs, credits, and incentives are consistently included in the optimisation process. Second, it provides the theoretical foundations for the numerical experiments in Section 3.4 that evaluate and compare model performance across these regulatory frameworks using representative operational data.

3.3.1 Mathematical Formulation of Profit Under Carbon Tax Strategy

Equation (3.1) defines the total profit function under the Carbon Tax Strategy and extends the baseline model from Chapter 2 by including the environmental cost of carbon emissions in the objective function. As originally formulated, profit is calculated by substracting total revenues from the sum of all operational expenses, including production, remanufacturing, shortages, inventory holding, transportation, acquisition, and returns. By including a new term, $TCX(Z)$, to

represent the total carbon tax cost accumulated over the planning horizon, this expanded version directly integrates environmental considerations into the economic optimisation process.

$$\text{Maximise } PRCX(Z) = \sum_{k=1}^{z}(R(Z) - (MC(Z) + RC(Z) + NSC(Z) + RSC(Z) + HRM(Z) + HNP(Z) + HRP(Z) + HUP(Z) + HIN(Z) + HIR(Z) + TC(Z) + ARM(Z) + RPC(Z) + (FT \times \alpha(k)) + TCX(Z)) \quad (3.1)$$

Equation (3.2) calculates the total cost of the carbon tax by multiplying the unit carbon tax price (*ucp*) by the cumulative carbon footprint (*CF*(*Z*)). The cumulative carbon footprint, which starts at CF_0=0 and calculates the total emissions generated at each stage of the supply chain, is displayed in equation (3.3). The acquisition of raw materials, production and remanufacturing processes, inventory holding across several warehouses and markets, and transportation movements are the main causes of these emissions, which comprise both the fixed and variable components of vehicle emissions.

$$TCX\ (\mathrm{Z}) = ucp \times CF(Z) \quad (3.2)$$

$$CF(Z) = \sum_{k=0}^{Z}\Big((em \times qrm(k)) + (en \times mn(k)) + (er \times rm(k)) + (erm \times wrm(k)) + (ewn \times wnp(k))) + (ewr \times wrp(k)) + (ecu \times wup(k)) + (enp \times inp(k)) + (erp \times irp(k)) + \big(etr \times trn(k)\big) + \big(etr \times trr(k)\big) + \big(etr \times tup(k)\big) + (eftr \times \alpha(\mathrm{k}))\Big) \quad (3.3)$$

This formulation enables the Carbon Tax mechanism to penalise emission-intensive activities by directly linking the supply chain's cost structure to the overall carbon footprint. Therefore, the optimisation model must encourage decisions that lower emissions while preserving operational effectiveness, striking a balance between economic performance and environmental responsibility. It provides a quantitative foundation for examining the effects of carbon taxes on production, remanufacturing, and transportation planning, and it forms the basis of the numerical analysis presented in Section 3.4.

3.3.2 Mathematical Formulation of Profit Under Carbon Cap-and-Trade Strategy

Equation (3.4) defines the total profit function under the Carbon Cap-and-Trade strategy. The general economic structure of the formulation used for the carbon tax case is the same. The total profit is determined by subtracting total operational and logistical costs from total revenues over the course of the planning horizon. The main distinction is the addition of *TCT*(*Z*), the carbon trading component that represents the profit or loss from trading emission allowances in a regulated carbon market.

$$\text{Maximise } PRCT(Z) = \sum_{k=1}^{z}(R(Z) - (MC(Z) + RC(Z) + NSC(Z) + RSC(Z) + HRM(Z) + HNP(Z) + HRP(Z) + HUP(Z) + HIN(Z) + HIR(Z) + TC(Z) + ARM(Z) + RPC(Z) + (FT \times \alpha(k)) + TCT(Z)) \quad (3.4)$$

In this instance, *TCT*(*Z*), which can be found in Equation (3.5), represents the total carbon trade value over the planning horizon. It is computed by multiplying the unit carbon trading price (*cct*) by the difference between the emission cap (*cap*), or the highest permitted level of emissions, and the actual cumulative carbon footprint (*CF*(*Z*)). When *CF*(*Z*) is below the emission cap, any unused carbon credits are sold to generate revenue for the surplus allowance $\big(cap - CF(Z)\big)$. The company must pay more to purchase the required credits, however, if the emissions are higher than allowed. This ensures that environmental regulations are respected as well.

$$TCT(Z) = \big(cap - CF(Z)\big) \times cct \quad (3.5)$$

As in the previous formulation, *CF*(*Z*) represents the total carbon footprint resulting from all system operations, including raw material procurement, production, remanufacturing, inventory storage, and transportation. Each of these processes contributes proportionately, depending on its emission coefficient. As a result, the Carbon Cap-and-Trade strategy provides an adaptable way to control emissions, with the system's profitability dependent on both its operational efficiency and its capacity to function within or below the designated emission threshold.

3.3.3 Mathematical Formulation of Profit Under Carbon Limit-and-Subsidy Strategy

Businesses are encouraged to maintain their total carbon emissions below a predetermined threshold by the Carbon Limit-and-Subsidy Strategy, which introduces an incentive-based

regulatory mechanism. Unlike the Carbon Cap-and-Trade approach, which permits excess allowances to be bought or sold within a market system, this strategy imposes a strict emission cap and offers a financial subsidy when the cumulative carbon footprint remains below the permitted threshold. Equation (3.6) defines the total profit function of the Carbon Limit-and-Subsidy framework. As in the previous formulations, the total profit is the difference between total revenue and the sum of all operating, manufacturing, remanufacturing, inventory, transportation, and acquisition costs over the planning horizon. The addition of the subsidy component, *SUB*(*Z*), which represents the financial gain obtained when the system operates below the *LIMC* (maximum allowable emission level), is the primary distinction.

$$\text{Maximise } PRCS(Z) = \sum_{k=1}^{z}(R(Z) - (MC(Z) + RC(Z) + NSC(Z) + RSC(Z) + HRM(Z) + HNP(Z) + HRP(Z) + HUP(Z) + HIN(Z) + HIR(Z) + TC(Z) + ARM(Z) + RPC(Z) + (FT \times \alpha(k)) + TCT(Z)) + SUB(Z)) \quad (3.6)$$

In this expression, *SUB*(*Z*) denotes the total subsidy value over the planning horizon and is defined as shown in Equation (3.7):

$$SUB(Z) = \begin{cases} S \text{ if } CF(Z) \leq LIMC \\ 0 \text{ otherwise} \end{cases} \quad (3.7)$$

where *S* represents the fixed subsidy amount (in monetary units) granted when total emissions are maintained below the threshold *LIMC*.

The following constraint (3.8) is introduced to guarantee that the total cumulative emissions, *CF*(*Z*), as defined in the sections that come before this chapter, do not surpass the regulatory environmental threshold and to preserve adherence to sustainability regulations:

$$CF(Z) \leq LIMC \quad (3.8)$$

The Carbon Limit-and-Subsidy mechanism encourages proactive emission reduction by linking environmental performance with financial gain, serving as a reward-based alternative to taxation and trading schemes. By balancing profitability, operational effectiveness, and environmental responsibility, the resulting optimisation encourages the development of a low-carbon, incentive-driven supply chain configuration. This formulation enables an integrated evaluation of economic and environmental performance by allowing the model to analyse trade-

offs between production planning and emission management strategies. The findings in Section 3.4 offer comparative insights into how the system responds to different carbon regulatory mechanisms when contrasted with the baseline configuration from Chapter 2, which operates without environmental regulation.

3.4 Numerical Studies

In this section, the carbon-conscious optimisation models are numerically implemented under the three regulatory frameworks: The Carbon Tax Strategy, the Carbon Cap-and-Trade Strategy, and the Carbon Limit-and-Subsidy Strategy. Building on the system described in Chapter 2, the analysis extends the multi-period supply chain model by adding environmental considerations through carbon emission parameters and associated policy mechanisms. The numerical experiments evaluate how these regulatory approaches affect operational performance and profitability compared to the baseline model that ignores environmental constraints. For both new and remanufactured products, the study uses the same supply chain setup, however, the input parameters have been expanded to include carbon emission data, pricing, allowable caps, and subsidies. These additions enable a comprehensive assessment of the trade-offs between economic efficiency and environmental responsibility across all strategies. The MILP models are implemented and solved using the CPLEX 22.1.1 solver, which ensures computational consistency and comparability with the results of the previous chapter.

3.4.1 Input Parameters

This section describes the input parameters for the extended optimisation model that incorporates carbon emission factors into the framework of the multi-period supply chain. In addition to the parameters listed in Chapter 2, additional input is added to capture the environmental impact of each operational stage (Table 3.1). These comprise the unit carbon tax, trading price, emission cap, maximum allowable emissions, and emission reduction subsidy, and they set the regulatory framework for the three carbon management strategies. The model also includes unit emission coefficients for all major supply chain activities.

The following section presents and analyses the outcomes of the optimisation framework after the model's input parameters and numerical data have been defined. The following section looks at system performance under the three carbon regulatory strategies. This structure makes it

possible to compare the three regulatory mechanisms and their impacts on production scheduling, profitability, and environmental performance. The study also compares the non-regulatory baseline system from Chapter 2 with the regulatory system developed in this chapter to evaluate the overall impact of carbon management policies on supply chain sustainability and efficiency.

Table 3.1. Environmental impact input parameters

ucp	***cct***	***cap***	***LIMC***	***S***	***em***	***en***	***er***	***erm***	***ewn***	***ewr***	***ecu***	***enp***	***erp***	***etr***	***efrt***
0.1	2	110000	95000	30000	5	60	10	1	2	2	1	3	3	1	3000

3.4.2 Obtained Results

3.4.2.1 The System's Performance Under Carbon Tax Strategy

A unit carbon price (*ucp*=0.1 monetary units per carbon unit) was used to run the optimisation model under the Carbon Tax Strategy. This led to a total profit of *PRCX*(*Z*)=99,800 mu and a cumulative carbon footprint of CF(Z)=112,516 units over the 24-period horizon. The comprehensive results, illustrated in Tables 3.2 and 3.3, describe the best practices and performance indicators for this regulatory environment. A carbon tax forces the system to balance economic efficiency with environmental responsibility by establishing a direct link between emissions and profitability. Acquisition quantities (*qrm* (*k*)), which vary somewhat in response to demand, support both manufacturing (*mn*(*k*)) and remanufacturing (*rm*(*k*)) operations. While the production of new products peaks in periods 3, 5, 13, and 21, remanufacturing activity increases in periods 3, 10, 13, and 21. This suggests that the two procedures work well together and that resources are being used efficiently.

Stable reverse logistics is ensured by transport flows (*trn*(*k*), *trr*(*k*), and *tup*(*k*)) that follow production trends and minimise unnecessary trips through selective vehicle activation ($\alpha(k)$). Because of this collaboration, emissions and transportation costs are reduced. Since sales quantities of both new and remanufactured products fully meet demand, customer service levels are maintained despite the tax-induced cost increase (*lnp*(*k*)=0, *lrp*(*k*)=0). The carbon tax promotes more thoughtful production and transportation scheduling, even though overall emissions are still high from an environmental standpoint. Better resource management and less operational excess offset the cost of integrating carbon, which is reflected in a slight economic decline in profits when

compared to the non-regulated baseline. All things considered, the Carbon Tax Strategy does a good job of increasing emissions awareness while maintaining system functionality. By demonstrating that modest carbon pricing can encourage cleaner operational practices without resulting in significant losses in profitability, it offers a foundation for comparison with the Carbon Cap-and-Trade and Carbon Limit-and-Subsidy strategies discussed in later sections.

3.4.2.2 The System's Performance under Carbon Cap-and-Trade Strategy

The Carbon Cap-and-Trade Strategy was used to run the optimisation model, with a unit carbon trading price (cct=2 mu per carbon unit) and an emission limit (cap=110,000 units). Tables 3.4 and 3.5 present the optimal results, which show a total profit of $PRCT(Z)$=112,252 mu and a cumulative carbon footprint of $CF(Z)$=99,643 units over the 24-period planning horizon. This arrangement demonstrates the effectiveness of combining market-based flexibility with regulatory constraints by achieving lower emissions and greater profitability than the Carbon Tax scenario. The acquisition plan ($qrm(k)$) alternates between active and inactive periods, strategically adjusting to stay within the emission cap while balancing material availability with environmental constraints. New product manufacturing ($mn(k)$) peaks during high-demand periods (3, 5, 13, and 21), while remanufacturing ($rm(k)$) compensates for it in periods 3, 10, 13, and 17. This adaptive scheduling ensures efficient capacity utilisation while staying within the carbon limit. The tight coordination of transport operations ($trn(k)$, $trr(k)$, and $tup(k)$) with production levels guarantees efficient forward and reverse logistics. The vehicle activation variable ($\alpha(k)$), which alternates between one and zero, indicates that transport only occurs when it is required.

Table 3.2. Optimal plans with *ucp*=0.1 ($Z = 24$)

k	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
mn(k)	0	29	66	9	80	0	0	20	69	24	2	54	56	80	0	41	33	27	38	7	80	0	0	0
rm(k)	0	9	46	1	22	0	0	2	21	35	18	11	60	33	0	40	25	24	60	3	60	0	0	0
qrm(k)	65	9	80	0	0	20	69	24	2	54	56	80	0	41	33	27	38	7	80	0	0	0	0	0
trn(k)	14	5	30	66	0	89	0	0	20	69	24	2	54	25	111	0	41	33	27	38	0	87	0	0
trr(k)	10	4	25	46	0	23	0	0	2	21	35	18	10	61	33	0	40	25	18	66	0	63	0	0
tup(k)	25	20	15	13	0	30	0	0	23	26	40	32	41	30	64	0	23	22	24	32	0	0	0	0

Table 3.3. Additional results with *ucp*=0.1 ($Z = 24$)

k	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
vnp(k)	29	20	5	30	35	31	35	41	13	20	69	24	2	54	25	61	50	41	33	27	30	8	62	25
vrp(k)	17	18	4	25	25	21	5	16	2	2	21	35	18	10	61	16	17	40	25	18	35	31	51	12
α(k)	1	1	1	1	0	1	0	0	1	1	1	1	1	1	1	0	1	1	1	1	0	1	0	0
lnp(k)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
lrp(k)	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 3.4. Optimal plans with *cct=2* and *cap*=110000 units (*Z* = 24)

k	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
mn(k)	29	0	66	29	80	0	0	0	69	24	2	54	56	80	21	80	0	0	38	7	80	0	0	0
rm(k)	9	0	46	0	13	0	0	0	21	9	18	11	60	33	5	60	0	0	54	0	51	0	0	0
qrm(k)	65	29	80	0	0	0	69	24	2	54	56	80	21	80	0	0	38	7	80	0	0	0	0	0
trn(k)	14	35	0	66	0	109	0	0	0	69	24	2	54	25	111	0	101	0	0	38	0	87	0	0
trr(k)	10	29	0	46	0	13	0	0	0	21	9	18	10	61	33	0	65	0	0	54	0	51	0	0
tup(k)	25	20	0	13	0	30	0	0	0	30	40	32	41	30	64	0	23	0	0	32	0	0	0	0

Table 3.5. Additional results with *cct*=2 and *cap*=110000 units (*Z* = 24)

k	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
vnp(k)	29	20	5	30	35	31	35	41	13	20	69	24	2	54	25	61	50	41	33	27	30	8	62	25
vrp(k)	17	18	4	25	25	21	5	8	0	0	21	9	18	10	61	16	17	40	25	0	35	19	51	0
α(k)	1	1	0	1	0	1	0	0	0	1	1	1	1	1	1	0	1	0	0	1	0	1	0	0
ln(pk)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
lrp(k)	0	0	0	0	0	2	0	8	2	2	0	26	0	0	0	0	0	0	0	18	0	12	0	12

This selective scheduling lowers emissions and transportation costs by cutting down on unnecessary travel. Sales of both new ($vnp(k)$) and remanufactured ($vrp(k)$) products closely follow demand, ensuring nearly complete market coverage. Overall service levels remain high, although there are sporadic minor shortages in the supply of remanufactured products during times of high demand due to emission restrictions.

The Carbon Cap-and-Trade Strategy is more economically viable than the Carbon Tax framework because it allows for the flexibility of trading carbon credits when it is advantageous. The substantial drop in overall emissions, from 112,516 to 99,643 units, validates the model's capacity to sustain strong environmental performance under market-driven regulation.

In summary, the Cap-and-Trade mechanism effectively and fairly combines economic and environmental objectives. It encourages greater profitability and operational efficiency while enforcing stricter emission control. These results demonstrate that market-based carbon policies can effectively support sustainable production planning and carbon-responsible supply chain management.

3.4.2.3 The System's Performance Under Carbon Limit-and-Subsidy Strategy

The best results under the Carbon Limit-and-Subsidy Strategy are displayed in Tables 3.6 and 3.7. This situation enforces a strict carbon limit of $LIMC$=95,000 units, and total emissions that remain below this limit are rewarded with a S=30,000 mu subsidy. With a total profit of 88,906 mu and a cumulative carbon footprint of 94,646 units, the optimisation verifies eligibility for the subsidy incentive and compliance with the emission limit.

Production and remanufacturing schedules operate cautiously and flexibly as a result of the stringent *cap*. Over time, the new product output ($mn(k)$) fluctuates as emission-sensitive periods (especially 9, 13, 15 and 19) decrease. Remanufacturing ($rm(k)$) occurs strategically and intermittently, especially during periods 7, 12, 16, and 21, to ensure supply continuity and reduce emissions. The decreased and irregular frequency of raw material orders ($qrm(k)$) indicates intentional upstream restraint. Similarly, transport activities ($trn(k)$, $trr(k)$) are selectively activated, and the round-trip variable ($\alpha(k)$) alternates between active and inactive states, ensuring that vehicles are used only when they are economically and environmentally justified.

Table 3.6. Optimal plans with *LIMC* =95000 and *S* =30000 (*Z* = 24)

k	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
mn(k)	10	13	60	12	60	3	50	62	0	54	59	47	4	50	5	49	9	60	2	11	56	10	0	0
rm(k)	0	0	0	0	0	0	49	0	0	0	11	60	0	33	0	42	0	18	35	0	51	6	0	0
qrm(k)	55	16	53	2	50	76	42	0	58	49	0	53	4	45	9	62	0	12	58	5	0	0	0	0
trn(k)	14	16	0	64	0	81	0	0	115	0	0	0	79	0	111	0	74	0	27	38	0	62	25	0
trr(k)	11	19	0	0	0	0	0	0	49	0	0	0	71	0	33	0	42	0	18	35	0	49	8	0
tup(k)	25	20	0	13	0	30	0	0	23	0	0	0	41	0	64	0	23	0	24	32	0	0	0	0

Table 3.7. Additional results with *LIMC* =95000 and *S* =30000 (*Z* = 24)

k	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
vnp(k)	29	20	5	11	35	29	35	41	5	20	69	24	2	54	25	61	50	41	33	27	30	8	62	25
vrp(k)	17	18	4	16	0	0	0	0	0	2	21	26	0	10	61	16	17	40	2	18	35	0	49	8
α(k)	1	1	0	1	0	1	0	0	1	0	0	0	1	0	1	0	1	0	1	1	0	1	1	0
lnp(k)	0	0	0	19	0	2	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
lrp(k)	0	0	0	9	25	23	5	16	2	0	0	9	18	0	0	0	0	0	23	0	0	31	2	4

Since sales of new and remanufactured products ($vnp(k)$, $vrp(k)$) normally follow demand but occasionally show shortfalls ($lnp(k)$, $lrp(k)$) during emission-restricted periods, there is an expected trade-off between service performance and environmental compliance. All things considered, the system complies with the emission restriction while maintaining sufficient demand fulfilment. The total profit of 88,906 mu is less than in the Carbon Tax and Cap-and-Trade scenarios because the subsidy incentive covered the cost of strict emission control. In terms of the environment, the carbon footprint remains below the predetermined level, indicating how effectively the mechanism promotes controlled emission management.

In conclusion, the Carbon Limit-and-Subsidy Strategy provides financial incentives for sustainable operations while enforcing strict environmental control. The system achieves complete compliance with little disruption to operations, despite declining profit margins. These findings show that by incentivising proactive environmental control and promoting the shift to low-carbon supply chain management, subsidy-based schemes have the potential to supplement traditional regulations.

3.4.2.4 Theoretical and Managerial Implications of the Model

Theoretically, traditional production-inventory theory is extended towards a model that is decision-coordinated and carbon-accountable by integrating carbon-related mechanisms into the multi-period optimisation framework. By directly incorporating emissions into the objective function, the framework emphasises the link between economic performance and environmental responsibility. It illustrates how production, remanufacturing, procurement, and logistics must all be balanced with environmental constraints in order to achieve sustainable supply chain optimisation. Reducing expenses alone is not enough. This advancement advances theoretical understanding of carbon-regulated supply chains by providing a methodical framework for evaluating trade-offs between operational flexibility, carbon limitation, and profitability. From the perspective of management, the findings offer valuable insights. Without affecting current production, the Carbon Tax Strategy is a simple and effective regulatory tool that encourages gradual behavioural change and emission reduction.

3.4.2.4 Comparison of Regulated versus Non-Regulated Scenarios

To evaluate the effect of environmental regulation on system performance, the outcomes of the three carbon management strategies developed in this chapter are contrasted with those of the non-regulated baseline model (Chapter 2, Section 2.4.2.1). Table 3.8 provides a combined summary of the economic and environmental outcomes for each scenario. The baseline configuration maximises profit but ignores sustainability concerns because it is not constrained by emissions. However, each regulatory mechanism creates a different balance between profitability and environmental performance. The Carbon Tax Strategy promotes moderate emission control through direct penalisation and cost internalisation. Businesses can trade emission credits and maximise compliance with the Carbon Cap-and-Trade Strategy by introducing flexibility through market-based adjustments. The strictest emission reductions are offset by financial incentives under the Carbon Limit-and-Subsidy Strategy.

Taking together, these results show how crucial carbon regulation is in promoting adaptable and sustainable supply chain decisions. Out of the three, the Cap-and-Trade mechanism balances profit and emission control the best and provides flexibility in a variety of market conditions. The Limit-and-Subsidy approach enforces stronger environmental discipline, promotes proactive emission reduction, and supports long-term sustainability goals, even at the cost of decreased profitability. When combined, these findings provide managers with useful guidance on how to select the regulatory framework that best suits their organization's operational priorities, sustainability objectives, and risk tolerance. As a result, the proposed model serves as a comprehensive decision-support tool that integrates operational optimisation and environmental accountability. It also demonstrates how well-designed carbon policies, whether they are punitive or incentive-based, can promote economic efficiency and environmental sustainability.

3.5 Conclusion

This chapter extended the optimisation framework developed in Chapter 2 by adding carbon emission considerations to multi-period supply chain planning. The updated model optimises choices about procurement, manufacturing, remanufacturing, and transportation while also accounting for the environmental impacts of each phase of operation. Three regulatory strategies, Carbon Tax, Carbon Cap-and-Trade, and Carbon Limit-and-Subsidy, were examined to determine their effects on profitability, operational behaviour, and emission performance.

Table 3.8. Regulated versus Non-Regulated Scenarios

Strategy / Scenario	Profit (mu)	Carbon Footprint (units)	Regulatory Parameters	System Behaviour and Key Observations	Main Advantage
Baseline (No Regulation)	111,091	113,405	None	▪ System operates as profitably as possible ▪ No emission control ▪ Balanced manufacturing and remanufacturing coordination ▪ Maximum profitability without any environmental constraints	▪ Maximises economic performance ▪ Serves as reference for evaluating regulatory impact
Carbon Tax Strategy	99,800	112,516	Unit carbon tax $ucp = 0.1$	▪ Stable production and transportation patterns ▪ Slight decline in profit due to tax costs ▪ Moderate decrease in emissions as a result of taxes	▪ Simple implementation ▪ Predictable cost structure
Carbon Cap-and-Trade Strategy	112,252	99,643	$cap = 110{,}000$ Trading price cct = 2	▪ Allows for flexible emission control through trading ▪ Efficiently balances new and remanufactured production ▪ Maintains the full-service level	▪ Optimal trade-off between profit and emission compliance ▪ Adaptive and market responsive
Carbon Limit-and-Subsidy Strategy	88,906	94,646	Emission limit $LIMC = 95{,}000$ Subsidy $S = 30{,}000$	▪ Strict emission controls ▪ Decline in production and transportation ▪ Small decline in demand ▪ Strong incentive for eco-friendly business practices	▪ Most effective emission reduction ▪ Fosters proactive environmental management

Carbon control measures significantly improve operational discipline and environmental compliance while lowering profit margins, according to a comparison of regulated and non-regulated systems. The Limit-and-Subsidy strategy yielded the largest emission reduction through incentive-driven regulation, while the Cap-and-Trade mechanism produced the most balanced result between profit and emission control among the three strategies. In contrast, the Carbon Tax approach used direct financial penalties to promote incremental behavioural change without interfering with production. The findings show that carbon regulation significantly affects both economic and environmental results. Theoretical contributions are found in extending conventional production-inventory optimisation to a framework that is decision-synchronised and carbon-accountable. From a managerial perspective, the model provides useful suggestions for aligning procurement, production, and logistics policies with sustainability objectives in diverse regulatory contexts.

In conclusion, by enhancing environmental performance without sacrificing operational efficacy, carbon-conscious planning facilitates the transition to robust, low-emission, and sustainable supply chains. The next chapter builds on these findings and further integrates sustainability and efficiency in supply chain management by extending the framework to the joint optimisation of maintenance and transport decisions within a reverse logistics context.

Chapter 4: Integrated Optimisation of Vehicle Maintenance and Transport within a Supply Chain with Reverse Logistics

Abstract

In order to balance preventive and corrective interventions over a multi-period horizon, this chapter offers an optimisation framework for maintenance planning in a vehicle-based transportation system. In order to facilitate long-term decision-making, the model provides an organised approach by capturing the trade-off between operational reliability, cost effectiveness, and maintenance frequency. Even though infrequent interventions raise the risk of failures and service interruption, excessive preventive measures can raise costs. This is highlighted by incorporating maintenance scheduling into the comprehensive optimisation process. By demonstrating how responsive maintenance policies are to changes in cost structures, sensitivity analysis also emphasises the necessity of adaptable and data-driven planning. The findings support a shift in maintenance management from reactive to proactive, viewing reliability and cost control as interconnected objectives. All things considered, the chapter provides theoretical knowledge as well as practical guidance for developing strong, efficient, and long-lasting maintenance plans in complex supply-chain operations.

4.1 Introduction and Literature Review

Effective transport management remains a significant challenge in modern supply-chain systems, especially in networks with complex forward and reverse flows. Vehicle reliability and maintenance planning are critical to performance maintenance. The model developed in Chapter 2 assumed complete vehicle availability throughout the planning horizon because damage and failures can cause operational disruptions and lower delivery reliability. To get around this limitation, the current chapter integrates vehicle maintenance planning into a multi-period optimisation framework. Maintenance, which is considered a strategic aspect of logistics management, has a direct impact on vehicle availability, capacity, cost effectiveness, and service quality. In reverse logistics, where vehicles manage both forward and return flows, reliability and capacity must be balanced. Effective maintenance scheduling is necessary for this. By linking decisions regarding preventive and corrective maintenance to transportation operations, the extended model offers a more accurate and cost-effective representation of the supply chain. This approach enhances operational sustainability and resilience.

Recent studies have focused on the joint optimisation of maintenance and logistics. For example, (Wang and Djurdjanovic, 2025) proposed a joint optimisation framework linking maintenance and logistics decisions in supply-chain settings. (Rozas et al., 2024) developed a chance-constrained stochastic mixed-integer program that synchronises maintenance and spare parts provisioning with transport operations. (Liu et al., 2025a) developed a spatiotemporal joint optimisation model for preventive maintenance in vehicle networks with the goal of increasing operational efficiency and reducing downtime. Corrective (post-failure) and preventive (planned) maintenance strategies are the two primary types. Determining the optimal time and frequency for preventive maintenance, which is commonly chosen to minimise unplanned failures and ensure continuity, can be challenging in interdependent logistics networks. In terms of sustainability, vehicles with routine maintenance also have longer asset lives, run more smoothly, and emit fewer emissions.

Despite ongoing advancements, many studies continue to treat maintenance and transportation independently, neglecting interruptions and repair scheduling. There hasn't been much focus on maintenance coordination in reverse logistics systems, where vehicle utilisation is

high and return flows add complexity. Ignoring these elements may lead to operating costs that are underestimated and capacity allocation that is not optimal.

This chapter develops an integrated multi-period optimisation model to determine vehicle maintenance schedules and transport operations in a reverse logistics network. It builds on the framework of Chapter 2 by including vehicle availability and maintenance tasks as deciding factors. By finding the optimal balance between preventive and corrective actions, the overall expected maintenance cost per vehicle over the planning horizon is to be minimised. The chapter makes three major contributions. First, by considering maintenance as a decision variable, it enables dynamic adjustment of vehicle availability. It also looks at the trade-offs between maintenance expenses, downtime, and transportation efficiency. Third, it shows how coordinating maintenance and transportation planning improves the sustainability and resilience of the supply chain. This chapter concludes by highlighting the interdependence of transportation and maintenance operations. By incorporating maintenance planning into an overall optimisation framework, it offers a practical way to improve the long-term sustainability, dependability, and cost effectiveness of reverse logistics systems.

4.2 System Description and Modelling Assumptions

This chapter builds on the integrated supply-chain model introduced in Chapter 2, which optimised decisions regarding procurement, production, remanufacturing, and transportation over a variety of time periods. Although the previous framework was successful in coordinating material and product flows in both forward and reverse directions, it operated under the simplifying assumption of full vehicle availability and failed to account for durability degradation or maintenance requirements. The enhanced model developed here addresses this limitation by incorporating vehicle maintenance planning into the optimisation process. It recognises that the condition and availability of the transport vehicle is critical to maintaining consistent supply-chain performance. Unlike the previous formulation, where transport capacity was assumed to be uninterrupted, the new framework explicitly accounts for damage, deterioration, and the resulting impact on vehicle reliability. By integrating maintenance as a strategic decision variable, the model captures the trade-offs between operational efficiency, maintenance frequency, and vehicle downtime. This approach ensures that maintenance planning directly supports both short-term transport allocation and the long-term reliability of the supply-chain network. In the remainder of

this section, the vehicle problem is presented in detail, along with the notations and underlying assumptions adopted in its formulation.

4.2.1 Vehicle Problem Description

In this problem, a vehicle operates over a finite time horizon Z. λ, which is divided into periods of equal length λ. During each period, the vehicle may or may not be assigned to transport a load of weight ($trn(k)+trr(k)$), subject to a maximum carrying capacity TRV of the vehicle . To maintain operational reliability, the vehicle undergoes preventive maintenance actions every T time units, where $T=n\times\lambda$, and n represents the number of periods between two successive preventive maintenance. Two types of maintenance actions are considered.

The proposed maintenance strategy is noted in literature (Gertsbakh, 2000) as perfect preventive maintenance strategy with minimal repair at failures. More precisely, during each preventive maintenance action, vehicles are restored to an “as good as new state” whereas at failure, only minimal repairs are performed to allow them to continue operating. Point of view reliability after every preventive maintenance the failure rate is restored as zero, and the repair at failure don’t impact the evolution of the failure rate. We noted that, when the vehicle is not solicited the failure rate take the same level and don’t increase failure (Gertsbakh, 2000).

Figure 4.1 illustrates the evolution of the vehicle's failure rate, $\theta(t)$, over successive maintenance cycles throughout the full planning horizon Z. λ. Each cycle, indexed by j, spans k periods of duration λ, forming a maintenance window $T = n \times \lambda$. Within each cycle, the failure rate increases as the vehicle operates, especially when heavier loads are transported. This increase is represented by the rising green segments, reflecting the growing stress on the system. We note that the average number of failures is estimated by the area under the failure rate curve $\theta(t)$.

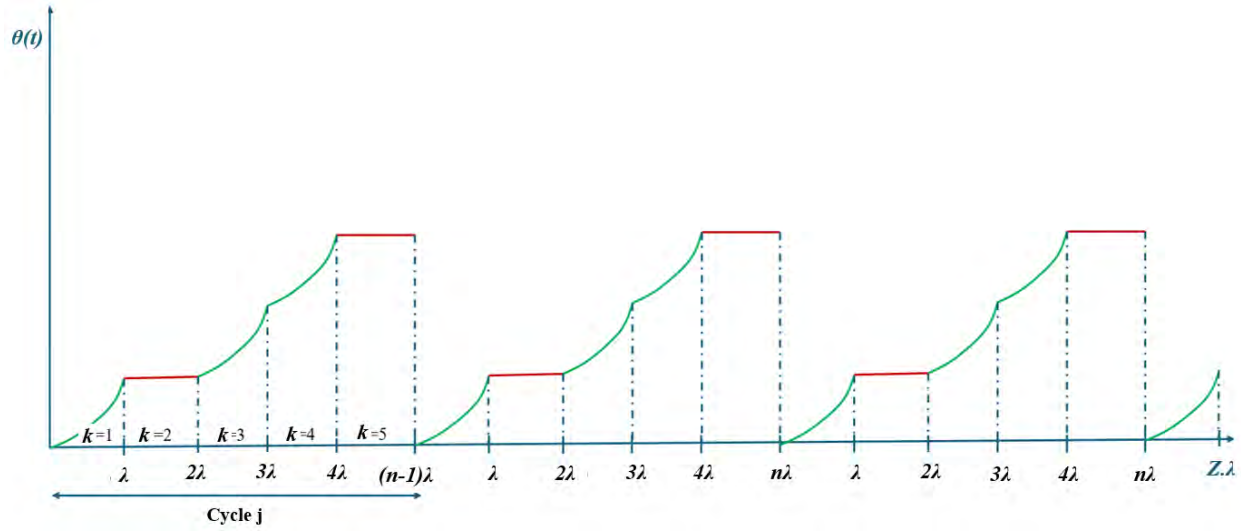

Figure 4.1. The evolution of the vehicle's failure rate

4.2.2 Notations and Definitions

To support the formulation and analysis of the vehicle maintenance and transport planning model, we present below a list of notations and their corresponding definitions within the context of the system:

$Z.\lambda$	Total time horizon of the study, expressed in discrete intervals λ
λ	Unit time interval
TRV	Maximum load capacity of the vehicle
CM	Cost of performing corrective maintenance action
PM	Cost of performing preventive maintenance intervention
$TMC(n)$	Total maintenance cost over the horizon $Z.\lambda$
$trn_j(k) + trr_j(k) + tup_j(k)$	Quantity of products transported during period k
T	Preventive maintenance interval, defined as $T=n\times\lambda$
$N_{Ent\left(\frac{Z.\lambda}{n}\right)+1}$	Expected number of failures occurring between the last preventive maintenance and the end of the horizon $Z.\lambda$

N_j	Expected number of failures during maintenance cycle *j*, spanning from 0 to $n \times \lambda$
$\theta_k(t)$	Failure rate function at production period k
$\theta_n(t)$	Failure rate under nominal operating conditions (maximum acceptable failure rate)
n	The number of periods between two successive preventive maintenance actions.

4.2.3 Modelling Assumptions

The proposed model operates under the same set of assumptions as the conceptual framework established in Chapter 2 but is extended to incorporate the effects of maintenance. The unit costs of preventive and corrective maintenance actions and the failure law of vehicles are known.

4.3 Analytical Study

Before the mathematical formulation of the total maintenance cost is introduced, it is necessary to define both equation (4.1) and (4.2) below of the vehicle's nominal failure rate over periods 1 and k, denoted by $\theta_1(t)$ and $\theta_k(t)$, as discussed in the preceding section. It varies according to the transported load, where *t* represents the time within the period. Inspired from the mathematical model developed in (Ayed et al., 2011) we can express the failure rate over the first period 1 as following.

$$\theta_1(t) = \frac{trn(k) + trr(k) + tup(k)}{TRV} \times \theta_n(t) \quad (4.1)$$

$$\forall\ t{=}0,\ldots,\lambda\ (k{=}1)$$

Taking into account the recursive mathematical model developed in (Ayed et al., 2011), the failure rate fo every period *k* can be expressed in the equation (4.2) as follows.

$$\theta_k(t) = \theta_{k-1}(\lambda) + \frac{trn(k) + trr(k) + tup(k)}{TRV} \times \theta_n(t) \quad (4.2)$$

$$\forall\ t{=}0,\ldots,\lambda \forall\ k{=}1,\ldots j$$

4.3.1 Mathematical Formulation of the Total Cost of Maintenance Actions

The Total Maintenance Cost *TMC* in Equation (4.3) represents the combined cost for preventive and corrective maintenance incurred during $Z.\lambda$. This formulation considers both regular maintenance frequency and the probability of failure occurring between cycles in an operational period.

$$TMC(n) = \frac{\sum_{j=1}^{Ent\left(\frac{Z.\lambda}{n\times\lambda}\right)}\left([PM+N_{j,[0,n\times\lambda]}\times CM]\right)+N_{\left(Ent\left(\frac{Z.\lambda}{n\times\lambda}\right)+1,\left[0,Z.\lambda-Ent\left(\frac{Z.\lambda}{n\times\lambda}\right)\times n\times\lambda\right]\right)}\times CM}{Z.\lambda} \quad (4.3)$$

Term n denotes the number of periods between two preventive maintenance actions. While λ is the unit time interval. Hence $T = n * \lambda$ represent the interval of preventive maintenance. In each cycle j the average number of failures, $N_{j,[0,n\times\lambda])}$, is estimated which affects the average cost of corrective maintenance actions. Preventive maintenance costs (*PM*) are incurred at each preventive maintenance action, whereas corrective maintenance costs (*CM*) are incurred at each failure.

4.3.2 Average Number of Failures During Maintenance Cycle

Equation (4.4) defines the average number of failures, $N_{j,[0,n\times\lambda]}$, occurring during maintenance cycle j (for $j \in \left[1,2 \dots Ent\left(\frac{Z.\lambda}{n\times\lambda}\right)\right]$)over the interval [0, $n \times \lambda$]. This expression accounts for both the periods when the vehicle is in use and when it is idle, capturing the relationship between utilisation, failure rate, and operational scheduling:

$$N_{j,[0,n\times\lambda]} = \sum_{k=1}^{n}\left(\lambda \times \theta_{k-1,j}(t) \times (1 - X_k) + \int_{(k-1)\times\lambda}^{k\times\lambda} \theta_{k,j}(t) \times X_k dt\right) \forall\, k \in [1,2 \dots n] \quad (4.4)$$

The binary variable X_k represents the operational state of the vehicle during period k:

$$X_k = \begin{cases} 0 & \text{if the vehicle is not used during period } k \\ 1 & \text{if the vehicle is used during period } k \end{cases}$$

This variable is crucial in modelling vehicle utilisation, availability, and maintenance scheduling within a mixed-integer optimisation framework.

The instantaneous failure rate of the vehicle, $\theta_{k,j}(t)$, is defined by the equation (4.5) below:

$$\theta_{k,j}(t) = \frac{trn_j(k) + trr_j(k) + tup_j(k)}{TRV} \times \theta_n(t) \tag{4.5}$$

The initial failure rate is set to $\theta_0 = 0$, indicating that no degradation is assumed before the start of operations.

4.3.3 Average Failures Between Last Preventive Maintenance and End of Horizon

The expression in the equation (4.6) estimates the average number of failures that occur after the final scheduled preventive maintenance action and before the end of the total planning horizon $Z.\lambda$ where $j = Ent\left(\frac{Z.\lambda}{n}\right) + 1$. It represents the final segment of the operating period, where the vehicle continues to function without further preventive intervention.

$$N_{\left(Ent\left(\frac{Z.\lambda}{n}\right)+1,\left[0,Z.\lambda-Ent\left(\frac{Z.\lambda}{n}\right)\times n\right]\right)}$$

$$= \sum_{k=1}^{Z.\lambda-\left(Ent\left(\frac{Z.\lambda}{n}\right)\times n\right)} \left(\lambda \times \theta_{k-1,Ent\left(\frac{Z.\lambda}{n}\right)+1}(t) \times (1 - X_t) + \int_{(k-1)\times\lambda}^{k\times\lambda} \theta_{k,Ent\left(\frac{Z.\lambda}{n}\right)+1}(t) \times X_t dt \right) \tag{4.6}$$

$$\forall\, k \in \left[1, \ldots \left[Z.\lambda - Ent\left(\frac{Z.\lambda}{n}\right) \times n\right]\right]$$

The term $\theta_{k,\left(Ent\left(\frac{Z.\lambda}{n}\right)+1\right)}(t)$ represents the instantaneous failure rate during this terminal phase and is defined by the equation (4.7) below.

$$\theta_{k,\left(Ent\left(\frac{Z.\lambda}{n}\right)+1\right)}(t) = \frac{t_{k,\left(Ent\left(\frac{Z.\lambda}{n}\right)+1\right)}}{TRV} \times \theta_k(t) \tag{4.7}$$

The optimal maintenance interval $n^*$is obtained when the marginal change in total cost with respect to the maintenance interval becomes zero. Mathematically, this condition is expressed in the equation (4.8).

$$\frac{dTMC(n)}{dn}\Big|_{n=n*} = 0 \tag{4.8}$$

In other words, $n*$ represents the optimal number of periods between two successive preventive maintenance actions. The relationship between n and $TMC(n)$ is convex in the case of

an increased nominal failure rate (Gertsbakh, 2000). The optimal solution n^*therefore represents the point where the trade-off between preventive effort and corrective risk is economically balanced, yielding the minimum total expected cost per vehicle over the planning horizon.

4.4 Numerical Results

To carry out the numerical experiments and obtain the simulation results presented in this chapter, we relied on Python as the main programming language. Its flexibility, readability, and wide range of scientific libraries made it a convenient choice for implementing the model, managing data inputs, and solving optimisation problems in an efficient and structured way.

4.4.1 Input Parameters

This section describes the input parameters (see Table 4.1 below) for the integrated maintenance-transport optimisation model that incorporates data about the horizon, the vehicle capacity, the cost of preventive action, the cost of corrective action, the shape parameter, the scale parameter and the mean up time. The Weibull distribution and its parameters are presented below.

Probability Density Function (PDF): $f(\mathrm{t}) = \left(\frac{m}{\eta}\right)\left(\frac{t}{\eta}\right)^{m-1} exp\left(-\left(\frac{t}{\eta}\right)^{m}\right)$

Failure or Hazard rate: $\theta(t) = \left(\frac{m}{\eta}\right)\left(\frac{t}{\eta}\right)^{m-1}$

Where:

- t: time variable
- m: shape parameter
- η: scale parameter
- $f(t)$: probability density function
- $\theta(t)$: failure (hazard) rate function

We note that we considered the shape parameter m =2 (m >1), meaning that we have an increased failure rate. This choice confirms the existence of an optimal preventive maintenance strategy.

Table 4.1. Input parameters (Initial Setup)

$Z.\lambda$	*TRV*	*CM*	*PM*	m	η *(months)*	*Mean up time (MUT)*
60	170	1500	200	2	10	≈ 9 months

Since the Gamma function value is $\Gamma(1.5) = \frac{1}{2}\sqrt{\pi} \approx 0.886$, the mean uptime is calculated as:

$$MUT = \eta \cdot \Gamma(1 + \frac{1}{m}) = 10 \cdot \Gamma(1 + \frac{1}{2}) = 8.86 \approx 9 \text{ months.}$$

This implies that, on average, a failure may occur approximately every nine months.

4.4.2 Obtained Results

4.4.2.1. Optimal Results

According to the numerical analysis presented in Table 4.2, the optimal number of preventive maintenance activities is n^*=7, which minimises the overall average cost over the 60-month planning horizon. The monthly total maintenance cost (*TMC*) now stands at 58.10 um, which is its lowest value. This research indicates that performing preventive maintenance every seven months results in the best balance between preventive and corrective costs. After this, the total cost increases because longer intervals between interventions increase the probability of costly failures. On the other hand, shorter intervals lead to high costs because more frequent maintenance provides few additional reliability benefits. These findings highlight the importance of accurately modifying the maintenance interval to preserve system dependability and long-term cost effectiveness.

❖ *Evolution of the total average cost TMC according to n*

Figure 4.2 illustrates how the total average cost evolves as a function of the number of periods *n* between two consecutive preventive maintenance actions. We clearly observe a sharp decline in cost for the small values of n, followed by a well-defined minimum point around $n = 7$, after which the cost gradually increases again. This U-shaped curve reflects a classic trade-off; when maintenance is too frequent, the preventive costs accumulate excessively; but when it's too infrequent, corrective costs due to failures begin to dominate.

Table 4.2. Numerical results for n from 1 to 60 months

n	***TMC (um/month)***	***n***	***TMC (um/ month)***	***n***	***TMC (um/ month)***	***n***	***TMC (um/ month)***	***n***	***TMC (um/ month)***
1	204.7088	**13**	74.00098	**25**	120.8373	**37**	152.9598	**49**	210.1804
2	109.1529	**14**	76.51569	**26**	123.9608	**38**	162.9216	**50**	216.1804
3	79.55784	**15**	80.4451	**27**	130.6725	**39**	159.9333	**51**	220.6745
4	68.37647	**16**	81.25882	**28**	137.9961	**40**	156.9451	**52**	225.5451
5	62.67059	**17**	88.64118	**29**	149.4784	**41**	171.0804	**53**	230.3333
6	61.00392	**18**	92.81765	**30**	144.9843	**42**	168.5098	**54**	244.3922
7	**58.10196**	**19**	94.87353	**31**	151.2892	**43**	165.9392	**55**	243.798
8	59.01569	**20**	99.72941	**32**	147.251	**44**	180.1922	**56**	260.8275
9	61.70882	**21**	95.99608	**33**	143.2127	**45**	178.0039	**57**	260.548
10	65.46471	**22**	100.0549	**34**	150.4745	**46**	183.2569	**58**	276.4745
11	63.49902	**23**	106.5637	**35**	146.7686	**47**	192.0127	**59**	276.4745
12	74.0549	**24**	111.0314	**36**	156.298	**48**	203.2039	**60**	276.4745

The curve makes it evident that n=7 is the most economical choice over the 60-month horizon, ensuring a balanced strategy between prevention and repair.

❖ *Evolution of the expected number of failures according to n*

As the interval n between two preventive maintenance actions increases, the expected number of failures changes as shown by the curve in Figure 4.3. It makes sense that there would be very few failures at first, with shorter intervals (small values of n), because the vehicle is regularly maintained, keeping it in a nearly perfect state. However, as n increases, meaning the time between maintenance actions becomes longer, we observe a steady and almost linear increase in the total number of failures. This trend highlights how delaying maintenance results in greater system degradation, which translates into more frequent failures. This graph gives strong justification for the selection of an optimal n in the cost analysis, as increasing n reduces maintenance frequency but increases the number of unexpected failures.

4.4.2.2. Sensitivity Analysis

This section aims to explore how sensitive the optimal maintenance policy is to changes in key cost parameters, namely, the cost of preventive maintenance (*PM*) and the cost of corrective maintenance (*CM*). By observing how the optimal number of periods between preventive actions shifts in response to these variations, we gain valuable insight into how the model reacts to economic trade-offs. The goal is to better understand how cost dynamics can influence maintenance timing, overall expenses, and system reliability. The results are presented in the form of tables and interpreted in detail.

❖ *Effect of varying preventive maintenance cost*

As shown in Table 4.3, there is a clear and expected trend: the more expensive the preventive maintenance action (*PM*) becomes, the more spaced out the optimal maintenance schedule turns. This is captured by the increase in the optimal number of periods between preventive actions, noted by n^*. For instance, when *PM* is only 10 um, maintenance is frequent (every 2 periods), but as *PM* rises to 1500 um, the optimal frequency stretches to every 21 periods. This behaviour represents a realistic trade-off between decreasing failure rates while controlling maintenance costs. In other words, even though there is a slight increase in the risk of corrective interventions, it is more efficient to perform preventive maintenance less frequently when it is expensive.

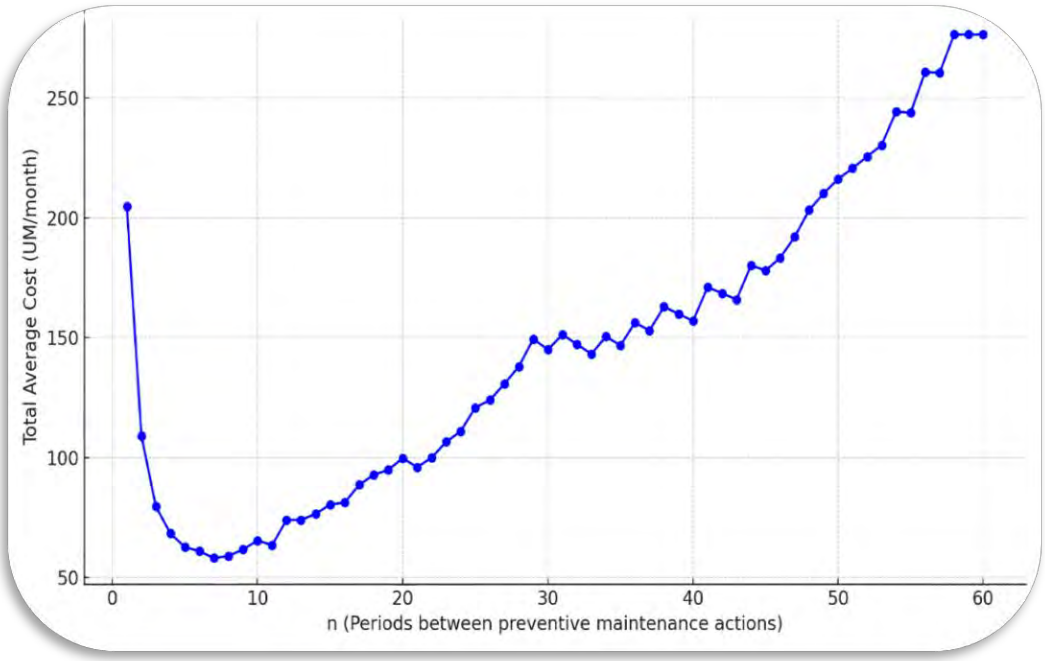

Figure 4.2. Evolution of the total average cost *TMC* according to *n*

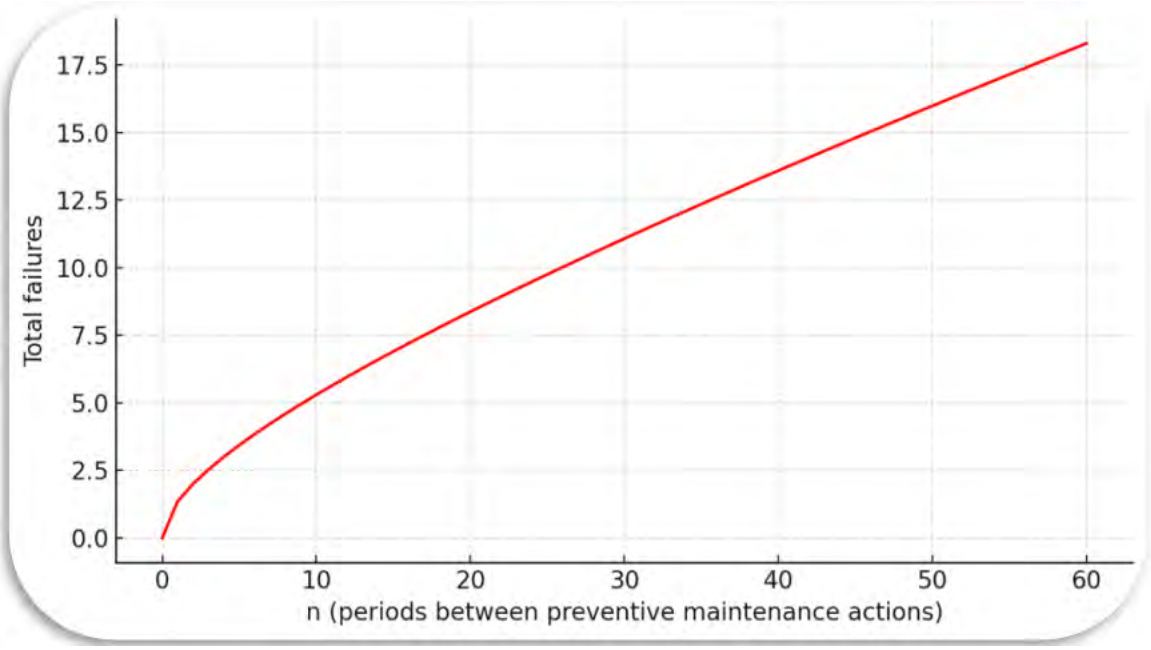

Figure 4.3. Evolution of the expected number of failures according to *n*

Table 4.3. Effect of varying preventive maintenance cost (*PM*)

PM	***n****	***TMC**** **(*um/month*)**
10	2	14
50	3	29
100	5	43
150	7	51
200	7	58
300	8	70
500	11	88
1000	16	121
1500	21	139

❖ *Effect of varying corrective maintenance cost (CM)*

Variations in the corrective maintenance cost *CM* have an effect on both the optimal maintenance frequency $n*$ and the overall average monthly cost, as shown in Table 4.4. The results demonstrate that the system reduces the interval between preventive maintenance procedures in response to growing corrective maintenance expenses. In other words, $n*$ drops. This suggests that the vehicle receives more frequent maintenance in order to avoid costly malfunctions. For instance, when *CM*=200, the optimal interval between maintenance tasks is n^*=21. However, when *CM* rises to 3500, $n*$ drops to just 4. The results make sense logically. When failures are expensive, the model favours preventive actions, even if they carry their own cost, because they help avoid the high financial impact of corrective repairs. When failures are expensive, the model favors preventive actions, even if they carry their own cost, because they help avoid the high financial impact of corrective repairs.

4.5 Theoretical and Managerial Implications of the Model

The analysis provides theoretical and managerial insights into developing reliable and cost-effective maintenance plans. The results confirm that there is a perfect balance between preventive and corrective measures. At $n*$=7, the total maintenance cost shows a U-shaped trend, with an average monthly cost of 58.10 um over a 60-month horizon. Therefore, doing preventive maintenance every seven months strikes the best balance between cost and dependability; shorter intervals result in unnecessary expense increases, while longer ones increase the probability of failure.

Table 4.4. Effect of varying corrective maintenance cost (*CM*)

CM	***n****	***TMC**** **(*um/month*)**
200	21	18
500	11	32
800	11	41
1200	7	51
1500	7	58
2000	7	68
2500	5	78
3000	5	85
3500	4	93

Sensitivity analysis shows how sensitive the model is to price fluctuations. While higher preventive maintenance costs increase the optimal interval, higher corrective costs shorten it, which promotes more frequent interventions. In keeping with realistic expectations, these results show how cost structures affect the frequency and dependability of maintenance. From a managerial standpoint, maintenance should be seen as a strategic decision variable. Managers must adjust maintenance schedules in response to shifting operational needs and economic conditions. A data-driven approach improves performance and efficiency by determining when preventive measures are better than repairs.

In practice, putting such flexible and optimised maintenance policies into place improves resilience and long-term competitiveness. Sustainable cost control is promoted, unplanned downtime is reduced, and system reliability is raised by integrating this analytical technique into larger planning frameworks. According to the study, cost-driven maintenance intervals can significantly improve economic efficiency and operational performance, offering a reliable and practical foundation for maintenance planning in complex supply-chain systems.

4.6 Conclusion

This chapter describes the development of a maintenance optimisation model to balance corrective and preventive actions in a transportation system. The model links maintenance choices to operational effectiveness, cost reduction, and dependability while capturing the trade-off between the probability of failure and the frequency of interventions. The analysis indicates that maintenance planning is dynamic rather than regular. Both excessive and insufficient maintenance

result in inefficiencies, either through increased failure risks or unnecessary costs. It's critical to determine when preventive actions that maintain stability and reduce overall expenses are most effective. From the perspective of management, maintenance should be viewed as a strategic decision variable. Managers must consider how costs, reliability goals, and operational constraints evolve over time. A flexible, data-driven approach improves equipment availability and overall performance by enabling better informed decisions. The chapter ends by highlighting how knowledge of cost-reliability relationships can inform efficient maintenance scheduling. The proposed framework promotes the creation of proactive and sustainable maintenance plans that increase system resilience and supply chain efficiency.

Chapter 5: Data-Driven Predictive Modelling and Integrated Optimisation for Multi-Period Planning in a Carbon-Conscious Supply Chain with Reverse logistics

Abstract

This chapter presents a comprehensive multi-period optimisation model for a carbon-conscious supply chain that combines forward and reverse logistics while respecting operational and environmental constraints. To precisely forecast demand and return quantities, the framework employs hybrid SARIMA–VAR forecasting, which combines optimisation and predictive modelling. Scenario analyses show that the model can adjust to changing market conditions while reducing expenses and emissions while maintaining service quality. The findings draw attention to the trade-off between profitability and carbon compliance, showing that environmental objectives can be achieved without compromising operational resilience with the aid of cleaner technologies and proactive planning. The study advances our theoretical knowledge of how predictive analytics and carbon regulation interact in integrated supply-chain systems. It emphasises how important it is for managers to incorporate emission performance into strategic decision-making in order to balance sustainability and competitiveness and support the long-term sustainability of supply chains subject to carbon regulations.

5.1 Introduction

This chapter presents a multi-period optimisation model for a data-driven, carbon-conscious supply chain that integrates reverse logistics. Building on the analytical foundations of previous chapters, the framework incorporates a city-based collection centre, explicit transport decisions, and dual-vehicle operations coordinated with contract carriers. These enhancements provide a more realistic representation of urban logistics by capturing the complexity of coordinating production, remanufacturing, transportation, and procurement under economic and environmental constraints. By balancing sustainability, efficiency, and profitability goals through the joint modelling of forward and reverse flows, the system advances our understanding of environmentally responsible supply-chain optimisation (Safaei et al., 2024).

Over the past few years, there has been an increase in research on how supply-chain planning and strategic decisions can be significantly impacted by incorporating carbon-tax mechanisms with international environmental frameworks, especially the Paris Agreement (Abassi et al., 2025). Given the increasing impact of carbon pricing and emission targets on logistics strategies, these studies emphasise the importance of models that take into account the interaction between regulatory compliance and economic optimisation. The model developed in this chapter considers the impact of carbon policies, particularly the Paris Agreement and the Carbon Tax Strategy, on network performance and long-term planning decisions.

Meanwhile, advancements in predictive modelling have enabled new forms of data-driven optimisation. Forecasting accuracy in dynamic markets has increased due to hybrid time-series techniques, such as SARIMA-VAR and SARIMA-LSTM (Abassi et al., 2025), which can capture both linear and nonlinear demand patterns (Aldahmani et al., 2024). Forecasts of consumer demand and returned products are produced by these hybrid models and directly integrated into the optimisation process within this framework. This approach ensures that planning decisions are adaptable, data-driven, and sensitive to market and operational volatility.

The logistical realism of the model is enhanced by the inclusion of contract carriers and multi-vehicle operations, which capture significant trade-offs between cost effectiveness, service reliability, and emission compliance. Unlike earlier models that assume infinite capacity or continuous operation, the current framework specifically accounts for finite storage and capacity

limitations across both upstream and downstream facilities. This enhancement provides a more realistic representation of the operational constraints common to sustainable logistics systems (Safaei et al., 2024).

In all, this chapter contributes three things. First, it incorporates environmental policy into a multi-period supply-chain optimisation model to quantitatively evaluate how carbon taxes and global climate commitments, such as the Paris Agreement, affect decision-making. Through the use of hybrid forecasting models, it also integrates predictive analytics directly into the optimisation process to ensure data-driven and flexible planning. Third, it makes urban logistics more feasible by accounting for vehicle diversity, contractual operations, and capacity constraints. Together, these elements form a comprehensive, useful framework that promotes supply-chain management that is robust, cost-effective, and sustainable.

This is how the remainder of the chapter is organised. Section 5.2 outlines the problem description and modelling assumptions that form the basis of the analysis, while Section 5.3 develops the corresponding mathematical model and analytical formulation. Section 5.4 explains the predictive-optimisation approach and how the model uses predicted demand and returns data. In addition to highlighting the model's performance and applicability for sustainable logistics planning, Section 5.5 concludes with a discussion and display of the numerical results.

5.2 Problem Description and Working Assumptions

The proposed system, illustrated in Figure 5.1, builds upon the carbon-conscious framework developed in Chapter 3 by embedding predictive analytics, dual-vehicle logistics, and data-driven environmental assessment within a single multi-period optimisation structure. While the previous model incorporated carbon regulation mechanisms such as the Carbon Tax, Cap-and-Trade, and Limit-and-Subsidy strategies, the present framework advances this formulation by explicitly linking forecasted market behaviour to operational and environmental planning. In this way, the model captures the dynamic interaction between production, remanufacturing, transport, and emissions under uncertain and evolving demand conditions. The demands for newly manufactured and remanufactured products, denoted $dnp(k)$ and $drp(k)$, are predicted rather than deterministic. Once the most accurate predictive model has been selected, forecasts are generated

using a hybrid SARIMA–VAR approach, which combines statistical and machine-learning techniques to account for seasonal variation, random fluctuations, and long-term market trends.

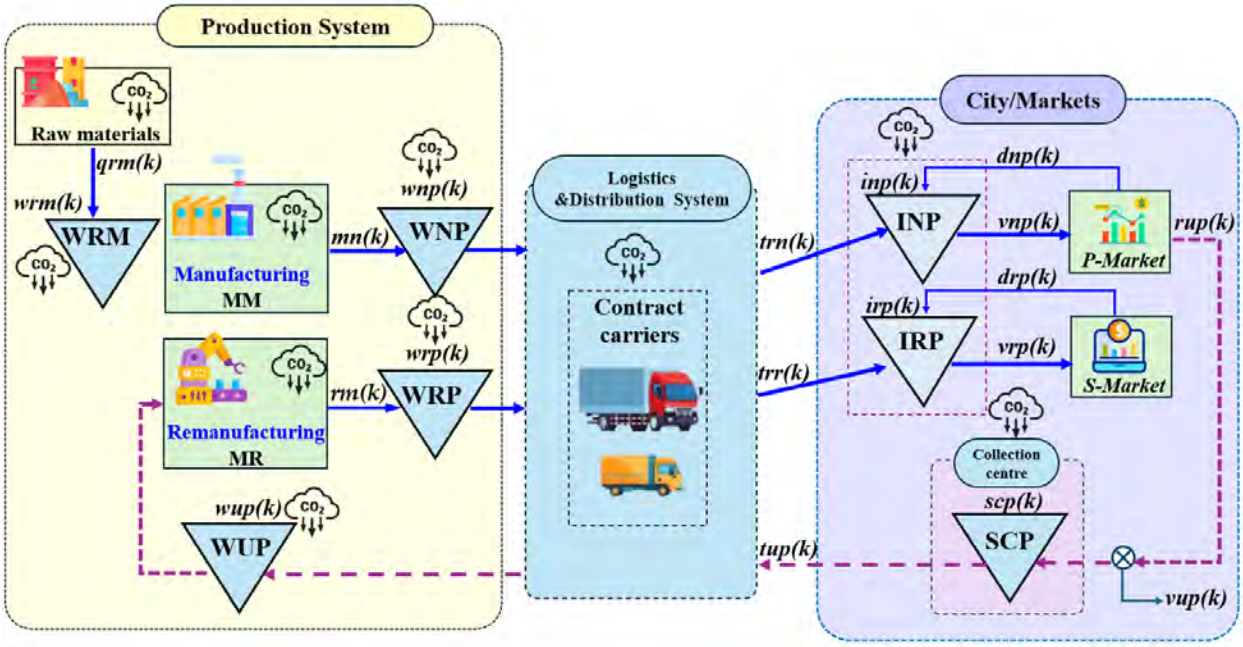

Figure 5.1. Comprehensive carbon-conscious supply chain

Similarly, the volume of returned products $rup(k)$ is forecasted using historical data on consumer behaviour and product-lifecycle patterns. By incorporating these predicted parameters, the system operates on a data-driven basis, allowing production and logistics decisions to adapt proactively to anticipated fluctuations in both forward and reverse flows. The urban collection centre (*SCP*) continues to function as the core node for receiving and storing used products. However, in contrast to earlier configurations, the storage process is now modelled with dynamic capacity constraints, meaning that excess returns $vup(k)$ are deferred or rescheduled for later processing or resale. This formulation captures the variability inherent in urban reverse logistics, where collection frequency and space utilisation depend directly on predicted return patterns. Transport operations are also refined to reflect realistic fleet heterogeneity. The model introduces two vehicles *V1* and *V2* of differing fixed capacities, complemented by contract carriers, enabling adaptive scheduling and allocation according to shipment size and emission performance. This design provides a more accurate depiction of modern logistics systems in which mixed fleets and outsourced carriers operate jointly to meet service and environmental objectives. The transport module thus captures key trade-offs among cost efficiency, delivery reliability, and

carbon intensity, particularly under emission-constrained policies. The system maintains as in chapter 3 a detailed representation of carbon emissions across all supply-chain stages. With the addition of the emission from the warehouse *SCP* in this system (*esc*). Transportation remains the dominant emission contributor (*etr*), with additional fixed components (*efrt1*, *efrt2*) assigned to each vehicle type.

In conclusion, this system is a methodological development of the previous framework. The carbon-conscious supply chain is transformed into a predictive and flexible optimisation model, where operational decisions are informed by predicted demand and returns, and emission results are continuously assessed within the profit function. For strategic decision-making in carbon-conscious, sustainable supply chains, the combination of forecast-driven planning, dual-vehicle logistics, and explicit environmental costing offers a practical and robust analytical tool.

The working assumptions outlined in Chapters 2 and 3 are still relevant in this chapter in order to maintain methodological coherence and continuity across all modelling frameworks.

5.3 Analytical Model

5.3.1 Notations and Decisions Variables

Before presenting the mathematical formulation, it is necessary to introduce the new notations that are built upon the system design outlined in this chapter. These are built upon the foundational framework established in Chapters 2 and 3, which was previously restricted to a single-vehicle context. The original definitions remain valid despite the addition of new symbols to reflect the dual-vehicle structure, contract carriers, and the explicit modelling of carbon-related parameters. Collectively, these notations maintain consistency with the earlier framework while expanding the current model's larger scope.

$PRCX(Z)$	Total profit considering carbon tax strategy over the horizon Z. λ
$vup(k)$	Quantity sold of collected products at the end of period k
$vup0$	Quantity sold of collected products at the start of period 1
$scp(k)$	Warehouse level of collected used products in *SCP* at the end of period k
$scp0$	Warehouse level of collected used products in *SCP* at the start of period 1

cs	Warehousing cost of one collected product unit in *SCP*
FT_1	Fixed round trip cost for vehicle $V1$
FT_2	Fixed round trip cost for vehicle $V2$
pv	Unit selling price for collected product
SP	Maximum capacity of *SCP*
$TRV1$	Capacity of the transport vehicle $V1$
$TRV2$	Capacity of the transport vehicle *V2*
$\gamma 1(k)$	Transport decision variable for the vehicle $V1$
$\gamma 2(k)$	Transport decision variable for the vehicle *V2*
$HCP(Z)$	Inventory holding cost of collected products stock over horizon Z. λ
etr	Unit carbon emissions from transporting new, remanufactured, or returned products
$efrt1$	Fixed quantity of carbon emitted by vehicle $V1$
$efrt2$	Fixed quantity of carbon emitted by vehicle $V2$

The optimal plans are derived using the same process as in the earlier models in order to maximise total profit $PRCX(Z)$ and to guarantee continuity across the system designs presented in the preceding chapters. The next section presents the extra equations and definitions needed to represent the expanded version of the system, building on the formulations previously established. Without being modified, the previously defined variables and constraints are still relevant and are included in the integrated framework.

5.3.2 Total Expected Profit Formulation

Before presenting the constraints and the equations in this section, it is essential to introduce two binary decision variables $\gamma 1(k)$ and $\gamma 2(k)$, which are used to indicate whether a specific transport vehicle is assigned to perform a round-trip during period k. More precisely,

$$\gamma 1(k)=\begin{cases}1 \text{ if vehicle } V1 \text{ will do the round trip}\\ 0 \text{ otherwise}\end{cases}$$

$$\gamma 2(k)=\begin{cases}1 \text{ if vehicle } V2 \text{ will do the round trip}\\ 0 \text{ otherwise}\end{cases}$$

For supply chain transportation operations to be managed and monitored, these binary indicators are crucial. By explicitly modelling vehicle availability, the system ensures that logistical constraints are satisfied, particularly when decisions involving transport capacity, cost, or environmental impact must be made. This formulation also enables the model to more accurately represent fleet scheduling in the real world within the larger optimisation framework.

Equation 5.1 presents the objective function, which aims to maximise the total profit over the planning horizon by capturing the difference between total sales revenues and the aggregate of all costs incurred considering the carbon tax strategy.

$$\begin{aligned}\text{Maximise } PRCX(Z) = {} & R(Z) - \Big(MC(Z) + RC(Z) + NSC(Z) + RSC(Z) + \\ & HRM(Z) + HNP(Z) + HRP(Z) + HUP(Z) + HIN(Z) + HIR(Z) + HCP(Z) + \\ & TC(Z) + ARM(Z) + RPC(Z) + TCX(Z) + \big(FT1 \times \gamma 1(k)\big) + \big(FT2 \times \gamma 2(k)\big)\Big)\end{aligned} \tag{5.1}$$

Under the following:

- Linearisation constraints:

$$trn(k) + trr(k) \leq TRV1 + (BN \times (1 - \gamma 1(k))) \tag{5.2}$$

$$trn(k) + trr(k) \geq (TRV1 + 1) - (BN \times (1 - \gamma 2(k))) \tag{5.3}$$

$$trn(k) + trr(k) \leq BN \times (\gamma 1(k) + \gamma 2(k)) \tag{5.4}$$

The above set of constraints ensures that product transportation in each period remains feasible with respect to inventory levels and is logically linked to the activation of vehicles *V1* and *V2*. Constraint (5.2) specifies that when vehicle *V1* is activated ($\gamma 1(k)$=1), the total quantity transported cannot exceed its capacity *TRV1*. Conversely, if the vehicle is inactive ($\gamma 1(k)$=0), the inequality becomes non-restrictive through the inclusion of the large constant *BN*. The lower-bound constraint (5.3) guarantees that when $\gamma 2(k)$=1, the total transported quantity meets a minimum threshold, ensuring that the vehicle is dispatched only when operationally justified. Finally, constraint (5.4) ensures that no transportation occurs unless at least one vehicle activation decision is made. Collectively, these constraints provide a coherent, inventory-aware, and decision-driven framework for managing vehicle utilisation and product dispatch across the planning horizon.

- Transportation capacity:

$$trn(k) + trr(k) + tup(k) \leq TRV2 \tag{5.4}$$

$$tup(k) \leq (\min (scp\,(k-1),\ WP - wup\,(k-1))) \tag{5.5}$$

To ensure feasibility in the distribution phase of the supply chain, transportation constraints are imposed on the movement of finished products. Specifically, the total quantity of products transported during period *k*, which includes both new products *trn*(*k*), remanufactured products *trr*(*k*), and recovered products *tup*(*k*) must not exceed the carrying capacity of the designated transport vehicle *V2*, represented by *TRV*2 (see constraint 5.4 above). Constraint (5.5) regulates the movement of recovered products in the reverse flow. It ensures that the quantity transported to the recovered used products warehouse, $tup(k)$, does not exceed the available capacity, defined as the minimum between the stock of collected items from the previous period, $scp(k-1)$, and the remaining storage space in the recovered used-product warehouse, $WP - wup(k-1)$. This restriction maintains feasibility by preventing capacity overflow in collection and storage operations.

- Balance Inventory of the Warehouse SCP

Equations (5.6) and (5.7) below describe the inventory flow of collected used products within the warehouse facility *SCP* over time. To update the storage level at the end of each period *k+1*, equation (5.6) specifically adds the quantity of newly collected used products from the market *rup*(*k+1*) and subtracts the quantity of recovered products transported to the remanufacturing facility *tup*(*k+1*). This balance ensures that the storage level reflects both outgoing and incoming flows at each time step. Equation (5.7) defines the initial condition for this dynamic by defining the stock level at the end of period 1 as a function of the initial stored quantity *scp0*, the used products collected at the start *rup*(*1*), and the number transported for processing *tup*(*1*). Together, these formulas enable the model to accurately track the availability of used products in the reverse logistics system for all planning periods $k = 0, \ldots, Z - 1$, and account for changes in remanufacturing output and return volumes. They are particularly important for capturing the dynamics of a sustainable supply chain that includes real-time product returns, temporary storage, and remanufacturing flows.

$$scp\,(k+1) = scp(k) + rup\,(k+1) - tup\,(k+1) \quad \forall\, k = 0,\ldots, Z-1 \tag{5.6}$$

$$scp(k) = scp0 + rup(1) - tup\,(1) \tag{5.7}$$

- Total sales revenue

$$R(Z) = pn \times \sum_{k=1}^{Z} vnp(k) + pr \times \sum_{k=1}^{Z} vrp(k) + pv \times \sum_{k=1}^{Z} vup(k) \tag{5.8}$$

Equation (5.8) above defines the total revenue generated over the planning horizon *Z*. λ, accounting for all streams of product sales within the system. The revenue is calculated by adding the three components. The first term, where *pn* is the unit selling price and *vnp*(*k*) is the quantity sold during period *k*, represents the revenue from selling new products. The second term, where *pr* is the unit price and *vrp*(*k*) is the quantity sold, collects revenue from remanufactured products. The third component accounts for sales of excess collected products, where *pv* is the unit price and *vup*(*k*) is the quantity sold. By summing up all sales income over all time periods, this formula offers a comprehensive evaluation of system-level revenue and aids in determining the financial performance and market efficacy of a closed-loop supply chain.

- Inventory Holding Cost

Equation (5.9), *HCP*(*Z*), computes the storage cost of collected used products in the reverse logistics inventory *SCP*, based on a unit cost *cs*.

$$HCP(Z) = cs \times \sum_{k=1}^{Z} scp\,(k) \tag{5.9}$$

- Transport cost

$$TC(Z) = ct \times \sum_{k=1}^{Z} \big(trn(k) + trr(k) + tup(k)\big) \tag{5.10}$$

Equation (5.10) above displays the total transport cost, denoted as $TC(Z)$, incurred over the entire planning horizon. This cost includes the transportation of recovered used products ($tup(k)$), remanufactured products ($trr(k)$) and new products ($trn(k)$) from the collection point *SCP* to the upstream processing unit *WUP*. To keep things simple, the total of these transported quantities over all time periods is multiplied by the unit transportation cost (ct), which is taken to be constant across product types. By incorporating all flows, both forward and reverse, this expression ensures that the overall model accurately represents the cost impact of logistical operations. This is particularly important in supply chains with reverse logistics, where cost reduction and system efficiency depend on managing delivery and return logistics.

- Carbon Footprint

Equation (5.11) below captures the carbon footprint of the entire supply chain over the planning horizon. It accounts for emissions from a number of operational stages, including the procurement of raw materials, the production of new and remanufactured products, and all associated transportation and storage activities.

In addition to taking into account emissions associated with storage operations, the model considers raw materials, new products, remanufactured products, collected products, and sales inventories. Along with the fixed emissions generated by every transport vehicle utilised in the system, it also includes emissions from the transportation of new, remanufactured, and returned products. By adding up these emissions over all time periods, the formulation offers a comprehensive overall view of carbon output. This makes it easier to make decisions that support the objectives of a low-carbon supply chain and makes it possible to incorporate sustainability factors into the optimisation model in a meaningful way.

$$\begin{aligned} CF(\mathrm{Z}) = \sum_{k=0}^{Z} \Big(& (em \times qrm(k)) + (en \times mn(k)) + (er \times rm(k)) \\ & + (erm \times wrm(k)) + (ewn \times wnp(k))) + (ewr \times wrp(k)) \\ & + (esc \times scp(k)) + (ecu \times wup(k)) + (enp \times inp(k)) \\ & + (erp \times irp(k)) + \big(etr \times trn(k)\big) + \big(etr \times trr(k)\big) \\ & + \big(etr \times tup(k)\big) + \big(eftr1 \times \gamma 1(k)\big) + \big(eftr2 \times \gamma 2(k)\big)\Big) \end{aligned} \tag{5.11}$$

Before moving on to the numerical analysis and results discussion, the following section looks over the prediction and optimisation strategy that supports the model. Particular attention is given to the estimation of future demand and return quantities, which are important input parameters for the following numerical analysis.

5.4 Prediction and Optimisation Approach

5.4.1 Two-Stage Framework Approach

To support effective decision-making across multiple planning horizons, the proposed approach integrates prediction and optimisation in a two-stage framework as shown in Figure 5.2 below. In the first stage, key input parameters $dnp(k)$, $drp(k)$, and $rup(k)$ are forecasted over a defined planning horizon (24 periods) using historical data and appropriate predictive methods. These predicted values serve as inputs for the second stage, in which a MILP model is executed to identify the optimal manufacturing, remanufacturing, transportation, and procurement plans.

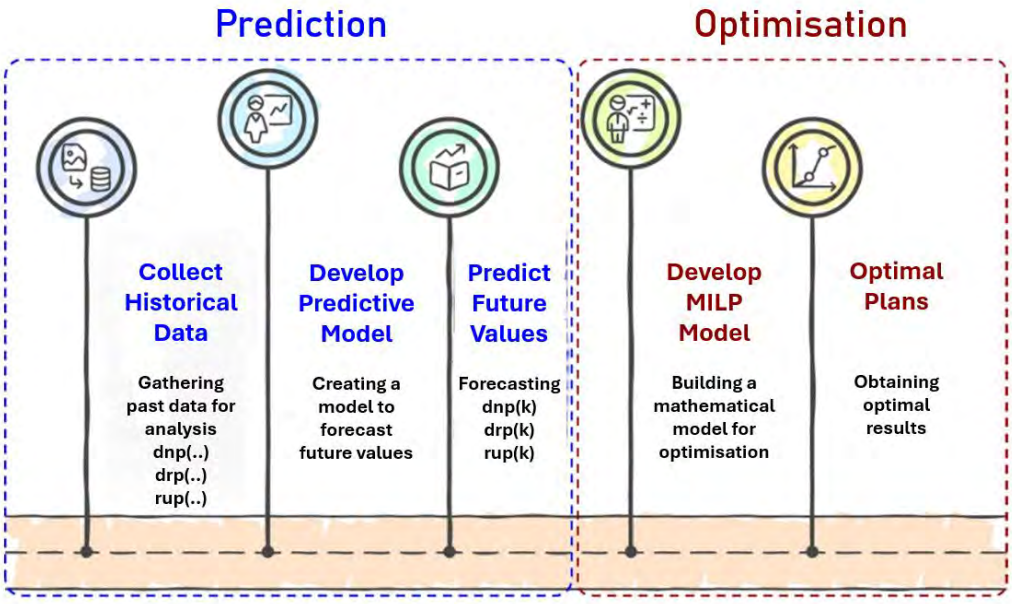

Figure 5.2. Prediction and optimisation approach

In the following case study, which is based on the two-stage framework mentioned above, we report the expected values of the key input parameters over the 24-period horizon and demonstrate how these forecasts inform the development of optimal planning decisions.

5.4.2 Case Study and Prediction Results

The following section presents the case study and the corresponding prediction results, which serve as the foundation for evaluating the performance and applicability of the proposed optimisation approach.

5.4.2.1 Case Study

In this section, the approximate data collected on past demand and returned used microwaves are presented in Table 5.1. The data were obtained from a system belonging to a home appliance company that produces and sells both new and remanufactured microwaves.

5.4.2.2. Prediction Results

The following subsection presents the prediction results, starting with the use of machine learning techniques to estimate future values of $dnp(k)$, $drp(k)$, and $rup(k)$. These predicted parameters are essential for guiding the optimisation model in the second stage of the proposed framework.

- ✓ *Prediction-based Machine Learning of future values of dnp(k), drp(k), and rup(k)*

This subsection targets predicting the future values of $dnp(k)$, $drp(k)$, and $rup(k)$ that will be used as input data for determining the optimal plans over the next 24 periods (planning horizon). The collected data represent the recorded monthly demand and returned products values over the past 60 periods (i.e., 60 months), which will be used in the different steps of the prediction process shown in the following Figure 5.3.

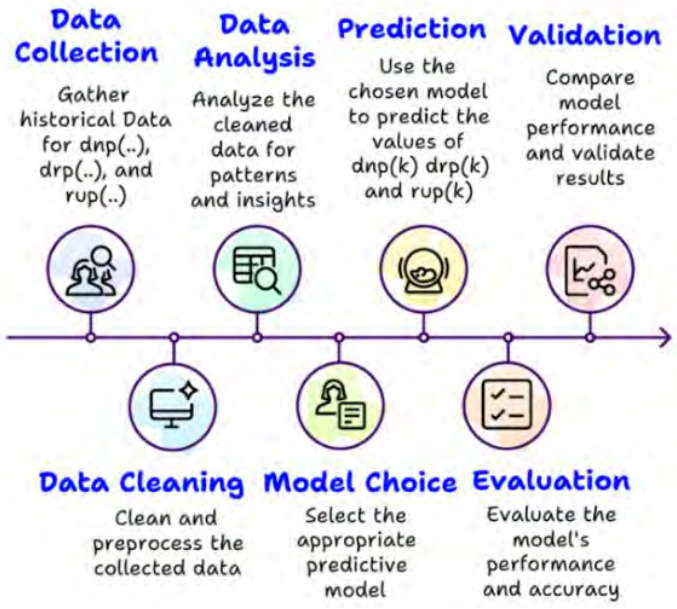

Figure 5.3. Prediction process

✓ *Data analysis and selection of candidate models*

Before analysing the collected data, we checked whether it was missing any values, contained outliers, or had non-standardised values. We then concluded that the data were clean and ready for use. To analyse the data, we have created a time-series plot for the demands and returned products values over the past 60 periods in Figure 5.4 below.

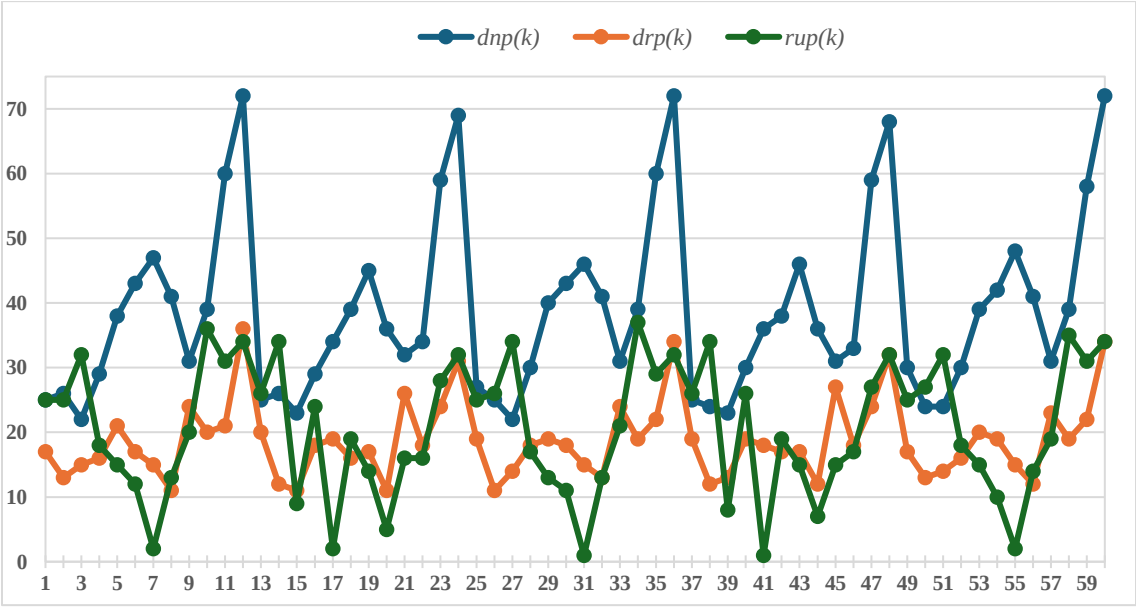

Figure 5.4. Time-series plot for *dnp*(*k*), *drp*(*k*), and *rup*(*k*)

Table 5.1. Collected data during 60 periods

P	*dnp*(*k*)	*drp*(*k*)	*rup*(*k*)	P	*dnp*(*k*)	*drp*(*k*)	*rup*(*k*)	P	*dnp*(*k*)	*drp*(*k*)	*rup*(*k*)
1	25	17	25	**21**	32	26	16	**41**	36	18	1
2	26	13	25	**22**	34	18	16	**42**	38	17	19
3	22	15	32	**23**	59	24	28	**43**	46	17	15
4	29	16	18	**24**	69	31	32	**44**	36	12	7
5	38	21	15	**25**	27	19	25	**45**	31	27	15
6	43	17	12	**26**	25	11	26	**46**	33	18	17
7	47	15	2	**27**	22	14	34	**47**	59	24	27
8	41	11	13	**28**	30	18	17	**48**	68	32	32
9	31	24	20	**29**	40	19	13	**49**	30	17	25
10	39	20	36	**30**	43	18	11	**50**	24	13	27
11	60	21	31	**31**	46	15	1	**51**	24	14	32
12	72	36	34	**32**	41	13	13	**52**	30	16	18
13	25	20	26	**33**	31	24	21	**53**	39	20	15
14	26	12	34	**34**	39	19	37	**54**	42	19	10
15	23	11	9	**35**	60	22	29	**55**	48	15	2
16	29	18	24	**36**	72	34	32	**56**	41	12	14
17	34	19	2	**37**	25	19	26	**57**	31	23	19
18	39	16	19	**38**	24	12	34	**58**	39	19	35
19	45	17	14	**39**	23	13	8	**59**	58	22	31
20	36	11	5	**40**	30	19	26	**60**	72	34	34

According to the series plot, the demands and returned products values exhibit fluctuations with several peaks and troughs over the observed 60 periods. Furthermore, they do not follow a strict upward or downward trend, meaning they might be influenced by factors. Regarding seasonality, the series of *dnp*(*k*) and *drp*(*k*) display recurring peaks and troughs every 12 periods. The series of *rup*(*k*) also shows repetitive peaks and troughs, but a definitive seasonality cannot be determined. The peaks in the series *dnp*(*k*) often coincide with changes in *drp*(*k*) and *rup*(*k*), indicating a possible interaction and interdependence between the variables. Some movements in the series of *rup*(*k*) appear to follow *dnp*(*k*) with a delay, indicating a time-lagged relationship. Based on this analysis and our literature study, we suggest five candidate models from the literature that are capable of handling the temporal complexity and interactions: VAR, SARIMA, SARIMA/VAR, LSTM, and HWES.

✓ *Prediction and choice of the best model*

This subsection evaluates the candidate models based on their prediction results and metrics. Each model is implemented using a machine learning algorithm that use 80% of the data for training and 20% for testing. It then determines the predicted values (future values) of *dnp*(*k*), *drp*(*k*), and *rup*(*k*). Thus, the candidate algorithms are generated using Python software 3.13.1, and the results are presented below, which include the test evaluation, predicted values, and metrics MSE (Mean Squared Error), MAE (Mean Absolute Error), R^2 (Coefficient of Determination), and MAPE (Mean Absolute Percentage). We recall that when the values of MSE and MAE are low (compared to the target variable), $R^2>0.8$ and MAPE<10% indicates good performance of the model. Below, the results are analysed to identify the best algorithm. Below, each model's results are presented in a single figure that simultaneously displays the actual collected data, the training data (used to train the model), the testing data (used to evaluate prediction accuracy), the test prediction (results based on the trained model), and the forecasted future values.

VAR algorithm

The VAR algorithm differs from the other candidate models by capturing the interdependencies between the three series. It is defined by its key parameter, the maximum lag (referred to as maxlag), which specifies the maximum number of lagged observations included in the model. This parameter determines how many past times steps the algorithm considers when predicting the current values of the system's variables. Thus, we have elaborated a program that

varies the value of "maxlag" and determines the optimal prediction based on the metrics. In our case, the best prediction using the VAR algorithm corresponds to maxlag = 15 with the overall metrics MAE = 1.86, MSE = 6.01, R^2 = 0.94, and MAPE = 10.08%.

The results in Figure 5.5 demonstrate that the VAR algorithm performs acceptable prediction, but the test prediction shows that it lacks precision on the *dnp*(*k*) and *rup*(*k*) prediction. Although the value of R^2 indicates that this algorithm has a good correlation between the prediction and actual data, the values of MAPE and MSE are a little high. This suggests that the model effectively captures the overall trend and relationships between the variables. However, it is highly sensitive to the linearity of these relationships, and when they are nonlinear, the model may fail to make accurate predictions.

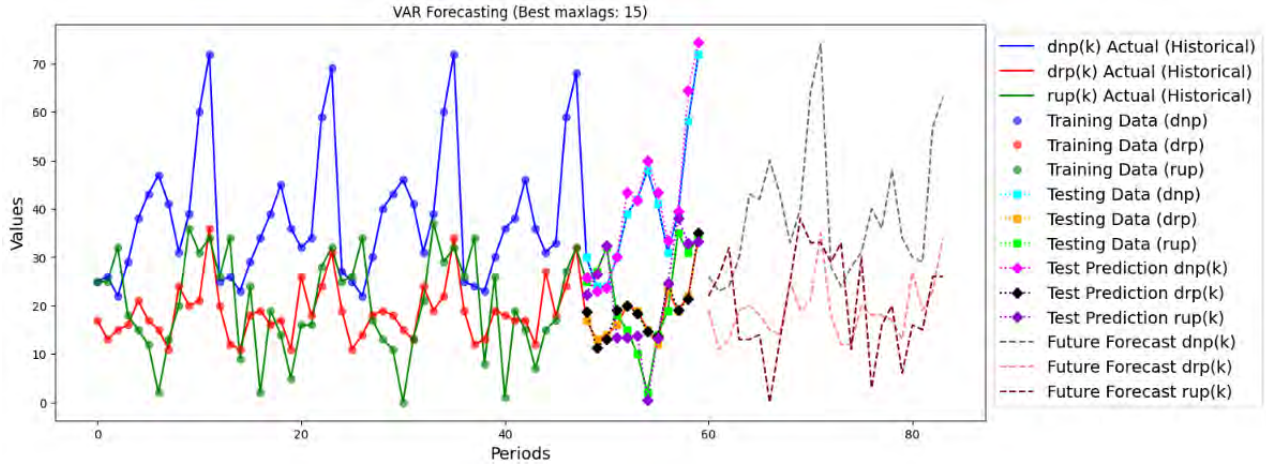

Figure 5.5. VAR prediction

SARIMA algorithm

The SARIMA differs from the other candidate models by its handles of trend, seasonality, and external effects. Compared to the VAR model, SARIMA is better in capturing seasonality. It performs well with small datasets, where LSTM may struggle. Compared to the HWES model, SARIMA is more flexible for multiplicative seasonality and complex patterns. SARIMA is characterised by its parameters for both non-seasonal (p, d, q) and seasonal (P, D, Q, s) components. Thus, a program is elaborated that varies these parameters and determines the optimal prediction. The optimal SARIMA parameters, testing, and prediction results are presented in the figure 5.6. The overall metrics results are MAE = 1.19, MSE = 2.07, R^2 = 0.98, and MAPE = 7.76%. The results in Figure 5.6 demonstrate that the SARIMA algorithm performs excellent

prediction. The test prediction shows that predicted curves are expected to closely follow the actual data. The high R^2 value and the low MAPE, MAE, and MSE values indicate a strong correlation between the predictions and the actual data for this algorithm.

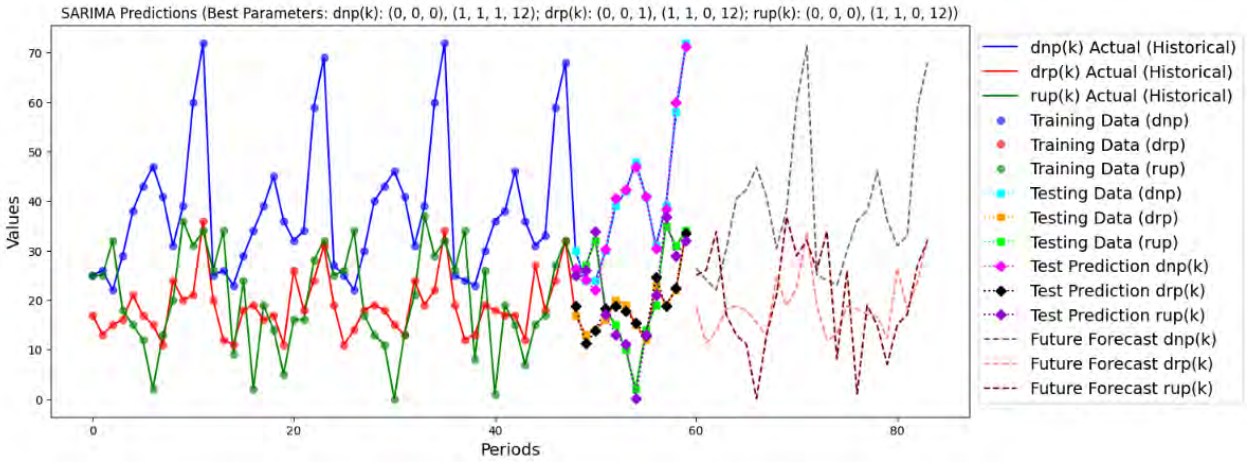

Figure 5.6. SARIMA prediction

SARIMA–VAR Hybrid algorithm

The SARIMA–VAR model differs from the other candidate models by incorporating trend, seasonality, and multivariate relationships. It is thus characterised by both SARIMA (non-seasonal and seasonal) and VAR (maxlag) parameters. A program is integrated into the algorithm to adjust these parameters and identify the optimal prediction. The optimal SARIMA–VAR parameters, testing, and prediction results are presented in Figure 5.7.

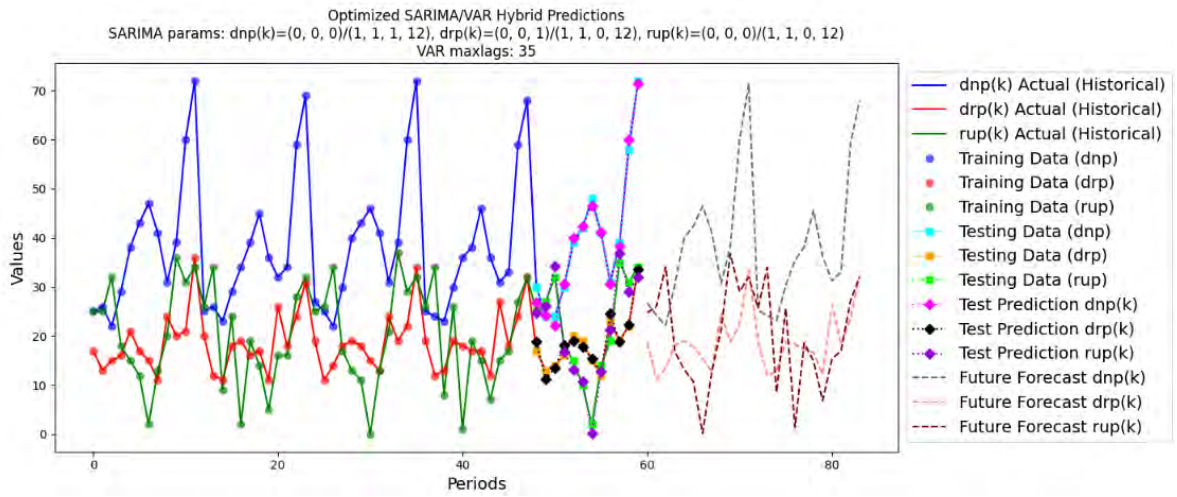

Figure 5.7. SARIMA–VAR prediction

Furthermore, the overall metrics results are MAE: 1.19, MSE: 1.99, R^2: 0.98, MAPE: 7.61%. The results in this figure show that the SARIMA–VAR algorithm performs excellent prediction. In addition, the test prediction demonstrates that predicted curves are expected to closely follow the actual data. The high R^2 value and the low MAPE, MAE, and MSE values indicate a strong correlation between the predictions and the actual data for this algorithm. Compared to the results of the SARIMA algorithm, the test predictions and future forecasts appear visually similar in Figures 5.6 and 5.7. However, when evaluating overall metrics, the SARIMA–VAR model demonstrates slightly better robustness, as it achieves a lower MSE (1.99) and MAPE (7.61%) compared to SARIMA (MSE = 2.07, MAPE = 7.76%).

LSTM algorithm

The LSTM differs from other candidate models in that it effectively handles nonlinear relationships and elaborates with both univariate and multivariate data. It is primarily characterised by two parameters: the number of units (neurons) and the depth (number of layers). Therefore, a program is implemented that varies these parameters to determine the optimal prediction. The optimal LSTM parameters, testing, and prediction results are presented in Figure 5.8. The overall metrics obtained results are MAE: 5.75, MSE: 60.51, R^2: 0.68, MAPE: 38.68%.

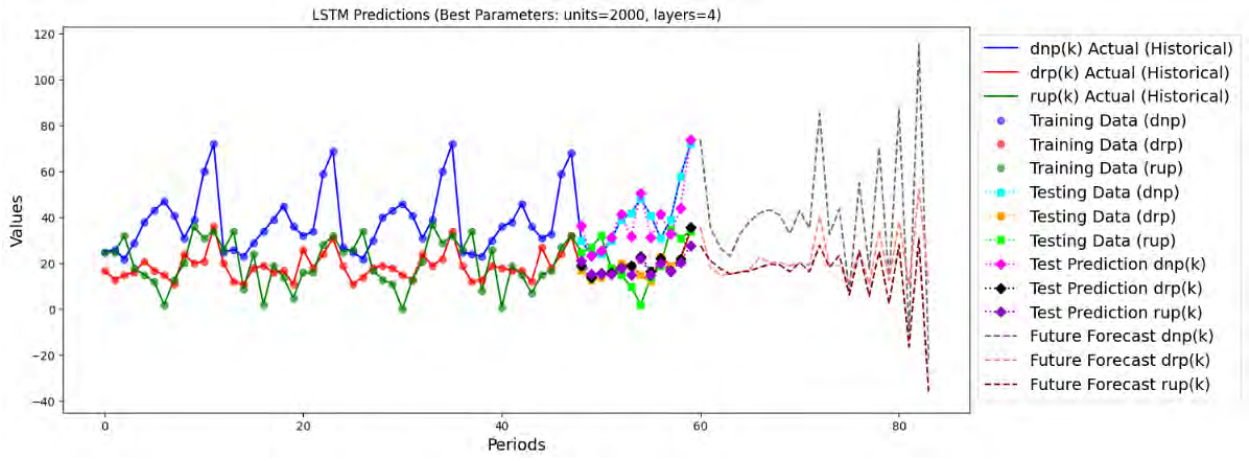

Figure 5.8. LSTM prediction

The results in the above figure indicate that the LSTM algorithm delivers poor predictions. Additionally, the test predictions reveal that the predicted curves do not align well with the actual data. The low R^2 value, combined with the high MAPE, MAE, and MSE values, suggests a weak correlation between the predictions and the actual data for this algorithm. Despite testing a large

number of units, the predictions remain poor, which may be explained by the fact that LSTM requires a large amount of data to generate accurate predictions.

HWES algorithm

The HWES captures level, trend, and seasonality using exponential smoothing. These parameters are adjusted automatically in the HWES algorithm for providing optimal prediction. It is known when:

Level=True\None, means the model includes\not a level component;

Level = True\None, means the model includes\not a level component;

Trend = True\None, means the model includes\not a trend component;

Seasonal = mul\add, means that her seasonality is multiplicative\additive.

The results are given in Figure 5.9 below, with the global metrics results as MAE = 2.71, MSE = 13.55, R^2 = 0.92, and MAPE = 18.98%. The test prediction indicates that the algorithm lacks precision and shows a weak correlation between the predicted and actual data. Additionally, although the predictive model achieves decent MAE, MSE, and R^2, the high MAPE suggests that it is not very robust, and its inability to adapt to structural changes.

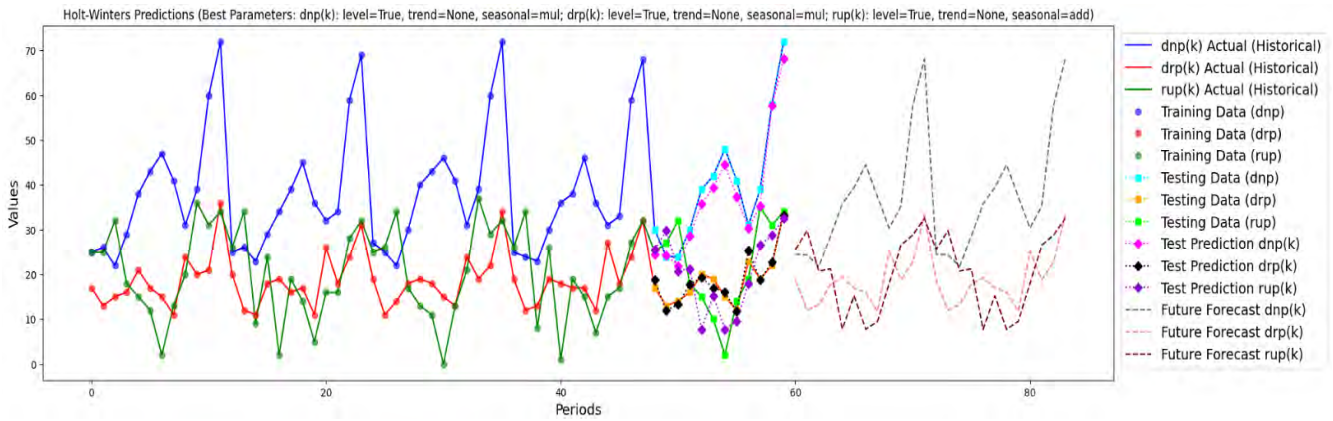

Figure 5.9. HWES prediction

Conclusion and choice of the best model

The choice of the model is based on the predictions provided above and also on the metrics results that are summarised in Table 5.2 below.

Table 5.2. Comparison of metrics results

Algorithm	MAE	MSE	R^2	MAPE
VAR	1.86	6.01	0.94	10.08%
SARIMA	1.19	2.07	0.98	7.76%
SARIMA/VAR	1.19	1.99	0.98	7.61%
LSTM	5.75	60.51	0.68	38.68%
HWES	2.71	13.55	0.92	18.98%

Comparing the results in Figures 5.5–5.9, both the SARIMA and SARIMA–VAR algorithms demonstrate excellent predictive performance and strong correlations between predictions and actual data (Figures 5.6 and 5.7). Therefore, the choice of the best model will be between these two. An ideal algorithm should minimise MAE, MSE, and MAPE while maximising R2. According to the summary table, both models achieve MAE = 1.19 and R^2 = 0.98, indicating excellent predictive accuracy. However, SARIMA–VAR outperforms SARIMA by achieving a lower MSE (1.99) and MAPE (7.61%), which signifies higher accuracy and reduced error.

As a result, SARIMA is slightly less accurate than SARIMA–VAR due to its marginally higher MSE and MAPE. Consequently, SARIMA–VAR emerges as the best-performing algorithm, offering superior predictive accuracy with minimal error values. Thus, its prediction results will be used as the future values of *dnp*(*k*), *drp*(*k*), and *rup*(*k*) and they are presented in Table 5.3 below.

Table 5.3. Predicted demand and returned products

k	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
dnp(k)	26	21	19	26	35	39	43	36	28	35	55	69	24	22	20	25	31	35	41	33	27	30	56	65
drp(k)	17	11	13	16	19	17	15	11	22	19	21	34	18	10	11	18	17	16	17	10	25	18	23	31
rup(k)	23	25	32	16	13	10	0	13	19	35	29	32	25	32	8	24	0	17	14	5	14	15	27	30

The prediction outcomes summarised in the table above will serve as essential input data for the next section, where they are incorporated into the proposed optimisation framework. On this basis, the subsequent numerical results are generated using realistic forecasts, ensuring that the model's performance is evaluated under data-driven and practically relevant conditions.

5.5 Numerical Studies

5.5.1 Input Parameters

Table 5.3 in the previous section shows the predicted values of product returns and customer demand over a 24-period planning horizon, or two future years, which are used in this section. Table 5.4 provides more details on costs, capacities, prices, and carbon emissions and Table 5.5 describes the related initial conditions.

5.5.2 Obtained Results

5.5.2.1 The System's Performance

Prior to incorporating carbon emission constraints, the model's responsiveness to real supply-chain dynamics was assessed in a neutral scenario ($ucp = 0$). As shown in Tables 5.6 and 5.7, the optimisation generated a total profit of 63,512 mu over 24 planning periods, proving the effectiveness of the integrated decision framework.

Production and remanufacturing schedules demonstrate a strategic transition between active and empty periods, striking a balance between inventory management and meeting demand. Raw material procurement dynamically adjusts to stock levels to prevent unnecessary orders and match supply with production demands. Transportation choices are adjusted in response to shifts in production and demand to ensure the smooth flow of new, remanufactured, and returned products. Demand is almost entirely satisfied, with only minor shortages in remanufactured products and none in new products. The fleet utilisation is well-coordinated between *V1* and *V2*, maximising capacity utilisation and decreasing empty time, according to the binary variables that govern vehicle allocation. The model effectively synchronises production, logistics, and procurement in a manufacturing-remanufacturing setting to maximise profitability while maintaining operational balance. All things considered, it demonstrates excellent coherence and flexibility.

Table 5.4. Input parameters for coding

x	***A***	***b***	***y***	***wx***	***wa***	***wb***	***wc***	***ct***	***ca***	***cb***	***cs***	***sn***	***sr***	***FT1***
18	75	20	15	0.1	0.5	0.4	0.1	1	3.5	1	1	400	320	500
pv	***Pn***	***pr***	***RM***	***NP***	***RP***	***N***	***R***	***GM***	***SP***	***GR***	***BN***	***TRV1***	***TRV2***	***FT2***
17	145	110	150	220	200	160	110	80	150	60	10000	70	100	600
ucp	***Em***	***en***	***er***	***erm***	***ewn***	***ewr***	***esc***	***ecu***	***enp***	***erp***	***etr***	***efrt1***	***efrt2***	
0.01	5	60	1	1	1	2	1	1	3	3	1	2500	2800	

Table 5.5. Initials values for coding

qrm0	***mn0***	***rm0***	***trn0***	***trr0***	***wrm0***	***wnp0***	***wrp0***	***wup0***	***inp0***
30	30	20	30	20	30	20	30	10	30
irp0	***tup0***	***vnp0***	***vrp0***	***scp0***	***lnp0***	***lrp0***	***γ1(k)***	***γ2(k)***	***vup0***
20	10	50	40	10	0	0	1	0	0

Table 5.6. Optimal plans with *ucp*=0 (*Z*=24)

k	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
mn(k)	16	26	74	0	43	64	0	35	64	68	38	0	45	0	66	0	74	0	57	0	56	65	0	0
rm(k)	0	15	26	0	15	33	0	34	6	32	32	0	25	0	34	0	26	0	43	0	23	31	0	0
qrm(k)	56	0	43	64	0	35	64	68	38	0	45	0	66	0	74	0	57	0	56	65	0	0	0	0
trn(k)	17	19	26	74	0	43	64	0	35	64	68	38	0	45	0	66	0	74	0	57	0	56	65	0
trr(k)	8	13	24	26	0	15	33	0	34	6	32	32	0	25	0	34	0	26	0	43	0	23	31	0
tup(k)	23	25	32	16	0	23	0	0	32	35	29	32	0	57	0	32	0	17	0	19	0	29	0	0

Table 5.7. Additional results with *ucp*=0 (*Z* = 24)

k	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
vnp(k)	26	21	19	26	35	39	43	36	28	35	55	69	24	22	20	25	31	35	41	33	27	30	56	65
vrp(k)	17	11	13	16	19	15	15	11	22	19	21	32	18	10	11	18	17	16	17	10	25	18	23	31
γ1(k)	1	1	1	0	0	1	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0	0
γ2(k)	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0	1	0	1	0	1	0	1	1	0
lnp(k)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
lrp(k)	0	0	0	0	0	2	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0

5.5.2.2 Results Based on Carbon Tax Price

The analysis of carbon taxation in Figure 5.10 shows the strong correlation between financial performance and environmental regulation. Since the total carbon footprint ($CF(Z)$) essentially remains unchanged as tax rates increase, the results show that the carbon price (ucp) is too low to result in significant emission reductions within the tested range. There is a noticeable decline in total profit ($PRCX(Z)$) after $ucp = 0.01$, though, suggesting a clear trade-off between profitability and adherence to environmental regulations.

Higher tax levels (e.g., $ucp = 0.5$) result in a significant increase in profit reduction, suggesting that taxes alone may not be enough to promote sustainability unless combined with more strict regulations or technological incentives. These findings emphasise the need for balanced policy frameworks, such as those established in the Paris Agreement, that promote emission reduction while preserving economic stability.

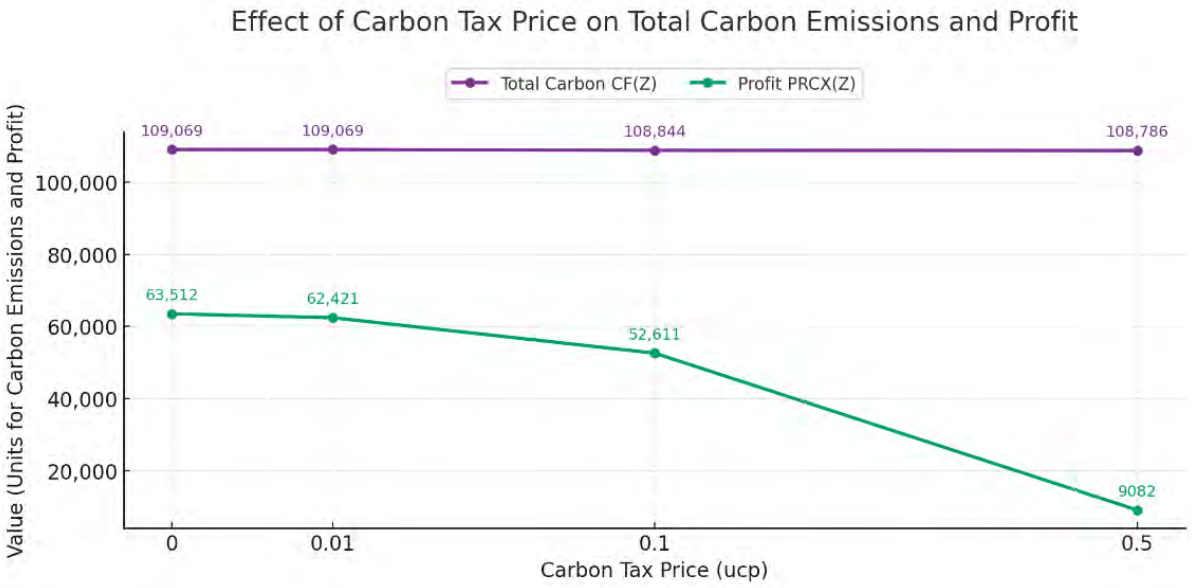

Figure 5.10. Impact of carbon tax pricing on total carbon footprint and profit.

5.5.2.3. Results Based on Paris Agreement Limitation

The Paris Agreement, which was adopted at COP21 in 2015, establishes a global framework for mitigating climate change by limiting global warming to well below 2 °C, with an aspirational target of 1.5 °C over pre-industrial levels. The Nationally Determined Contributions (NDCs), which outline specific targets for cutting greenhouse gas emissions, must be submitted and updated

by participating nations. The agreement promotes the use of renewable energy, carbon pricing, and sustainable industrial practices while wealthy nations provide financial and technological assistance to developing nations. Despite being voluntary, the Paris Agreement remains a vital instrument for advancing global decarbonisation and cooperative climate action towards a net-zero future (Eyberg et al., 2024).

The findings in Table 5.8 show the trade-off between economic performance, carbon reduction, and service level. Without emission limits, the system achieves its maximum profit (63,512 mu) and order fill rate of 99.69%, demonstrating nearly optimal efficiency. The financial cost of stricter regulation is demonstrated by the steady decline in profits as carbon restrictions tightened, from 58,510 mu at a 2.5% reduction to 40,413 mu at a 10% reduction. At the same time as the demand for new and remanufactured products keeps increasing, the order fill rate drops to 95.35 percent. This decline demonstrates that, despite their environmental benefits, emission limits could compromise service reliability and profitability. These results emphasise the trade-off between sustainability and economic performance. While reducing emissions encourages environmental responsibility, it also raises costs and presents issues for service reliability and profitability. Therefore, cost-effective technologies and policy incentives must be integrated into carbon reduction strategies in order to minimise financial effects while pursuing sustainability objectives. As Figures 5.11 and 5.12 demonstrate, stricter emission targets result in a steady decline in profit as order fill rates fall and unmet demand rises. These trends show how, above certain thresholds, stringent carbon limits can negatively impact customer service. All things considered, the analysis provides managers with valuable insights into how to balance environmental objectives with operational and financial performance in carbon-conscious supply chains.

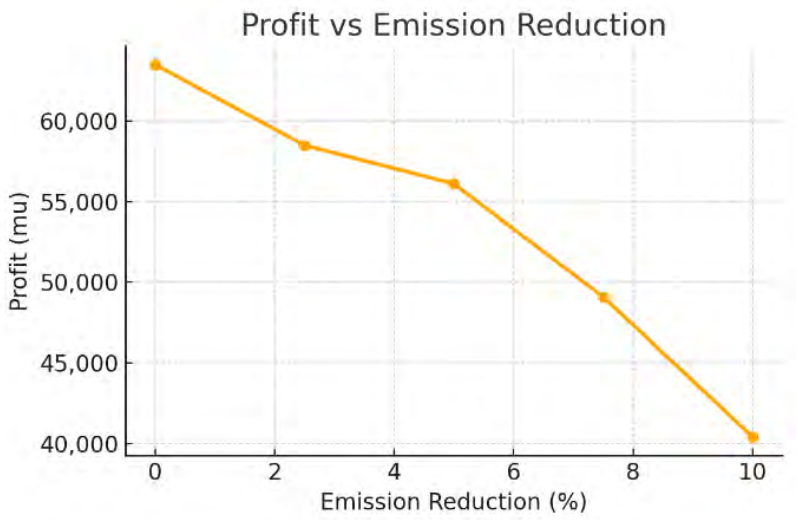

Figure 5.11. Impact of emission targets on profitability

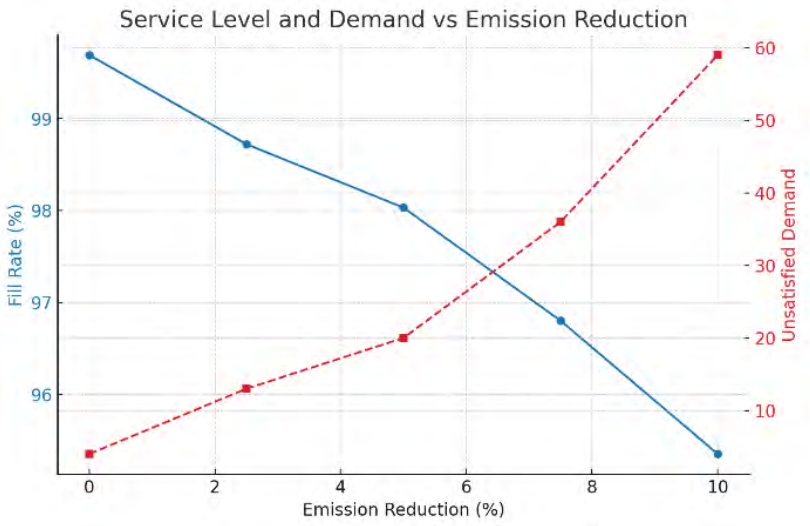

Figure 5.12. Effect of carbon constraints on service level and demand fulfilment

Table 5.8. Trade-off among carbon emission reduction, economic performance, and service levels

Case	Profit $PRCX(Z)$	Loss of Earnings	Total of $lnp(k)$	Total of $lrp(k)$	Total of $lnp(k)$ and $lrp(k)$	Global Service Level (Order Fill Rate)
Without limitation $CF(Z)$= 109,069	63,512	0	0	4	4	99.69%
2.5% reduction $CF(Z)$= 106,336	58,510	5002	12	4	16	98.74%
5% reduction $CF(Z)$= 103,615	56,118	7394	17	4	21	98.35%
7.5% reduction $CF(Z)$= 100,888	49,098	14,413	29	8	37	97.09%
10% reduction $CF(Z)$= 98,162	40,413	23,098	35	24	59	95.35%

5.5.2.4. Theoretical and Managerial Implications of the Model

The study highlights how important it is for managers to coordinate environmental responsibility and operational resilience. The decline in profitability and service levels under stricter carbon constraints highlights how emission targets can strain supply-chain performance if they are not accompanied by adaptive strategies. Managers should therefore plan for these trade-offs by investing in cleaner technologies, boosting production efficiency, and optimising resource and transportation use in order to maintain reliability within legal bounds.

In the broader context of the Paris Agreement, carbon emissions must be recognised as both an ecological issue and a strategic and financial factor that impacts competitiveness. Sustainability is no longer a constraint but rather a source of innovation and long-term value when carbon performance is taken into account when making decisions. Proactive planning, scenario analysis, and collaboration with regulators become essential to meet emission targets while preserving business continuity.

Theoretically, this research advances our understanding of data-driven, carbon-regulated optimisation. A realistic image of supply chains that are sensitive to environmental stress and uncertainty is produced by combining predictive analytics and multi-period modelling. The framework clarifies how emission constraints impact choices about production, remanufacturing, and logistics, laying a strong basis for future research on resilient and sustainable supply-chain design.

5.6 Conclusion

This chapter introduced a comprehensive optimisation model for multi-period planning in a sustainable supply chain with reverse logistics that combines transportation, remanufacturing, and manufacturing while accounting for carbon-related constraints. By combining forward and reverse flows, the model effectively depicts the operational complexity of a system that meets market demand while adhering to environmental regulations such as carbon taxes and emission limits. Scenario analyses showed how adaptable the model was to shifts in demand, return flows, and production schedules. Its value as a tool for managers trying to strike a balance between sustainability and profitability is confirmed by its capacity to maintain service quality while reducing excess inventory and unmet demand. The combination of carbon pricing and Paris

Agreement advanced the ongoing debate between supply chain optimisation and climate policy by enabling a better understanding of the trade-offs between environmental performance and economic efficiency. Finally, incorporating demand forecasting into the optimisation process, particularly with the hybrid SARIMA–VAR approach, improved the system's capacity to adapt to uncertainty. This predictive integration enhances the model's role as a practical and forward-thinking framework for supply chain management that is both environmentally responsible and operationally sound.

General Conclusion

This dissertation examined the connection between operational dependability, environmental responsibility, and economic performance through the design and optimisation of integrated, sustainable supply chains. It has demonstrated how, in both traditional and carbon-conscious contexts, multi-period optimisation models supported by data-driven and predictive techniques can enhance coordination between decisions about acquisition, production, remanufacturing, transportation, and maintenance. By bridging the gap between theoretical modelling and managerial relevance, the study advances the broader movement towards low-emission and circular industrial systems.

Chapter 1 established the theoretical foundations and research gaps, highlighting the need for integrated optimisation frameworks that simultaneously address economic and environmental factors. Chapter 2 introduced the baseline multi-period model that integrates production, logistics, and procurement in a reverse-flow structure to illustrate how coordinated planning reduces overall costs and increases productivity. To include carbon regulation, Chapter 3 extended this model by comparing the Carbon Tax, Cap-and-Trade, and Limit-and-Subsidy strategies. According to the research, Cap-and-Trade had the most balanced effect, increasing environmental compliance while marginally reducing profit. Chapter 4 discussed joint maintenance-transport optimisation and its strategic role in improving dependability, sustainability, and cost control. Lastly, Chapter 5 used a hybrid SARIMA–VAR model to integrate predictive analytics into the optimisation framework, strengthening adaptability under uncertainty and bridging the gap between theoretical design and real-world decision support. Together, these contributions improve supply-chain optimisation theory by combining economic, environmental, and reliability factors into a single framework for decision-making. In terms of management, they offer helpful guidance on how to align operational efficiency with sustainability goals through coordinated, model-based planning.

In essence, this dissertation shows that the future of supply-chain management depends on the integration of data, environmental responsibility, and operational intelligence. By combining optimisation with sustainable and predictive thinking, it helps industrial systems evolve towards resilience, circularity, and long-term sustainability. In addition to addressing the new challenges

of global supply-chain management through multi-agent coordination, stochastic modelling, and real-time data integration, future research could expand on this work by incorporating predictive techniques for forecasting raw material procurement.

In terms of publications, this doctoral work has resulted in two presentations at international conferences and two journal articles:

Journals:

- ABASSI, B., TURKI, S. & DELLAGI, S. 2025. Optimal Multi-Period Manufacturing–Remanufacturing–Transport Planning in Carbon Conscious Supply Chain: An Approach Based on Prediction and Optimisation. Sustainability, 17. 2025. DOI: 10.3390/su17115218
- ABASSI, B., TURKI, S., DELLAGI, S. & BELLAMINE, I. Low-carbon manufacturing-remanufacturing supply chain: systematic review and bibliometric analysis. Supply Chain Forum: An International Journal, 1-23, 2025. DOI: 10.1080/16258312.2025.2468633

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- ABASSI, B., TURKI, S., DELLAGI, S. & BELLAMINE, I. Optimal production planning for manufacturing-reconditioning- transport supply chain system. 20th IEEE International Conference on Networking, Sensing and Control (ICNSC 2023). Aix-Marseille, France, 2023. DOI: 10.1109/ICNSC58704.2023.10319056
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Abstract

This dissertation examines the integrated optimisation of procurement, production, remanufacturing, maintenance, and transportation within the context of carbon-conscious and sustainable supply chains that adhere to reverse logistics principles. Chapter 1 lays out the theoretical foundations and explains how modern supply chains have changed to become more resilient, sustainable, and digitally integrated. It highlights lack of existing models and the need for an integrated framework that simultaneously addresses economic and environmental objectives. Chapter 2 develops a multi-period Mixed-Integer Linear Programming (MILP) model to coordinate procurement, manufacturing, remanufacturing, and transportation decisions in order to maximise profit under operational and capacity constraints. The results show that hybrid procurement contracts improve flexibility and cost-effectiveness while coordinated transport planning reduces unnecessary flows and improves overall performance. In Chapter 3, carbon regulation tools like the Carbon Tax, Cap-and-Trade, and Limit-and-Subsidy plans are added to the framework. According to the analysis, which uses carbon footprint as a sustainability indicator, stricter controls increase operational discipline and emission performance but also reduce profitability. Chapter 4 integrates maintenance optimisation into the supply-chain model by balancing preventive and corrective actions to improve reliability and reduce system costs. Sensitivity analyses highlight the importance of maintenance frequency and how much it affects transportation decisions. Chapter 5 presents a comprehensive multi-period optimisation model using a hybrid SARIMA–VAR approach that integrates environmental regulation, realistic transport capacities, and predictive forecasting. This integration enhances decision accuracy in the face of uncertainty and harmonises long-term sustainability objectives with economic performance. The dissertation facilitates the transition to robust, low-carbon, and efficient industrial systems by providing a coherent framework for decision-making that incorporates environmental responsibility and predictive intelligence into supply-chain optimisation.

Keywords: Integrated Optimisation, Sustainable Supply Chain, Reverse Logistics, Predictive Forecasting, Carbon Footprint.

Résumé

Cette étude met l'accent sur l'optimisation intégrée de l'approvisionnement, la production, la remanufacturation, la maintenance et le transport au sein des chaînes d'approvisionnement durables et conscientes du carbone, en se basant sur les principes de la logistique inverse. Le premier chapitre présente les fondements théoriques et démontre la progression des chaînes d'approvisionnement contemporaines vers une meilleure résilience, un plus grand développement durable et une intégration numérique accrue. Il met en évidence les limites des modèles actuels et la nécessité d'une structure unifiée qui puisse allier simultanément les objectifs économiques et écologiques. Le Chapitre 2 établit un modèle de programmation linéaire en nombres entiers mixtes (MILP) sur plusieurs périodes. Ce système a pour objectif de synchroniser les décisions concernant l'achat, la fabrication, la remanufacturation et le transport afin d'augmenter le profit tout en tenant compte des restrictions opérationnelles et de capacité. Les données indiquent que les contrats d'approvisionnement hybrides améliorent la flexibilité et le profit, tandis qu'une gestion coordonnée du transport réduit les flux inutiles et optimise l'efficacité globale. Le Chapitre 3 comprend des mécanismes de contrôle du carbone, tels que la Taxe Carbone, le Système de Plafonnement et d'Échange, ainsi que la Limitation avec Subvention, dans le contexte de l'optimisation. L'évaluation, qui s'appuie sur l'empreinte carbone comme critère de durabilité, révèle que des contrôles plus stricts renforcent la rigueur opérationnelle et l'efficacité écologique, bien qu'ils entraînent une baisse légère de la rentabilité. Le Chapitre 4 inclut l'optimisation intégrée de la maintenance et du transport dans le modèle de chaîne d'approvisionnement, ayant pour objectif d'harmoniser les actions préventives et correctives afin d'améliorer la fiabilité et de réduire les dépenses liées au système. Les analyses de sensibilité soulignent l'importance primordiale de la fréquence des interventions et son impact sur les décisions de transport. Le Chapitre 5 expose un modèle d'optimisation multi-périodique global basé sur une méthode hybride SARIMA/VAR, intégrant la régulation écologique, des capacités de transport réalistes et des prévisions anticipatives. Cette intégration améliore la prise de décisions précises en situation d'incertitude et aligne les objectifs de durabilité à long terme avec la performance économique. Dans l'ensemble, cette thèse doctorale propose un modèle décisionnel intégré qui intègre la responsabilité

environnementale et l'intelligence prédictive pour améliorer les chaînes d'approvisionnement. Cela aide à la transition vers des systèmes industriels efficaces, robustes et émettant peu de carbone.

Mots-clés : Optimisation intégrée, Chaîne d'approvisionnement durable, Logistique inverse, Prévision prédictive, Empreinte carbone.

Résumé de la thèse

Cette thèse s’inscrit dans le contexte de la mutation radicale des chaînes logistiques industrielles, caractérisées par une complexité croissante, des exigences intensifiées en termes de durabilité écologique et une pression constante sur les performances économiques. Autrefois considérées comme des systèmes linéaires et séparés, les chaînes d'approvisionnement sont désormais perçues comme des réseaux dynamiques, faisant appel à des flux directs et inverses, à des prises de décision interdépendantes et à diverses contraintes. Ce manuscrit propose une approche intégrée, multi-période et axée sur les données, pour l'optimisation des chaînes d'approvisionnement incluant la logistique inverse, tout en prenant en compte de manière simultanée les aspects économiques, environnementaux et opérationnels.

L’objectif principal de l'étude est d'élaborer un cadre décisionnel qui, au sein d'un même modèle, coordonne les décisions concernant l'acquisition de matières premières, la production et la remanufacturation, la gestion des stocks, le transport et la maintenance, tout en incorporant les stratégies de réduction des émissions de carbone ainsi que les outils prédictifs basés sur les données. Cette démarche cherche à dépasser les contraintes des modèles classiques, qui gèrent ces fonctions de manière isolée, et à proposer des solutions plus réalistes, robustes et adaptées aux enjeux contemporains des chaînes logistiques durables.

La première partie de la thèse se concentre sur une étude détaillée de l’état de l’art en gestion et de l'optimisation des chaînes logistiques. Elle souligne la progression progressive des systèmes de production et de distribution, passant de structures linéaires à des architectures circulaires intégrant la logistique inverse et la remanufacturation. Cette progression est principalement stimulée par la raréfaction des ressources, l'instabilité croissante de la demande, ainsi que par les politiques environnementales de plus en plus strictes.

Les études antérieures montrent que l'optimisation des chaînes logistiques s'appuie généralement sur des modèles mathématiques visant des fonctions spécifiques, comme la production, le transport ou la gestion des stocks. Toutefois, ces approches partielles négligent souvent les interactions fortes entre les différentes décisions et à minimiser les impacts de la coordination.

La revue de littérature met également l'accent sur l'importance croissante des considérations environnementales, notamment à travers l'intégration des émissions de carbone dans les fonctions objectives, ainsi que le rôle émergent des techniques de prévision et d'apprentissage automatique pour améliorer la qualité des décisions.

Un autre axe majeur abordé dans cette revue concerne la maintenance des systèmes de transport, souvent considérée comme une contrainte externe. La fiabilité, la disponibilité et les performances environnementales des véhicules sont directement liées aux stratégies de maintenance mises en place, ce qui met en évidence une lacune en matière de modèles intégrés prenant conjointement en compte la maintenance, le transport et les flux de logistique inverse. Sur la base de cette analyse critique, la thèse se positionne comme une contribution originale visant à combler ces lacunes, en proposant un cadre unifié intégrant l'ensemble de ces dimensions dans un modèle cohérent et opérationnel.

La deuxième partie de la thèse développe un premier modèle d'optimisation intégrée multi-période pour la planification conjointe de l'approvisionnement, de la fabrication, de la remanufacturation et du transport au sein d'une chaîne logistique avec logistique inverse. Le système étudié comprend des fournisseurs de matières premières, des unités de production et de remanufacturation, des centres de distribution et des marchés finaux, ainsi que des flux de retour de produits en fin de vie.

Le modèle proposé repose sur une formulation en programmation linéaire en nombres entiers mixtes. Il vise à maximiser le profit global de la chaîne logistique, en tenant compte des coûts d'approvisionnement, de production, de remanufacturation, de stockage et de transport, ainsi que des contraintes de capacité, de demande et de disponibilité des ressources. Une distinction explicite est opérée entre les produits neufs et les produits remanufacturés, reflétant les pratiques industrielles réelles.

Une attention particulière est accordée aux stratégies d'approvisionnement, notamment les politiques à lot fixe et les stratégies hybrides combinant contrats à long terme et approvisionnement flexible. Les résultats numériques montrent que ces stratégies contractuelles permettent d'améliorer significativement la flexibilité du système et de réduire les coûts globaux, tout en assurant un meilleur niveau de service.

La troisième partie étend le modèle précédent en intégrant explicitement les émissions de carbone générées par les activités de production, de remanufacturation, de transport et de stockage. Dans un contexte réglementaire de plus en plus strict, la prise en compte de ces émissions devient indispensable pour évaluer la performance globale des chaînes logistiques.

L'étude examine trois formes de politiques environnementales : la taxe carbone, le mécanisme de plafonnement et de commerce de droits d'émission (cap-and-trade), ainsi que la stratégie de restriction accompagnée d'une subvention. Ces politiques sont toutes incorporées dans f et les restrictions du modèle, ce qui permet d'examiner leurs effets spécifiques sur les choix opérationnels et la profitabilité. Les analyses indiquent que, même si certaines mesures peuvent causer une diminution marginale des bénéfices à court terme, elles contribuent à une répartition plus efficace des ressources, une baisse importante des rejets et un perfectionnement de la performance globale du système. Le système d'échange de droits d'émission semble être un compromis particulièrement performant entre l'efficacité économique et la réalisation des objectifs environnementaux.

La quatrième partie de la thèse introduit la dimension de la maintenance des véhicules de transport dans le cadre d'optimisation de la chaîne logistique. Contrairement aux hypothèses classiques de disponibilité parfaite des moyens de transport, le modèle développé prend en compte la dégradation progressive des véhicules, les pannes et les actions de maintenance préventive et corrective.

La maintenance est modélisée comme une variable de décision stratégique, influençant directement la disponibilité des véhicules, les coûts opérationnels et la fiabilité du système. En s'appuyant sur des modèles de dégradation et de fiabilité, notamment basés sur la loi de Weibull, le modèle permet de déterminer des politiques de maintenance optimales en fonction des coûts et des risques de défaillance. Les analyses numériques mettent en évidence l'intérêt d'une maintenance préventive bien planifiée, qui permet de réduire les interruptions de service, d'allonger la durée de vie des équipements et de diminuer les émissions associées aux défaillances et aux interventions d'urgence. L'intégration conjointe de la maintenance et du transport conduit ainsi à une amélioration notable de la performance globale de la chaîne logistique.

La dernière partie développe un modèle d'optimisation multi-périodes appliqué à une chaîne d'approvisionnement intégrant l'acquisition, la production, le remanufacturing, le transport et la logistique inverse, tout en tenant compte de contraintes économiques et environnementales. Formulé sous la forme d'un modèle MILP, il intègre des capacités réalistes de stockage et de transport ainsi que l'impact de différentes politiques carbone, telles que la taxe carbone et les engagements issus de l'Accord de Paris. L'articulation des flux directs et inverses permet de représenter fidèlement la complexité opérationnelle du système et de rechercher un compromis entre performance économique et durabilité environnementale.

Dans ce cadre, la thèse propose une approche intégrée combinant prévision et optimisation afin de mieux gérer l'incertitude liée à la demande et aux flux de retour. Des modèles prédictifs avancés fondés sur les séries temporelles et l'apprentissage automatique, notamment le modèle hybride SARIMA-VAR, est mobilisé pour estimer les volumes futurs, puis directement intégré au processus d'optimisation multi-période. Cette intégration permet d'ajuster de manière dynamique les plans de production, de transport et de remanufacturation, améliorant ainsi la réactivité du système face aux fluctuations du marché. Les analyses de scénarios, études de cas et simulations confirment la capacité du modèle à s'adapter aux variations de la demande et des retours, tout en réduisant les coûts liés aux surstocks et aux ruptures. Ce travail met ainsi en évidence l'apport des approches data-driven pour renforcer la robustesse des décisions et proposer un cadre opérationnel conciliant rentabilité, qualité de service et performance environnementale.

Au-delà des contributions méthodologiques, les résultats obtenus dans cette thèse permettent de dégager plusieurs enseignements importants pour les décideurs industriels et les gestionnaires de chaînes logistiques. Tout d'abord, l'intégration conjointe des décisions d'approvisionnement, de production, de remanufacturation et de transport met en évidence l'importance d'une coordination globale plutôt que d'optimisations locales. Les analyses indiquent que des décisions qui paraissent bénéfiques à court terme, lorsqu'ils sont pris de manière isolée, peuvent engendrer d'importantes inefficacités à l'échelle globale du système.

Les stratégies d'approvisionnement hybrides étudiées dans ce travail illustrent particulièrement bien ce phénomène. En combinant des contrats à long terme garantissant une base d'approvisionnement stable avec des mécanismes flexibles permettant d'ajuster les volumes en fonction de la demande et des retours, les entreprises peuvent à la fois sécuriser leurs flux et

améliorer leur réactivité. Cette flexibilité s’avère essentielle dans les environnements caractérisés par une forte incertitude et par des exigences accrues en matière de durabilité.

Du point de vue environnemental, l’intégration explicite des politiques carbone dans les modèles de décision modifie profondément les arbitrages traditionnels entre coûts et performances. Les résultats numériques montrent que les mécanismes de tarification du carbone incitent à repenser la localisation des activités, les choix de transport et les volumes produits ou remanufacturés. À moyen et long terme, ces politiques favorisent des configurations à faibles émissions, tout en maintenant un niveau de rentabilité acceptable. Cette observation est particulièrement pertinente dans le contexte des engagements internationaux en faveur de la neutralité carbone.

Sur le plan méthodologique, ce travail de recherche propose un cadre innovant s'appuyant sur l'association de diverses approches habituellement non employées conjointement. L'emploi de modèles d'optimisation sur plusieurs périodes permet de considérer les dépendances dans le temps entre les choix logistiques, notamment en ce qui concerne les inventaires, les capacités opérationnelles et la planification. Il est essentiel d'inclure le facteur temporel pour décrire avec précision le fonctionnement des chaînes d'approvisionnement industrielles et pour évaluer les effets différés des décisions prises à court terme.

Un des aspects essentiels de ce travail est l'intégration de la maintenance en tant que critère indépendant pour la prise de décision. En prenant en considération la dégradation progressive des véhicules et des équipements, le modèle dépasse les hypothèses de disponibilité parfaite généralement acceptés. Les informations révèlent que la maintenance influe directement sur la fiabilité du système, les coûts d'exploitation et les performances environnementales, soulignant son rôle stratégique au même titre que le transport ou la production. En adoptant cette approche globale, l'intégration des flux de logistique inverse transforme les articles retournés en ressources potentielles qui peuvent être valorisées via des stratégies de remanufacturation appropriées.

De plus, l'intégration d'outils de prévision basés sur les données accentue la signification opérationnelle du modèle suggéré. L'emploi de modèles hybrides, combinant techniques statistiques et apprentissage automatique, facilite une anticipation plus précise des variations de la demande et des retours, permettant ainsi d'adapter les choix d'optimisation en fonction. Cette

liaison étroite entre la prédiction et l'optimisation renforce la réactivité et la solidité du système face à l'incertitude.

Enfin, l'intégration explicite des politiques environnementales dans le processus décisionnel constitue un autre composant structurant. Tenant compte des émissions de carbone dans le processus d'optimisation, le modèle met en lumière les compromis entre profit économique et bénéfice écologique. Les résultats suggèrent que les systèmes de tarification du carbone pourraient évoluer vers de véritables leviers d'amélioration globale, en favorisant une gestion plus efficiente des ressources, un perfectionnement des réseaux de transport et une application accrue des concepts de l'économie circulaire.

D'un point de vue managérial, les résultats de cette étude soulignent l'importance d'une coordination transversale des chaînes logistiques. La mise en œuvre des modèles proposés suppose une coordination renforcée entre les différentes fonctions de l'entreprise, ainsi qu'un partage accru de l'information entre les acteurs internes et externes. Dans ce cadre, les outils d'aide à la décision développés peuvent contribuer à structurer les échanges, à éclairer les arbitrages stratégiques et à accompagner les entreprises dans leur transition vers des modèles plus durables et résilients.

Comme tout travail de recherche, cette thèse présente certaines limites, liées notamment aux hypothèses de rationalité et de disponibilité de l'information nécessaires à la modélisation, qui peuvent être mises à l'épreuve dans des contextes industriels fortement incertains. Néanmoins, ce travail ouvre des perspectives de recherche prometteuses, telles que l'optimisation conjointe des décisions de transport, de maintenance et de logistique inverse, l'intégration de méthodes de prévision avancées fondées sur l'apprentissage automatique, ainsi que la prise en compte de mécanismes environnementaux et de critères sociaux supplémentaires, afin d'élargir le cadre vers une approche pleinement durable.

En définitive, cette thèse apporte une contribution significative à la recherche en optimisation des chaînes logistiques en proposant un cadre intégré, multi-période et orienté durabilité. Elle montre qu'une prise de décision coordonnée, appuyée sur des modèles analytiques et des outils de prévision fiables, permet de concilier performance économique, fiabilité opérationnelle et responsabilité environnementale. Les travaux présentés fournissent ainsi des bases solides pour le

développement de systèmes d’aide à la décision capables d’accompagner les entreprises dans un environnement industriel en constante mutation.

En conclusion, cette thèse propose une contribution substantielle à la recherche en optimisation des chaînes logistiques durables et circulaires. En développant un cadre intégré et multi-période qui combine approvisionnement, production, remanufacturation, transport, maintenance, prévision et politiques environnementales, elle démontre qu’il est possible de combiner performance économique, fiabilité opérationnelle et responsabilité environnementale.

Les résultats obtenus mettent en évidence l’importance d’une prise de décision coordonnée, basée sur des outils d'analyse et axés sur les données, pour relever les défis complexes des chaînes logistiques contemporaines. Cette recherche établit donc un socle robuste pour l'élaboration de systèmes d'aide à la décision adaptés aux exigences présentes et futures des secteurs en transition vers des modèles plus durables et résilients.