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Sustainable Optimisation of Cold Food Supply Chains: A Bi-Objective Inventory–Routing Model under Demand Uncertainty

Thesis presented by

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for the degree of

Master by Research

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2025

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Declaration

This is to certify that the work I am submitting is my own and has not been submitted for another degree, either at University College Cork or elsewhere. All external references and sources are clearly acknowledged and identified within the contents. I have read and understood the regulations of University College Cork concerning plagiarism.

I declare that the work presented in this thesis is my own and was carried out independently as part of the requirements for the award of the Master by Research degree at University College Cork. Except where otherwise stated, the analyses, modelling, computational experiments, interpretation of results, and written content are the original work of the author. Any external sources of information, data, or ideas have been appropriately acknowledged and referenced.

I acknowledge the guidance and supervision provided by my supervisory team throughout the research process. I further recognise the contributions of Mr. Suheyl Gulecyuz, whose involvement took place after the completion of the main thesis research, specifically in the context of preparing and refining the journal publication based on this work. His role is fully detailed in Chapter 3, Section 3.6, and I confirm that the conceptualisation, development of the integrated inventory–routing model, computational setup, data generation, analysis, and thesis writing were conducted primarily by me.

I also declare that the only artificial intelligence tool used in the preparation of this thesis was ChatGPT (OpenAI), including versions GPT-4, GPT-4.1, GPT-5, and GPT-5.1, and these tools were used solely for rewriting, paraphrasing, language refinement, and improving clarity of expression.

Signature:



Date: 2025-11-27

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Glossary of Terms

Analytic Hierarchy Process (AHP)

American Production and Inventory Control Society (APICS)

Ant Colony Optimisation (ACO)

Augmented Epsilon Constraint (AEC)

Carbon Dioxide (CO_2)

Cold Food Supply Chain (CFSC)

Cold Food Supply Chain Logistics (CFSCL)

Cold Food Supply Chain Management (CFSCM)

Cold Food Supply Chain Performance (CFSCP)

Cold Pharmaceutical Supply Chain (CPSC)

Cold Supply Chain (CSC)

Cold Supply Chain Logistics (CSCL)

Cold Supply Chain Management (CSCM)

Coefficients of Variation (CV)

Computational Fluid Dynamics (CFD)

Decision Support Systems (DSS)

Distribution Centre (DC)

Epsilon Constraint (EC)

First-In, First-Out (FIFO)

Food Supply Chain (FSC)

Global Positioning System (GPS)

Greenhouse Gas (GHG)

Information Technology (IT)

Integer Linear Programming (ILP)

Internet of Things (IoT)

Inventory Routing Problem (IRP)

Linear Programming (LP)

Mixed Integer Linear Programming (MILP)

Mixed Integer Programming (MIP)

Multi-Criteria Decision-Making (MCDM)

Multi-Objective Programming (MOP)

Nonlinear Programming (NLP)

Performance Measurement (PM)

Performance Measurement System (PMS)

Radio Frequency Identification (RFID)

Supply Chain (SC)

Supply Chain Management (SCM)

Supply Chain Performance (SCP)

Supply Chain Performance Measurement System (SCPMS)

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

Travelling Salesman Problem (TSP)

Vehicle Routing Problem with Time Windows (VRPTW)

Wireless Sensor Networks (WSN)

Abstract

Cold Food Supply Chain (CFSC) plays a critical role in ensuring the availability, safety, and freshness of temperature-sensitive products, yet they remain particularly vulnerable to demand volatility, energy-intensive operations, and rising sustainability pressures. Maintaining precise temperature conditions throughout transportation and storage significantly increases energy consumption and operational cost, while also contributing to elevated Carbon Dioxide (CO_2) emissions. These challenges are compounded by the fact that demand for perishable goods is frequently non-stationary and difficult to predict, with fluctuations driven by weather, promotions, consumer behaviour, and seasonal variations. Traditional replenishment policies such as the fixed-order (R, Q) approach lack the flexibility required in such uncertain environments and often produce inflated safety stocks and inefficient routing decisions. In cold chains, where excessive storage accelerates spoilage, increases energy use, and undermines product freshness, the consequences are particularly severe.

Responding to these challenges, this thesis develops an integrated, bi-objective Mixed-Integer Programming (MIP) model based on the adaptive (R, S) replenishment policy. The model jointly optimises replenishment timing, order-up-to levels, and vehicle routes in a multi-period distribution environment characterised by non-stationary stochastic demand. Two conflicting objectives are addressed simultaneously: (I) minimising total expected cost, and (II) minimising total expected CO_2 emissions arising from transportation activity and refrigeration load. Given the combinatorial complexity of the multi-period Inventory Routing Problem (IRP) under uncertainty, the Augmented Epsilon Constraint (AEC) method is employed to generate Pareto-efficient solutions, supported by lexicographic optimisation to construct an accurate payoff table. All models are solved using IBM ILOG CPLEX, and solution robustness is assessed through 10,000-run Monte Carlo simulations.

The findings demonstrate that the (R, S) policy consistently outperforms the conventional (R, Q) policy across all examined demand patterns including constant, increasing, decreasing, life cycle, and erratic. In the case study, the (R, S) policy reduces total cost by 2.2% and CO_2 emissions by 8.5%. Across 400 randomly generated problem instances, cost improvements grow with longer planning horizons and higher Coefficients of Variation (CV), highlighting the model's effectiveness in volatile environments. The results also reveal that while modest emission reductions can be achieved with limited cost increases, deeper decarbonisation requires disproportionately higher investment, reflecting a clear non-linear trade-off along the Pareto frontier.

Overall, the thesis provides an analytic and practical framework for uncertainty-aware, energy-efficient cold-chain planning. The contributions support managers and logistics planners in making informed decisions that balance cost efficiency, operational responsiveness, and environmental responsibility, ultimately fostering more sustainable and resilient CFSC.

1. Introduction

This chapter establishes the context and motivation for the research. It begins by outlining the key challenges facing Cold Food Supply Chains (CFSCs), including demand uncertainty, energy intensity, and sustainability pressures. It then identifies the specific research problem that this thesis addresses, sets out the research objectives that guide the study, and concludes with an overview of the thesis structure.

1.1. Background and Research Context

The global food chain is facing significant and complex sustainability challenges, and the Food Supply Chain (FSC) has emerged as a critical area of concern. The FSC, encompasses the complete journey of food from farmland to the consumer's plate. It includes production, processing, packaging, distribution, retailing, consumption, and waste management. Within this chain, logistics plays a central role because it determines not only how quickly food reaches consumers, but also how much energy is consumed and how much waste is generated along the way.

Cold Food Supply Chains (CFSC) are particularly demanding. They handle products that must remain within narrow temperature ranges at every stage. Any deviation can lead to rapid quality deterioration, food safety risks, and economic losses. Studies such as Montanari (2008), Aung and Chang (2014), and Mercier et al. (2017) highlight that temperature sensitivity and perishability make cold chains significantly more fragile than ambient chains. Maintaining the cold environment requires energy intensive processes in storage facilities and refrigerated vehicles, which in turn contribute heavily to Greenhouse Gas (GHG) emissions. As noted by the Food and Agriculture Organisation (FAO, 2019) and the International Energy Agency (IEA, 2020), refrigeration and transport activities are responsible for a considerable share of global energy use and carbon emissions.

Transport routing within food logistics is therefore crucial. Effective routing reduces delivery time, energy consumption, operational costs, and Carbon Dioxide (CO_2) emissions. Over the past decade, a growing body of research has focused on vehicle routing in food logistics (Bottani et al., 2019; Fikar, 2018). Traditionally, routing and inventory management emphasised cost reduction and operational responsiveness. However, sustainability is now recognised as a fundamental dimension of Supply Chain Performance (SCP). Recent studies increasingly incorporate environmental objectives into their models (Amorim and Almada-Lobo, 2014), with particular emphasis on CO_2 emissions because they are directly linked to transportation and inventory decisions. According to the UN Environment Programme (2019), freight transport and storage activities are projected to account for more than one third of all permissible emissions by 2050.

These environmental concerns are heightened in cold chains because temperature control significantly increases energy demand. As Babagolzadeh et al. (2020) and Shashi et al. (2018) observe, both transportation and storage of chilled or frozen products require continuous energy input, making them major contributors to the carbon footprint of the FSC. A well-designed CFSC model is therefore essential to manage costs and emissions effectively. Such a model must account for the tight link between inventory levels, replenishment timing, vehicle routing, and environmental impact. By quantifying the trade-off between total expected cost and CO_2

emissions, decision makers can evaluate scenarios that optimise both economic and environmental performance (Meneghetti and Monti, 2014).

Operating under non-stationary and uncertain demand further complicates Cold Food Supply Chain Management (CFSCM). Demand patterns in modern food retailing shift constantly due to weather, promotions, consumer behaviour, and social trends. High spoilage risk and strict service level expectations make these fluctuations even more consequential. Traditional replenishment strategies such as the (R, Q) policy assume fixed order quantities and predetermined ordering times. While suitable for stable environments, they provide limited flexibility when uncertainty is high. As a result, they often create excessive safety stock, heightened energy consumption, and unnecessary waste (Tarim and Kingsman, 2006). In contrast, more adaptive policies such as (R, S) allow replenishment quantities to adjust dynamically based on actual demand, offering a more effective approach for perishable and uncertain environments.

Altogether, these challenges demonstrate the need for analytical models that integrate inventory planning, routing decisions, uncertain demand, and sustainability considerations in a single framework. This thesis responds to that need by examining a cold chain setting where decisions about replenishment timing, order quantities, and vehicle routing must be made simultaneously while balancing cost efficiency and environmental responsibility. The goal is to better understand how such chains behave under realistic uncertainty and to provide decision makers with tools that support fresher, more sustainable, and more cost-effective operations.

1.2. Research Problem

Although the CFSC has always been complex, the challenges facing today's industry are far more demanding than in the past. Companies must operate in an environment where demand fluctuates unpredictably, energy prices continue to rise, and consumers always expect fresh products on shelves. At the same time, organisations are under strong pressure to reduce their environmental footprint and demonstrate that their logistic chains are aligned with sustainability goals. These forces create a difficult balancing act for planners, who must simultaneously maintain service levels, protect product quality, and control both costs and emissions.

A central challenge arises from non-stationary and uncertain demand. Unlike durable goods, chilled and frozen products are heavily affected by small changes in purchasing behaviour. Weather variations, promotions, seasonal shifts, and changes in consumer tastes can alter demand from one period to the next. Studies such as Masudin and Safitri (2023), and Aung and Chang (2014) show that even slight deviations in demand can create significant waste in cold chains due to short shelf life and strict freshness requirements. Overestimating demand leads to excessive safety stocks, higher electricity usage in cold storage, and increased spoilage. Underestimating demand risks stockouts, lost sales, and reduced customer satisfaction. For these reasons, uncertainty is not just an inconvenience in cold food logistics; it is a defining characteristic of the chain.

At the same time, transportation and refrigeration costs have become major concerns. Refrigerated vehicles and storage facilities require constant energy input to maintain temperature conditions. According to the International Energy Agency (IEA, 2020) and Babagolzadeh et al. (2020), energy consumption in cold chains is significantly higher than in

ambient Supply Chain (SC), especially because refrigeration units operate continuously during transport and storage. Inefficient routing or unnecessary replenishment trips directly translate into higher fuel consumption, faster degradation of refrigeration equipment, and increased CO_2 emissions.

These environmental concerns are further reinforced by global sustainability regulations and international policy targets. Reports from the UN (2019) and Meneghetti and Monti (2014) highlight that freight transport and temperature-controlled logistics will account for a substantial portion of global emissions by 2050. As a result, companies can no longer focus on cost alone. They must understand the trade-offs between economic and environmental objectives, especially when planning replenishment schedules and vehicle routing.

Despite the complexity of these decisions, many firms still rely on traditional replenishment methods, particularly the (R, Q) policy. This approach determines both the quantity and timing of each replenishment at the start of the planning horizon, offering little flexibility when demand changes over time. Research by Tarim and Kingsman (2006) and Soysal et al. (2014) shows that fixed order quantity mechanisms perform poorly in non-stationary environments, often leading to unnecessary safety stock and inefficient routing decisions. In cold chains, where products cannot be stored indefinitely, this limitation can be particularly costly.

These challenges highlight the need for more adaptive and integrated models. Routing and inventory decisions are interdependent: the timing of replenishment affects how vehicles must travel, and routing choices influence the feasibility and cost of meeting service levels. Treating these decisions separately leads to suboptimal solutions. Planners must consider them jointly, especially in chains where temperature, perishability, and uncertainty play a central role.

This thesis addresses these issues by focusing on a replenishment policy that offers greater flexibility, the (R, S) policy, and embedding it in a multi objective inventory–routing framework that acknowledges nonstationary stochastic demand. The aim is to provide a tool that can support decision makers in understanding how replenishment frequencies, order quantities, and routing choices shape both operational costs and environmental performance. By modelling cost and CO_2 emissions together, the research seeks to reveal how improvements in one domain affect the other, and how companies can design chains that are financially efficient while moving toward lower carbon logistics.

1.3. Research Gaps

Although extensive research has examined various aspects of food logistics, the literature still lacks a comprehensive framework that reflects the realities of CFSC, particularly their uncertainty, perishability, and sustainability pressures. Existing studies have contributed valuable insights into inventory management, vehicle routing, and emissions modelling, yet these components are often investigated in isolation rather than as an integrated chain.

A major gap concerns the treatment of stochastic and non-stationary demand. Many classical inventory models, including those summarised by Silver et al. (1998) and Nahmias (2011), assume stable or stationary demand behaviour. Even more advanced contributions, such as Tarim and Kingsman (2006), incorporate uncertainty but mainly under stationary conditions and usually for single echelon chains. In real cold chains, however, demand fluctuates across periods due to weather, promotions, or customer behaviour. These fluctuations significantly

affect replenishment timing, safety stocks, and freshness, yet very few inventory routing models capture this temporal instability.

A second gap concerns the integration of inventory and routing decisions. The Inventory Routing Problem (IRP) is well known to be NP-hard (Jemai et al., 2012), and it provides a suitable structure for coordinating replenishment with vehicle routing. While general IRP research is abundant, reviews by Coelho et al. (2014) and Moin and Salhi (2007) highlight that most formulations assume deterministic demand and ignore perishability. In cold logistics the situation is even more limited. Only a handful of studies combine routing and inventory control under uncertainty, and most apply fixed replenishment rules. For instance, Soysal et al. (2014) use an (R, Q) policy, which prespecifies replenishment times and quantities at the start of the planning horizon. This predetermination reduces flexibility and often forces the model to maintain high safety stocks which is an especially problematic issue for perishable products.

A third research gap arises from the lack of models that incorporate both economic and environmental objectives. Although sustainability is increasingly emphasised in SC research, many models evaluate CO_2 emissions only after optimisation or treat them as secondary indicators. Works such as Accorsi et al. (2016), Govindan et al. (2020), and Meneghetti and Monti (2014) emphasise the importance of integrating environmental impact directly into decision-making. Yet integrated, bi-objective optimisation models specifically tailored for CFSC remain rare. Importantly, no existing study fully examines how replenishment frequency, safety stock levels, and route selection jointly influence CO_2 emissions under non-stationary uncertainty.

A fourth missing component relates to the choice of replenishment policy. Although the (R, S) policy has proven effective in handling stochastic demand (Tarim and Kingsman 2004, 2006; Nielsen and Larsen 2005), there is very limited research embedding this policy into a mixed-integer IRP model for cold chains. Most existing IRP studies rely on the more rigid (R, Q) policy, despite evidence that it performs poorly in dynamic and perishable environments. As a result, the literature lacks a clear understanding of how a flexible (R, S) policy behaves when combined with routing decisions and environmental considerations.

Finally, while multi-objective optimisation is well established, the methods used in cold chain studies remain limited. Techniques such as the weighted sum, classical epsilon-constraint, and goal programming have been applied across different domains (Ehrgott, 2005). However, few cold chain studies apply the Augmented Epsilon Constraint (AEC) approach (Mavrotas 2009), which offers stronger guarantees for generating only efficient (non-dominated) solutions. Consequently, there is little empirical evidence on the shape of the cost–emissions Pareto frontier in cold food logistics.

Taken together, these gaps reveal the absence of an integrated model that simultaneously accounts for:

- non-stationary stochastic demand,
- a flexible (R, S) replenishment policy,
- joint inventory and routing decisions,
- explicit carbon emission modelling, and
- a bi-objective optimisation framework that can generate Pareto-efficient solutions.

This thesis addresses these gaps by developing a mixed-integer bi-objective inventory routing model for CFSC, evaluating its performance under realistic conditions, and demonstrating how economic and environmental trade-offs emerge in practice. The gaps identified in the literature reveal that CFSCs require a modelling approach that goes beyond traditional, deterministic, and single-objective formulations. Uncertain and non-stationary demand, strict service-level requirements, the interdependence between routing and inventory decisions, and the growing emphasis on carbon reduction all point to the need for a more holistic framework. Building on these insights, this thesis establishes several research objectives that guide the development of the proposed model and shape the analyses conducted in later chapters.

1.4. Research Objectives

The first objective is to develop an integrated inventory–routing model capable of reflecting how replenishment timing, replenishment quantities, and route selection interact in a CFSC. Inventory choices influence the number of delivery trips and the vehicle routes required, while routing decisions determine the feasibility, cost, and timing of replenishment. To capture these interdependencies, the model coordinates these decisions within a single Mixed Integer Programming (MIP) structure.

The second objective is to incorporate non-stationary stochastic demand into this integrated model. Cold chains rarely operate under stable conditions, and their performance is highly sensitive to fluctuations in demand. By modelling demand as time-dependent and uncertain, the thesis aims to reflect the environment in which real-world cold chains operate. This objective includes enforcing a required service level and ensuring that inventory decisions remain robust even when actual demand deviates from expectation. Incorporating this uncertainty also enables a meaningful comparison between flexible and rigid replenishment policies.

The third objective is to evaluate the environmental consequences of these operational decisions, particularly carbon emissions from transport movements and refrigeration loads. Since refrigerated logistics is energy-intensive and a significant source of CO_2 emissions, the model integrates an explicit environmental objective. This enables decision-makers to observe how different replenishment frequencies, safety stock levels, and routing choices contribute to emissions, and how operational changes influence sustainability performance.

The fourth objective is to examine the performance of the (R, S) replenishment policy relative to the more traditional (R, Q) policy. The (R, Q) approach, although widely used, fixes replenishment quantities at the start of the planning horizon, limiting flexibility under uncertain demand. The (R, S) policy allows replenishment quantities to adapt based on observed demand. By implementing both policies using, the same modelling framework and solving them under identical conditions, the thesis aims to provide empirical insight into how these policies behave in non-stationary cold chain environments and how they affect costs, emissions, and safety stock levels.

The fifth objective is to adopt a bi-objective optimisation approach to identify trade-off solutions between economic cost and environmental impact. Using the AEC method allows the model to generate a set of Pareto-efficient solutions rather than a single outcome. This facilitates an understanding of where cost and emissions reductions can be achieved simultaneously and where improvements in one dimension require sacrifices in the other.

The sixth and final objective is to generate practical insights for managers and decision-makers working in cold food logistics. By interpreting model results within the operational context, the thesis aims to provide guidance on when flexible replenishment policies such as (R, S) offer advantages, how routing strategies influence emissions, and how demand uncertainty affects both cost and sustainability performance. The goal is not only to advance academic understanding but also to provide a decision-support tool that aligns with real-world operational challenges.

Collectively, these objectives form the foundation of the thesis and create a logical progression from the limitations identified in the existing literature to the contributions presented in subsequent chapters. They ensure that the proposed model is both theoretically grounded and practically relevant to the evolving needs of CFSCM.

1.5. Research Methodology Overview

Given the complexity of CFSCs and the interplay between perishability, uncertain demand, routing decisions, and sustainability requirements, a single modelling technique is insufficient to capture the full decision landscape. This thesis therefore adopts a multi-layered methodological approach combining formulation, optimisation, and simulation. Each component is designed to address a specific set of challenges identified in the problem motivation and literature review.

The first methodological step is the formulation of an integrated inventory–routing model, based on a MIP structure. By embedding inventory control and vehicle routing decisions into one mathematical framework, the model reflects how replenishment timing, replenishment quantities, and route selection influence one another in practice. This approach is grounded in the IRP, a well-established structure for such combined decisions, but one that has seldom been adapted for cold-chain environments with non-stationary uncertainty.

The second step involves incorporating non-stationary stochastic demand directly into the model. This is crucial because cold chains rarely operate under stable or predictable demand conditions. Rather than assuming fixed or stationary demand distributions, the thesis uses a time-dependent stochastic representation, allowing the model to reflect variations in customer consumption patterns across periods. A service-level constraint ensures that the chain remains robust against uncertainty by incorporating safety stock requirements that respond to observed demand.

To support this, the thesis adopts the (R, S) replenishment policy, originally developed by Tarim and Kingsman (2004, 2006). Unlike the more rigid (R, Q) policy, (R, S) allows order quantities to adapt based on actual demand, offering flexibility that is vital for perishable products under fluctuating conditions. Encoding the (R, S) policy within the MIP model allows replenishment frequencies and quantities to emerge endogenously from the optimisation rather than being predetermined at the start of the planning horizon.

The third methodological component is the integration of environmental modelling, specifically the quantification of CO_2 emissions associated with transportation and refrigeration. Since cold chains involve continuous energy consumption in both storage and transport operations, the model includes an environmental objective that accounts for emissions per kilometre travelled and emissions linked to the load carried by refrigerated vehicles. This

allows the optimisation not only to minimise monetary costs but also to assess how operational decisions influence carbon footprints.

The fourth step applies a bi-objective optimisation framework, using the AEC method to handle the dual objectives of cost minimisation and emission reduction. While traditional multi-objective techniques such as weighted sums may yield incomplete or biased results, the AEC method, following the work of Mavrotas (2009), ensures that only Pareto-efficient solutions are generated. This creates a clear Pareto frontier that decision-makers can use to understand the trade-offs between economic and environmental goals. The approach also leverages the lexicographic method to construct an accurate pay-off table and stabilise the search for efficient solutions.

To evaluate model performance, the fifth methodological step involves coding and solving the MIP formulations (both (R, S) and (R, Q)) using IBM ILOG CPLEX, a state-of-the-art optimisation solver capable of handling large-scale mixed-integer problems. The deterministic results obtained from CPLEX are then assessed under demand uncertainty through Monte Carlo simulation, running each scenario 10,000 times. This simulation layer captures variability in outcomes and provides statistically reliable estimates of expected cost and emissions for each policy.

Finally, the methodology includes an extensive set of computational experiments, ranging from a structured case study to 400 randomly generated problem instances. These instances vary in planning horizon length, CV, vehicle dispatching costs, and demand patterns (constant, increasing, decreasing, life cycle, and erratic). This experimental design ensures that the conclusions drawn about model behaviour and the comparative performance of the (R, S) and (R, Q) policies are robust across a broad spectrum of operational conditions.

Collectively, this methodological pathway creates a comprehensive and realistic framework for analysing CFSCs. It allows the thesis to explore how flexible replenishment policies, routing decisions, and sustainability considerations interact under uncertainty, and it provides a strong foundation for the insights presented in later chapters.

1.6. Thesis Structure

The remainder of this thesis is organised to lead the reader from the broader context of CFSCs to the methodological details, computational results, and practical implications of the proposed model. Each chapter builds on the previous one, forming a coherent narrative that connects the challenges identified earlier with the modelling and analysis that follow. Chapter 2 presents a comprehensive review of the existing literature on CFSCs, inventory management, vehicle routing, and sustainability. It highlights the main developments in each area and identifies the specific gaps that motivate the need for an integrated, uncertainty-aware, and environmentally focused inventory–routing model. Chapter 3 introduces the problem setting and provides the full mathematical formulation of the proposed model. It describes the operational context of the CFSC and outlines the decision variables, parameters, constraints, and objective functions. The Chapter also explains how non-stationary stochastic demand and service-level requirements are embedded into the model and how the environmental component is incorporated to quantify CO_2 emissions. This chapter concludes by presenting the bi-objective extension that forms the basis for later trade-off analysis. Chapter 4 describes the solution methodology. It explains how the lexicographic method is used to obtain the pay-off table and

how the AEC method is applied to generate Pareto-efficient solutions. This chapter outlines the rationale for using this method, discusses the role of slack variables and augmentation factors, and clarifies how the approach overcomes common limitations of traditional multi-objective techniques. Chapter 5 presents the computational experiments. This chapter begins with a detailed case study that compares the behaviour of the (R, S) and (R, Q) replenishment policies under controlled conditions. It then expands the analysis to a large set of randomly generated problem instances that vary in demand patterns, uncertainty levels, planning horizons, and vehicle dispatching costs. These results illustrate how the model responds across different operating environments and highlight when and why the (R, S) policy offers operational and environmental advantages. Chapter 4 examines the trade-off between economic cost and environmental impact. Using the Pareto frontier generated by the AEC method, this chapter analyses how improvements in CO_2 reduction influence chain cost and where the diminishing returns appear. The discussion focuses on identifying balanced solutions and interpreting the practical consequences of operating in different regions of the trade-off curve. Chapter 5 concludes the thesis by summarising the key findings, emphasising the theoretical contributions and practical implications, and reflecting on how the model can support decision-making in cold food logistics. This chapter also discusses the limitations of the study and proposes several directions for future research, including extensions that incorporate perishability tracking, multi-echelon structures, and additional environmental or social sustainability metrics.

Together, these chapters form a complete, structured exploration of the IRP under uncertainty in CFSCs. They show how economic and environmental objectives can be analysed simultaneously and how flexible replenishment policies can support more robust and sustainable logistics operations.

2. Literature Review

This chapter provides a comprehensive review of the scholarly contributions that form the foundation of the present study, with the aim of identifying the existing research gaps and situating this work within the broader academic discourse. The body of literature examined encompasses several interrelated domains, beginning with conceptual clarifications of logistics, SC, and Supply Chain Management (SCM), before narrowing the focus to the specific case of CFSC and CFSCM. Beyond definitions, the review also explores the principal challenges encountered in CFSCs, as well as the sustainability dimensions that increasingly shape their design and operation. Considerable attention is devoted to frameworks for assessing performance, including the development and application of relevant indicators and metrics. Furthermore, the analysis investigates the methodological approaches adopted in prior research to enhance Food Cold Supply Chain Performance (CFSCP) and highlights the extent to which these approaches have yielded actionable insights. Finally, the review evaluates how current studies contribute to the advancement of the field and discusses the managerial implications that can be derived, thereby linking academic findings to practical decision making in CFSCM contexts.

This chapter is structured to progressively narrow the focus from foundational concepts to the specific methodological gaps addressed in this research. Section 2.1 establishes the conceptual foundations of logistics, SCs, and SCM, clarifying key definitions and the evolution toward integrated SCM frameworks. Section 2.2 then focuses on CFSCM, examining its role and importance, preservation and quality requirements, food waste reduction, and the key operational elements that distinguish CFSCs from conventional SCs. Building on this context, Section 2.3 reviews sustainability considerations in CFSCs, with particular emphasis on energy use and carbon emissions arising from refrigerated storage and transportation. This section highlights the dominant emission drivers and the operational parameters that influence environmental performance. Finally, Section 2.4 reviews methodological approaches proposed in the literature to improve CFSCP. It synthesises quantitative decision-support methods through three complementary perspectives: hierarchical optimisation of decision levels, model components and integrated optimisation structures, and the role of data analytics as an enabling layer. Together, these sections identify how operational, environmental, and methodological considerations intersect and motivate the study's focus on integrated inventory–routing optimisation under stochastic demand.

2.1. Foundations of Logistics and SCM

To build a robust conceptual foundation for this study, it is essential to clarify the meaning of logistics, SC, and SCM, while also explaining the distinctions among these terms. Although the notion of the SC has gained widespread recognition in both academic research and managerial practice, explicit and standardized definitions of SC remain relatively scarce in the literature. In contrast, the concept of SCM has been the subject of far more detailed theoretical discussion, resulting in numerous definitions proposed over time. Notably, many of these interpretations tend to embed the idea of the SC within the broader framework of SCM, thereby positioning SC as an inherent component of its managerial scope (Corominas, 2013).

2.1.1. Evolution of Logistics

Traditionally, the term logistics was associated with the physical transfer of goods and resources across locations. Its earliest systematic application is traced back to military operations, where it involved not only the coordination of troop movements but also the planning and provision of essential supplies, including food, weaponry, and equipment (Lummus, 2001). The strategic importance of logistics became particularly evident during the First and Second World Wars, when the ability to maintain reliable and efficient supply lines played a decisive role in determining military outcomes. In line with this perspective, A Dictionary of Modern War characterizes logistics as encompassing the full range of activities and procedures required to equip and sustain armed forces, including aspects such as storage, transportation, and distribution (Luttwak, 1971).

With time, the role of logistics expanded beyond its military origins and became a fundamental element of commercial activities. In contemporary business practice, logistics is understood as encompassing more than just transportation; it also involves the storage and systematic management of inventory to balance product availability with cost effectiveness. Maintaining excessive stock increases holding costs and decreases organizational agility, whereas insufficient inventory may interrupt production processes and result in lost sales opportunities (Lummus, 2001). Cavinato (1982) conceptualized logistics as a set of activities that include procurement, transportation, and warehousing of materials and components, as well as the distribution of finished goods to end users. A widely cited and influential definition was later provided by the Council of Logistics Management (CLM, 1998), which framed logistics as the process of planning, executing, and controlling the efficient movement and storage of goods, services, and associated information from the point of origin to the point of consumption to satisfy customer demands. This interpretation explicitly integrates inbound, outbound, and internal flows, while also recognizing the central role of information management in coordinating these activities.

Drawing on both historical and contemporary perspectives, logistics may be characterized as the coordinated movement, storage, and management of goods, services, and information throughout the various stages of the supply process. This conceptualization shares significant overlap with the more recent notion of SCM. In its initial applications, SCM was frequently regarded as interchangeable with logistics; however, subsequent academic discourse has established that SCM represents a more comprehensive and integrative framework (Stock and Boyer, 2009). Hall and Braithwaite (2001) argue that SCM should be viewed as the strategic progression of logistics management, whereby the emphasis shifts from optimising discrete operational functions toward orchestrating the entire network of activities and relationships that constitute the SC.

From this perspective, logistics can be regarded as the operational foundation upon which the broader notion of the SC has developed. In its early applications, the central objective was to ensure the smooth flow of products and to maintain an appropriate balance between supply and customer demand. As business environments grew more competitive and complex, however, organizations increasingly recognized that long term advantage could be achieved not only through efficient transportation and warehousing, but also by coordinating material, information, and financial flows across the entire value creation process. Accordingly, logistics is often conceptualized as concentrating on the effective movement and storage of goods

between suppliers and consumers, whereas the SC is framed as an interconnected chain that integrates multiple upstream and downstream actors ranging from raw material providers to manufacturers, distributors, and ultimately end customers into a cohesive network (Bechtel and Jayaram, 1997).

2.1.2. Emergence of SC

The notion of the SC began to appear in the academic domain during the early 1980s, with one of the earliest references attributed to Oliver and Weber (1982). Although the concept was initially introduced at that time, it was not until the 1990s that both academic researchers and practitioners demonstrated heightened interest, leading to a significant increase in scholarly output. As noted by Stock and Boyer (2009), more than 5,000 articles addressing various dimensions of SCs were published in business-oriented outlets and peer reviewed journals throughout that decade. Nevertheless, despite this considerable growth in research activity, a universally agreed upon definition of the SC has yet to be established. This ambiguity largely arises from the diverse disciplinary lenses through which the concept has been studied, with different scholars emphasizing distinct facets such as organizational structures, material flows, and information exchanges. An illustrative example is provided by the American Production and Inventory Control Society (APICS), where Cox et al. (1998) offer two complementary descriptions of the SC.

- It may be viewed as the sequence of activities and stages through which raw materials are transformed and transferred until they reach the final consumer.
- It can be understood as the collection of organizational functions, both internal and external to the firm, that collectively contribute to creating value by ensuring that products and services are delivered to customers.

Taken together, these perspectives highlight that the SC extends beyond the mere transportation of goods; it also incorporates the broader set of resources, capabilities, and inter firm linkages that enable the efficient management of material, information, and service flows across the entire value chain.

An alternative line of research emphasizes the structural dimension of SCs. Within this perspective, Lummus and Alber (1997) characterize the SC as a chain of interconnected organizations through which materials move, encompassing upstream suppliers, transportation providers, production facilities, distribution nodes, retailers, and end consumers. This network-oriented view underscores the high degree of interdependence among the actors, whereby disturbances in one segment can propagate and affect the performance of the entire chain. In a similar vein, Christopher (1998) conceptualizes the SC as a configuration of resources and coordinated processes that convert raw materials into semi-finished or finished products and subsequently channel them to final markets. This interpretation reinforces the idea of the SC as a dynamic and integrated chain rather than a linear sequence of activities.

Building on earlier conceptualizations, Lummus and Vokurka (1999) broaden the understanding of the SC by describing it as the set of activities required to transform raw materials into finished goods, which involves procurement, production, warehousing, inventory control, order processing, distribution, delivery, and the exchange of information among all participating stakeholders. This interpretation makes it clear that the SC should be

regarded not only as a chain for the physical movement of goods, but also as an information processing structure that links actors and enables coordination. In a related but more globalized framing, Govil and Proth (2002) define the SC as an international network of firms that cooperate to accelerate the transfer of materials and information between suppliers and final consumers while seeking cost efficiency. Although this description draws attention to speed and economic performance, it has been critiqued for assuming a global scale, which does not necessarily reflect the characteristics of all SCs. Offering a more encompassing perspective, Chopra and Meindl (2012) conceptualize the SC as the total set of organizations such as producers, suppliers, logistics providers, Distribution Centres (DC), retailers, and customers that are directly or indirectly engaged in the production, storage, transportation, and delivery of goods and services to meet demand.

2.1.3. Integrative SCM Framework

A substantial portion of the academic discourse reveals a tendency to either understate or blur the "management" dimension of SCM, which has often contributed to conceptual overlap and ambiguity among the terms SC, SCM, logistics, and operations management. As emphasized by Lemay et al. (2017), the SC represents a network of organizations, resources, and interconnected flows of materials, information, and financial transactions. SCM, by contrast, is generally understood as the systematic process of designing, planning, coordinating, monitoring, and enhancing this network to achieve defined strategic and operational objectives. Within this broader framework, logistics is typically confined to the efficient handling, storage, and transportation of goods across organizational boundaries, while operations management is concerned primarily with the internal configuration and optimisation of processes within a single enterprise.

The formalization of SCM as a distinct concept date to the early 1980s, although its practical antecedents can be identified in earlier industrial practices. One significant milestone was the well-known investigation by Kurt Salmon Associates (1993) into the apparel and textile sector. This study analysed the time span required for raw materials to be processed into finished products and subsequently delivered to consumers. The results demonstrated that inefficiencies, such as delays in replenishment and mismatches between product availability and consumer demand, not only created lost sales opportunities but also generated excessive inventory related costs. In response, the study proposed a framework aimed at enhancing collaboration between manufacturers and retailers, particularly through the exchange of timely and accurate information. This approach, which sought to align supply more closely with real demand and accelerate responsiveness, became widely recognized as the foundation of the Quick Response strategy.

Since its emergence, a wide range of definitions for SCM have been advanced. Ellram and Cooper (1993) characterize SCM as an overarching philosophy that seeks to integrate and coordinate the entire flow of goods within a distribution channel, extending from initial suppliers to final consumers. A more comprehensive articulation was later provided by the SC Council (1997), which conceptualized the SC as stretching "from the supplier's supplier to the customer's customer" and incorporating all activities required to design, produce, and deliver a finished product. This includes functions such as demand planning, procurement of raw materials and components, manufacturing, warehousing, order management, distribution, and final delivery to the customer. The significance of this definition lies in its dual emphasis: it

frames SCM not only as a strategic decision-making framework for coordinating diverse functions, but also as a set of tangible operational activities that enable products and services to flow effectively across the chain.

Another important strand of scholarship emphasizes the integrative nature of SCM. Monczka and Morgan (1997) argue that integrated SCM should be understood as beginning with the needs of the end customer and subsequently coordinating all processes required to deliver value in a seamless, cross functional manner. Within this conceptualization, SCM is not merely the aggregation of individual activities but rather a unified process that interlinks diverse stakeholders across organizational boundaries. Building on this perspective, Lummus (2001) interprets SCM as an extended chain that connects suppliers, manufacturers, logistics providers, distributors, and retailers, while also incorporating technology partners, with the collective purpose of capturing demand information and making it accessible throughout the network. This broader view underscores the high degree of mutual dependence across participants, as the effectiveness of the entire chain is contingent on the performance and coordination of each individual actor.

Several scholars and practitioners have advanced definitions of SCM that adopt a functional orientation. For instance, CSX World Terminals (2004) characterizes SCM as the oversight and regulation of material and information flows throughout the logistics process, spanning from the procurement of raw inputs to the ultimate delivery of products. Lambert (1994) presents a broader interpretation, conceptualizing SCM as the coordination of business processes from end users back to suppliers to deliver products, services, and information that generate customer value. Giunipero and Brand (1996) extend this reasoning by framing SCM as a strategic instrument designed to enhance customer satisfaction, strengthen competitiveness, and improve profitability.

Over time, scholars have attempted to systematize these varied perspectives by delineating scope, function, and inter organizational relationships. A notable contribution in this regard is provided by Bechtel and Jayaram (1997), who examined more than fifty definitions and categorized them into five distinct “schools of thought.” These include:

1. The Chain Awareness School, which emphasizes the physical flow of materials from suppliers to consumers.
2. The Linkage/Logistics School, which focuses on the connections among functional areas such as logistics and transportation.
3. The Information School, which stresses the bidirectional exchange of data among SC partners.
4. The Integration School, which advocates a process oriented and systems-based view that transcends functional silos; and
5. The Future School, which envisions a demand driven and seamless supply pipeline, built upon collaborative relationships and efficient transactional exchanges.

Stock and Boyer (2009) conceptualize SCM as the administration of networks both intra and inter organizational together with the chains that facilitate bidirectional flows of materials, services, financial resources, and information between producers and final consumers. Within this framework, SCM is intended to enhance value creation by simultaneously improving customer satisfaction and organizational profitability. At the same time, this definition

underscores the heterogeneity of SCs, which differ markedly depending on their sectoral application and underlying objectives. For instance, the design and functioning of a SC in the automotive industry, in military logistics, or in food distribution diverge substantially with respect to the types of products involved, their handling requirements, the extent to which reverse flows are incorporated, the processes executed along the chain, and the channels through which distribution takes place. Consequently, while goal-oriented definitions such as that of Stock and Boyer capture important aspects of SCM, they may not be universally applicable across all contexts due to the inherent diversity of SC structures and purposes.

An important consequence of distinguishing between logistics and SCM lies in the way customers are positioned within each domain. In logistics, customers are primarily regarded as the final recipients of material flows, representing the endpoint of distribution activities. In contrast, SCM conceptualizes customers not merely as passive destinations but as active partners whose collaboration and feedback play a critical role in shaping, coordinating, and improving the overall performance of the network.

It is also apparent that many of the earlier conceptualizations of SCM do not fully satisfy the criteria of a robust definition, as they are often either too imprecise, excessively restrictive, or overly expansive. In response to these limitations, Gibson et al. (2005) revisited prior formulations and carried out a survey among members of the Council of SCM Professionals to establish a more widely accepted consensus. The definition that emerged describes SCM as encompassing the planning and management of all activities associated with sourcing, procurement, production, and logistics functions. In addition, it emphasizes the importance of coordination and collaboration with channel partners, including suppliers, intermediaries, third party service providers, and customers. Fundamentally, this perspective frames SCM as the integration of supply and demand management both within and across organizational boundaries. This formulation illustrates the progression of SCM from a logistics centred activity to a comprehensive and integrative discipline aimed at aligning material, information, and financial flows across entire value creating networks.

2.2. CFSCM

The globalization of food trade has fundamentally reshaped consumer access to perishable goods, making it possible for products such as fresh fruits, vegetables, meat, seafood, and dairy to be available throughout the year, regardless of seasonality or geographic origin. This constant availability is largely enabled by the establishment and growth of CFSC, which ensure that temperature sensitive products can be transported over long distances while maintaining safety and quality. However, this achievement has come at a significant cost, as CFSCs are highly energy intensive chains that rely on refrigeration, freezing, and temperature-controlled logistics, thereby contributing substantially to global energy demand (Neusel and Hirzel, 2022). Thus, CFSCs should not be viewed merely as extensions of traditional logistics networks, but rather as complex and energy demanding infrastructures that sustain the functioning of the modern global food economy.

In the following section, particular attention is given to the multifaceted role and importance of CFSCs. This includes their central function in preserving food quality and safety, the technological advancements that make temperature monitoring and control possible, and the managerial practices that ensure efficient coordination across stakeholders. Furthermore, the

discussion explores the structural components and key operational elements of CFSCs, highlighting how each stage, from harvesting and precooling to storage, transportation, distribution, and retail, contributes to maintaining product integrity and minimizing losses.

2.2.1. The Role and Importance

The globalization of food trade has made it possible for consumers to access perishable products from virtually any part of the world throughout the entire year. This availability has been achieved largely through the development and expansion of CFSCs, though it comes at the expense of significant energy consumption (Neusel and Hirzel, 2022). Therefore, CFSCs are not simply logistical infrastructures but energy demanding structures that support the universal food economy.

The Cold Supply Chain (CSC) can be described as the coordinated chain of preparation, storage, transportation, and monitoring processes applied to temperature sensitive products, particularly food commodities. Its effective operation requires knowledge of the biological and chemical properties that govern product perishability, combined with the use of technological solutions capable of maintaining defined temperature levels along the SC (Behdani et al., 2019). Therefore, the CSC is both a scientific and managerial issue, as it should incorporate product related requests with technological and operational abilities.

Beyond its technological foundations, the CSC is increasingly conceptualised as operating within an organisational context in which coordination mechanisms and workforce capabilities influence the consistency of temperature control and handling practices (Ndraha et al., 2018; Cawston, 2018). Although such human and organisational dimensions are seldom incorporated into formal optimisation models, they provide important contextual insight into observed variations in cold chain performance (Mangla et al., 2020; Shashi et al., 2018). CSCs are a critical component of the wider SC and must be managed with exceptional care due to the vulnerability of perishable goods. These products are not only dependent on strict environmental conditions, such as predefined levels of temperature, humidity, and airflow, but are also sensitive to physical handling. Vibrations, shocks, or improper treatment during transportation may accelerate degradation, leading to loss of quality or safety (Iyer, 2025).

From an economic perspective, the CSC has grown into a substantial segment of the global SC industry. In 2021, it accounted for approximately 5% of the global market, generating around $242 billion in revenue. Projections suggest that the sector will experience threefold growth over the next decade (Grand View Research, 2022; IMARC, 2022). Despite this growth potential, Cold Supply Chain Management (CSCM) faces complex challenges, many of which arise from dispersed customer bases, fluctuating and unpredictable demand patterns, and product specific differences in shelf life (Singh and Sharma, 2015).

Researchers classify CSCs into different categories based on product type. Liu et al. (2020) identify five groups: fruits and vegetables, bakery and confectionery, dairy and frozen desserts, fish and seafood, and pharmaceuticals. Herjolfsson (2019), however, simplifies this categorization into two dominant branches: the CFSCs and the Cold Pharmaceutical Supply Chain (CPSC). Within this distinction, the CFSCs is recognized as a dedicated division of the CSC, designed to maintain food products at optimal quality levels (Cerchione et al., 2018). Brenner (2015) highlights that CFSCs and CPSC exhibit different packaging requirements, while Shashi (2021) emphasizes that CFSCs operations tend to be more sensitive to time,

product quality, and packaging needs. Conversely, CPSC benefits from more standardized transport planning and higher levels of automation. Moreover, consumer driven changes in tastes and preferences introduce further complexities to CFSCs compared with CPSC (Aramyan et al., 2007). Taken together, these observations suggest that food CSCs operate under more diverse, dynamic, and demanding conditions than most other types of CFSCs.

Differences between CFSCs and CPSC also extend to regulatory frameworks. Ruiz Garcia and Lunadei (2010) note that variations in processing, organizational requirements, and transportation regulations create unique challenges for each sector. Brenner (2015) further distinguishes their challenges by pointing out that CFSCs difficulties are more pronounced at the level of overall chain performance, whereas CPSC issues often emerge at the manufacturing stage.

2.2.2. Preservation and Quality

Maintaining food at the desired temperature and humidity throughout its journey requires both high energy input and specialized handling. Perishable products naturally deteriorate over time, losing their nutritional value and quality because of environmental exposure. Refrigeration is therefore employed as a fundamental preservation technique to extend shelf life and slow down biochemical and microbiological activity. Ideally, refrigeration should begin immediately after harvest or production and continue consistently until the product reaches the consumer. Failure to establish a continuous refrigeration chain can result in accelerated spoilage, waste generation, and potential health risks to consumers (Aung and Chang, 2014; Wu et al., 2019).

According to Tiwari and Tiwari (2024), the key determinants of product quality in perishable goods are temperature, humidity, physical movement, chemical reactions, biological activity, and the total duration of the SC from origin to consumption. Among these, temperature control is considered the most critical factor in prolonging shelf life and ensuring safety (Aung and Chang, 2014).

Despite the widespread use of refrigeration, risks to product quality persist when inappropriate temperature ranges are applied. Even under refrigeration, perishables can lose nutritional content or experience microbial development if storage conditions deviate from optimal levels (Jol et al., 2006). Quality losses are further exacerbated by prolonged exposure to unsuitable temperatures, highlighting the dual importance of both correct temperature and storage duration (Ashby, 2006).

To address these challenges, CSCs employ specialized infrastructure such as precooling facilities, refrigerated warehouses, and temperature-controlled transport. These elements are vital to safeguarding the quality and nutritional characteristics of food products while ensuring compliance with hygiene and safety standards. Only through this coordinated chain can perishable items be reliably delivered to end consumers in an acceptable condition (Zhang, 2007).

Ensuring quality in perishable food products, whether in terms of texture, moisture retention, taste, or nutritional value, requires rigorous SCM from the point of harvest to final delivery. Effective management encompasses not only temperature and humidity control but also processes such as precooling, refrigerated storage, controlled transport, and minimization of physical stressors such as shocks and vibrations during handling. As Tiwari and Tiwari (2024)

emphasizes, such an integrated approach is indispensable for maintaining food integrity and meeting consumer expectations. Thus, CFSCM must be regarded as a holistic discipline, combining scientific knowledge, technological resources, and managerial practices to preserve food quality and reduce waste.

2.2.3. Food Waste Reduction

Food waste management represents one of the most critical strategies for reducing GHG emissions in CFSCs. Decomposing organic matter in landfills releases methane, a potent GHG with a significantly higher global warming potential than CO_2 (Tiwari and Tiwari, 2024). Beyond environmental degradation, food waste undermines the efficiency of food chains and contributes to resource misallocation and financial loss, while also posing public health risks through microbial contamination and spoilage (FAO, 2017b). These severe implications have been acknowledged at the international level, leading the FAO to prioritize the reduction of food loss and waste as a core component of the United Nations' 2030 Sustainable Development Goals (FAO, 2017a; 2017b; 2019a).

In this context, research on CFSCs has gained considerable momentum compared to other sectors of CSCL, largely due to the urgent necessity of addressing food waste. The high perishability of fresh food products, coupled with long and complex SCs, increases the probability of spoilage and waste. Consequently, scholars emphasize that improving food preservation is not only a financial issue but also a societal and environmental imperative (Bremer, 2018; Göransson et al., 2018; Shashi, 2021). The application of precise temperature and humidity control throughout the CSC is particularly effective in preventing food degradation, thereby reducing the volume of waste that ends up in landfills and mitigating its contribution to climate change (Tiwari and Tiwari, 2024). Hence CSCs can play a key role in reducing food waste by extending shelf life and maintaining perishable quality throughout SCs. However, its sustainability impact must be balanced against the energy use and GHG emissions of cold chains, which contribute substantially to agrifood chain emissions. Efficient logistics design and route planning, including optimized transport refrigeration units and minimized delivery times, can reduce fuel consumption and refrigeration duration, improving this trade-off. Advanced cold-chain optimization and predictive waste management models further enhance efficiency and emissions reduction while preserving food quality, making integrated refrigeration and logistics strategies essential for sustainable food chains (Friedman-Heiman and Miller, 2024; Flammini, et al 2024; Mohan and Amin, 2025).

2.2.4. Key Elements

CSCM refers to the specialized management of perishable agricultural and animal-based products, such as fruits, vegetables, dairy, poultry, seafood, and various types of meat, that require carefully controlled environments from the point of production or collection through to final delivery to consumers (Tiwari and Tiwari, 2024). Within this chain, effective control of environmental conditions such as temperature, humidity, and handling are indispensable to maintaining food safety and quality. Bogataj et al. (2005) and Fearne et al. (2006) conceptualize CSCM as the planning, execution, and supervision of both the movement and storage of perishable products, together with the supporting services and data flows, with the dual objective of enhancing customer satisfaction and minimizing costs. In line with this perspective, Christopher (2011) emphasizes that the overarching goal of CSCM is to deliver

the required service and product quality at the lowest possible cost through efficient coordination of these activities. This balance between product quality assurance and cost effectiveness lies at the very heart of CSCM.

In the case of food, CFSCM plays a decisive role in preserving the freshness of products, an attribute that consumers value highly (Awad et al., 2021). By ensuring that food is consistently maintained within specific temperature ranges, CSCs prevent contamination by microorganisms and significantly reduce the risk of spoilage (Joshi et al., 2011). Beyond safeguarding freshness, CFSCM contributes to a range of broader benefits: it reduces food waste and foodborne illnesses, extends product shelf life, and ensures that products retain their nutritional value. Furthermore, through the integration of real time information exchange among stakeholders, CFSCM can optimise the entire SC, reduce carbon emissions, mitigate environmental impacts, and improve both profitability and sustainability in food markets (Tiwari and Tiwari, 2024). In addition, by improving storage conditions and prolonging product shelf life, CSCs help stabilize supply and demand over time, thereby reducing price volatility and mitigating inflationary pressures (Bogataj et al., 2005).

Despite these advantages, food losses remain a critical challenge worldwide. It is estimated that approximately 25% of all food products and up to 50% of horticultural crops, are lost due to inadequate handling across SCs (Miles et al., 2008). Temperature mismanagement is one of the most significant contributors to these losses, making refrigeration a central mechanism for reducing waste (IIR, 2009). While controlled temperature is crucial, lifetime extension of food products also depends on the use of modern technologies and advanced information systems. These tools enable SCs to determine optimal temperature and humidity ranges for various products, classify perishables into appropriate categories, and conduct sensitivity analyses to evaluate the impact of deviations from defined parameters (Aung and Chang, 2014). The integration of such technological and analytical tools not only minimizes losses but also increases resilience in the face of rising global food demand.

The importance of CFSCs is amplified by demographic and environmental pressures. The global population is projected to reach 8.5 billion by 2030, a trend that intensifies the demand for secure and efficient food distribution chains (Ishangulyyev et al., 2019). Simultaneously, food waste along SCs represents an annual economic loss estimated at one trillion U.S. dollars, while also generating approximately 3.3 billion tons of CO_2 emissions each year (Panahi et al., 2022). These figures underscore the need for improved CSC practices to reduce both economic inefficiencies and environmental burdens.

Akkerman et al. (2010) classify food SCs into three categories based on storage and transportation temperature requirements. These include the Frozen Chain, which handles products such as ice cream; the Chilled Chain, which manages products such as fish; and the Ambient Chain, which refers to products that do not require cold storage or transportation, such as canned foods. Of these three, the frozen and chilled chains represent the core of the CFSC.

Within these chains, precise temperature control is paramount, as different products require specific ranges for safe storage and distribution. Researchers have proposed a variety of recommended ranges: for example, Smith and Sparks (2004) suggest –18 °C for frozen products, 0–1 °C for fresh meat, seafood, and poultry, and around 5 °C for cheese, butter, and fats. Thompson and Kader (2001) recommend 0–2 °C for vegetables and some fruits, 7–10 °C for moderately chill tolerant items, and 13–18 °C for chill sensitive products. In practice, the

target storage value for any perishable product is often determined as the midpoint of the recommended range that best preserves its quality.

A detailed illustration of recommended storage temperatures for selected fruits and vegetables, as compiled by Jobling (2000), is provided in the table below. This classification highlights the diversity of environmental requirements among perishable products and reinforces the need for highly tailored CSCM strategies.

Table 1. Recommended Storage Temperatures for Selected Fruits and Vegetables

1-4°C	***5-9 °C***	***10 °C+***
Apple	*Avocado*	*Avocado (subtropical)*
Asparagus	*Zucchini*	*Pawpaw*
Berry Fruits	*Bean (French)*	*Grapefruit, lemon*
Broccoli	*Passion Fruit*	*Mango*
Peach, plum	*Eggplant*	*Banana*
Cheery	*Capsicum*	*Pineapple*
Grape	*Cucumber*	*Sweet Potato*
Lettuce	*Mandarin, orange*	*Tomato (mature green)*
Mushroom	*Potato*	*Pumpkin*

Source: Jobling, 2000

Different categories of perishable products require carefully tailored thermal environments to ensure their safety, nutritional value, and marketability. For example, meat and seafood demand storage temperatures just above the freezing point, typically around 0 °C, whereas dairy products are generally preserved in cold rooms at approximately 5 °C. Fruits and vegetables can be stored at moderately higher ranges of 10–15 °C, depending on their sensitivity to chilling, while frozen items such as ice cream and frozen meals must be maintained at –18 °C or below to prevent microbial growth and structural deterioration (Berk, 2018). These distinctions demonstrate that no single CSC strategy can be universally applied; instead, food CSCs must be designed as product specific chains that integrate diverse technological and managerial requirements.

The CFSC spans the entire journey of perishable goods, beginning with production or harvesting and ending with consumption by the final user (Taghikhah et al., 2021). Along this chain, multiple stages are involved, each introducing its own risks, costs, and quality control challenges. These stages include initial precooling at the production site, storage in refrigerated facilities, transportation in temperature-controlled vehicles, specialized packaging to prevent physical and microbiological damage, and monitoring technologies that ensure traceability and compliance with regulations (Montanari, 2008). Awad et al. (2021) provides a practical illustration: harvested products are transferred to packaging facilities, transported to DCs via cold vehicles, and then delivered to retailers before finally reaching the end consumer. This sequential process highlights the interconnectedness of the CFSC, where failure at any single point may compromise product safety and result in waste across the entire chain.

Several scholars have proposed frameworks to better describe and analyse the CFSC. James and James (2010), Akdemir (2008), and Kuo and Chen (2010) classify CFSC activities into three broad processes: cold processing, cold storage, and cold transportation and distribution.

- Cold processing refers to the initial chilling and subsequent cooling treatments applied to products immediately after harvest or slaughter.

- Cold storage emphasizes long term preservation under carefully monitored temperature, humidity, and airflow conditions.
- Cold transportation and distribution focus on the timely and efficient movement of goods, involving sorting, dispatch, and delivery while ensuring continuous monitoring of environmental parameters.

Xuling et al. (2006) add another layer of understanding by identifying the systemic characteristics of Cold Supply Chain Logistics (CSCL) as the requirement of high capital investment for building and maintaining infrastructures, the need for timeliness and coordination among multiple actors, and the difficulty of balancing operational costs with quality assurance.

Tiwari and Tiwari (2024) further extend these classifications and identifies six interrelated components as the backbone of CFSCM. Harvesting and handling, precooling, refrigerated storage, refrigerated transport, distribution, and marketing. Each of these phases plays a decisive role in determining the overall CFSCP and the degree to which products retain their safety, quality, and consumer acceptability. A detailed discussion of each component illustrates how scientific principles, technological solutions, and managerial practices must converge to create a functional CSC.

1. **Harvest and handling**

The timing of harvest is fundamental to product quality. Crops harvested too early may lack full flavour and nutritional content, while those harvested too late may become overripe, fragile, and prone to spoilage. In general, agricultural goods should be harvested at a physiologically mature stage, although for some fruits, collection prior to full ripening is advisable, since these can mature under controlled storage conditions. Leafy vegetables, however, do not continue to ripen after harvest and therefore need to be harvested at their peak maturity (FAO, 2015). Once harvested, produce must be transported immediately to cleaning, sorting, packing, and precooling facilities. Delays in this stage accelerate biochemical reactions, reduce firmness, and promote microbial growth, leading to significant quality losses (Pokhrel, 2021). In other words, harvest and handling are the foundation of the CFSC, setting the stage for all subsequent preservation efforts.

2. **Precooling**

Precooling is an essential process designed to remove field heat rapidly and stabilize the product at the required storage temperature. This step reduces respiration rates, microbial activity, and enzymatic reactions, thereby extending shelf life. Without precooling, products depend solely on refrigerated rooms for cooling, which is slower and less uniform. The delay in lowering product temperature increases susceptibility to quality degradation, moisture loss, and microbial contamination (Tiwari and Tiwari, 2024). Methods of precooling vary, including forced air cooling, hydro cooling, and vacuum cooling, each chosen according to the commodity type and logistical circumstances. Thus, precooling acts as a critical bridge between harvesting and long-term storage.

3. **Refrigerated Storage**

Given that agricultural harvesting is seasonal while consumption occurs year-round, refrigerated storage enables continuous market supply by maintaining products over extended periods. These facilities not only regulate supply demand imbalances but also ensure that

transportation capacity is used efficiently (Tiwari and Tiwari, 2024). Beyond maintaining low temperatures, refrigerated rooms must also control humidity and air circulation to prevent dehydration and uneven cooling. Modern facilities increasingly use Controlled Atmosphere or Modified Atmosphere storage, where oxygen levels are reduced and CO_2 levels increased to slow biochemical and microbial activity, thereby prolonging storage life (Bideau et al., 2018). In this sense, refrigerated storage is not just a passive holding phase, but a highly managed environment designed to optimise preservation.

4. Refrigerated Transport

Transporting perishable goods under controlled conditions is one of the most complex stages of the CFSC. Modes of transport include trucks, trains, ships, and aircraft, often used in combination for long distance or international trade (Yavas and Ozkan Ozen, 2020). The performance of refrigerated transport is influenced by environmental conditions such as outside temperature, humidity, and solar radiation, which place varying demands on cooling chains (Artuso et al., 2019). Compared with stationary storage, transport refrigeration units typically have lower cooling capacities and therefore rely on maintaining products at precooling conditions. They must sustain uniform airflow, humidity, and temperature around products during the journey, which requires precise design and monitoring (Tassou et al., 2009). Failures in refrigerated transport not only compromise product safety but also undermine consumer confidence and generate substantial economic losses.

5. Distribution

The distribution phase involves the critical transfer of products between refrigerated storage facilities and transport vehicles. Even short exposures to external temperatures during loading and unloading can result in “temperature abuse”, which accelerates microbial growth and reduces shelf life. To minimize these risks, best practices include maintaining minimal distances between storage facilities and vehicles, equipping doors with sealing collars, and implementing airlock systems with double doors to reduce thermal exchange (Tiwari and Tiwari, 2024). DCs also act as nodes for consolidation, sorting, and dispatch, making them strategic points where efficiency and strict temperature management directly influence downstream product quality.

6. Marketing

The CFSC culminates at the marketing stage, where products are displayed and sold to consumers. Paradoxically, this stage often exhibits the highest levels of waste, primarily due to inadequate temperature and humidity control in retail environments (Derens et al., 2006; Derens Bertheau et al., 2015). Improper handling, poorly designed display systems, or lack of monitoring in supermarkets can cause cold and frozen foods to deteriorate rapidly, undermining the efforts made during earlier stages of the chain. Beyond economic waste, such failures pose significant risks to public health. Thus, marketing is not merely a commercial activity but the final quality assurance checkpoint of the CFSC, where consumer satisfaction, trust, and safety are ultimately determined

To better understand the unique characteristics of CFSCs, Bremer (2018) developed a dedicated conceptual reference framework that goes beyond earlier, more generic models of SC design. Unlike traditional frameworks that primarily focus on material, financial, and information flows in conventional SCs, this model explicitly incorporates the notion of “delivery through CSCs.” By doing so, it provides a more realistic representation of the

distinctive requirements of perishable products and the infrastructural arrangements needed for their preservation. The framework is not merely descriptive; it can be applied as a practical tool for the design, evaluation, and optimisation of food CSCs. This approach reflects the growing recognition that conventional SC frameworks cannot adequately capture the temperature sensitive and time critical characteristics of perishable food logistics.

The framework is structured around eight core process activities of packing, loading, transportation, unloading, unpacking, transfer, storage, and inspection. These activities collectively describe the key stages of product movement within a CFSC. These activities are sufficient to represent the fundamental flows of perishable goods, while also allowing flexibility for adaptation to different product categories and logistical contexts. To provide a comprehensive representation of the chain, Bremer organizes these activities into four overarching domains: the product domain, the Information Technology (IT) domain, the infrastructure and equipment domain, and the regulation and standards domain. Each of these domains addresses a different but interdependent dimension of CFSCM.

7. Product domain

The product domain emphasizes the way in which perishable goods are defined, classified, and tracked throughout their journey in the CSC. To ensure traceability and effective monitoring, Bremer proposes a hierarchical structure of product representation. At the lowest level are individual products, which are combined into packages or handling units. These packages can be grouped further into encasements, which in turn form part of a shipment that moves through the SC. This hierarchical classification system provides a systematic method for structuring product flows, facilitating not only operational management but also traceability and compliance with safety requirements. By defining products at multiple levels of aggregation, the model ensures that both macro level movements and micro level quality parameters can be effectively monitored and managed.

8. Information Technology domain

The IT domain focuses on the collection, processing, and application of information within the CFSC. In a context where even small deviations in temperature or humidity can result in substantial quality losses, the ability to capture and analyse real time data becomes indispensable. Different technologies enable this information flow, ranging from simple data loggers that record environmental conditions to sensor enabled Radio Frequency Identification (RFID) tags that combine product detection with automatic data transfer. More advanced configurations, such as Wireless Sensor Networks (WSN), allow multiple sensors and transceivers to communicate simultaneously, thereby providing continuous monitoring of temperature and other critical parameters across different points of the chain. Within this domain, data are structured hierarchically: logs represent complete datasets of processes over time, traces document specific instances or pathways of product movement, and events capture individual time stamped activities. The IT domain thus provides the informational backbone of the CFSC, enabling transparency, responsiveness, and data driven decision making.

9. Infrastructure and equipment domain

The infrastructure and equipment domain addresses the physical facilities and technological systems that support the CFSC. Within this framework, locations are defined as specific physical points in the SC, identified through tools such as the Global Location Number and often georeferenced by Global Positioning System (GPS). Each location can be further divided

into zones, which represent distinct microenvironments that may differ in temperature, humidity, or air circulation. This domain also incorporates thermal and environmental models used to predict the impact of external factors, such as heat exposure or CO_2 accumulation, on product quality. These models guide the selection and configuration of equipment, including refrigeration units, insulated containers, and smart control systems, that are necessary to maintain the desired conditions for food preservation. Both simple control mechanisms and more advanced intelligent control systems are discussed as strategies to ensure that environmental parameters remain within safe limits. By systematically linking infrastructure, equipment, and environmental modelling, this domain highlights the importance of technological investment in ensuring the stability and efficiency of CSCs.

10. Regulation and standards domain

The final domain emphasizes the regulatory, normative, and certification frameworks that shape the design and operation of CFSCs. Governmental authorities impose legal requirements to guarantee that food products remain safe for consumption and maintain expected quality levels. In addition, industry standards and certification systems establish benchmarks for best practices, often exceeding minimum legal requirements. Within Bremer's framework, two levels of compliance monitoring are identified: one conducted during the design phase by accreditation bodies, which ensures that the planned SC infrastructure meets regulatory and industry standards, and another carried out during day-to-day operations by regulatory authorities, which verifies ongoing adherence to prescribed guidelines. This domain underscores the fact that regulatory compliance is not a peripheral concern but a central pillar of CFSCM, shaping both the initial configuration of SCs and their continuous monitoring.

These key elements directly inform the study design, particularly with respect to its scope and the selection of performance measures. The study is confined to distribution activities between a central warehouse and regional centres (e.g. retail outlets) and therefore excludes multi-echelon SC structures. Given that the model focuses on hub-and-spoke distribution, it is especially applicable to the downstream distribution of finished goods rather than to upstream flows of raw materials. In addition, the identified key elements clearly delineate the relevant functional and temporal activities, along with their associated measures. The application of these measures (such as distance travelled and unloading time) is examined in greater detail in the following section, which reviews IRP characteristics alongside the environmental considerations addressed in prior studies.

2.3. Sustainability in CFSC

The sustainability of CSCs and the transition toward environmentally responsible or "green" operations have been widely examined in recent years (Govindan, 2018; Murphy and Adair, 2013). Early scholarly attention to sustainability in cold food SCs primarily emphasized product life cycle aspects, including maintaining freshness, extending shelf life, and reducing spoilage or waste. While these dimensions remain relevant, the research focus has progressively expanded to encompass broader environmental consequences, particularly the negative externalities associated with food losses and inefficiencies across the chain. Such impacts are most evident in terms of GHG emissions, which are influenced by multiple CSC activities such as refrigerated transportation, temperature-controlled warehousing, energy intensive retail operations, and the packaging of perishable goods (Masudin and Safitri, 2020).

From a conceptual perspective, sustainability within SCs can be understood as the integration of social, environmental, and economic objectives into SC design and management. This integration requires transparent, coordinated, and strategic collaboration among SC partners with the aim of improving long term economic viability while simultaneously addressing ecological and social responsibilities. As a result, there has been a growing demand for applying the Triple Bottom Line framework, which views sustainability not merely as an environmental challenge but as a balanced pursuit of profit, planet, and people considerations (Akram, 2023).

Considerable scholarly effort has been directed toward analysing the financial dimension of CFSCs. For example, Hsiao et al. (2017) distinguished between fixed transportation costs, such as those incurred for vehicle operations and refrigeration and variable costs that fluctuate with temperature settings, product types, and storage requirements. Their analysis emphasized the complexity introduced when vehicles are equipped with multiple compartments designed to maintain different temperatures for heterogeneous product groups. Similarly, Mustafa et al. (2024) associated the economic CFSCP with the interplay between food quantity and the temperature conditions required to preserve quality, highlighting trade-offs between cost efficiency and safety standards. Nakandala et al. (2016) further demonstrated that not only temperature levels but also vehicle speed substantially affects operational costs, illustrating how managerial and operational decisions can directly influence both expenditure and energy demand.

Despite the significance of financial considerations, contemporary research increasingly recognizes that the sustainability of CFSC cannot be limited to economic efficiency alone. A growing body of work now aims to embed environmental and social dimensions into SC models, moving beyond the traditional cost cantered paradigm. These expanded approaches integrate issues such as carbon emissions, energy efficiency, labour practices, and social equity into performance assessments and strategic decision making (Al Theeb et al., 2020). This broader perspective reflects the acknowledgment that CFSCs are embedded within global sustainability agendas, and that their performance must be evaluated not only in terms of profitability but also with respect to their contributions to climate mitigation, responsible resource use, and societal well-being.

The following section therefore turns to a more focused discussion of CO_2 emissions, which constitute one of the most extensively studied aspects of CFSC sustainability.

2.3.1. Carbon Footprint

The environmental dimension of CFSC s has received growing scholarly attention, particularly with respect to GHG emissions. Research demonstrates that the aggregated carbon footprint of an entire SC often far exceeds the emissions generated by individual firms operating within it (Phillips, 2017). This observation highlights the systemic nature of emissions, where the cumulative impact of interconnected activities creates a significantly larger environmental burden than the sum of isolated company level operations. Recent studies further emphasize that CSCs, which rely heavily on refrigeration, contribute substantially to global emissions. It is estimated that approximately 1% of worldwide CO_2 emissions can be attributed to CSC operations (Akram, 2023). This statistic underscores the urgency of improving efficiency through advanced technological and organizational measures (Poulsen and Sampson, 2020).

The challenge is even more pronounced in food CFSCs, where the dependency on energy intensive refrigeration and temperature-controlled logistics is unavoidable. It has been reported that transportation and storage alone are responsible for more than one third of total emissions generated in CFSC operations (Waltho et al., 2019). As a result, the accurate measurement and subsequent reduction of CO_2 emissions within cold food chains have emerged as critical priorities for both researchers and practitioners. Developing effective mitigation strategies requires a thorough understanding of the multiple parameters that jointly determine the magnitude of emissions along the chain.

A considerable body of literature has attempted to quantify emissions from transportation within CFSCs, with particular attention to the role of empty vehicle movements. Scholars such as Mallidis et al. (2012), Pan et al. (2013), Soysal et al. (2014), Danloup et al. (2015), Moheb Alizadeh and Handfield (2017), Musavi and Bozorgi Amiri (2017), Hariga et al. (2017), Zhen et al. (2019), and Li et al. (2019) have developed models to estimate the emission rates associated with vehicles operating without cargo. Their findings demonstrate that even empty trips significantly increase total carbon output, thereby stressing the importance of optimising vehicle utilization across the SC.

Other studies have adopted different perspectives by focusing on emissions from fully loaded refrigerated vehicles. For instance, Bozorgi et al. (2014) and Bozorgi (2016) analysed emissions as a function of several operational variables, including the number of trucks deployed, the average load carried, and the distance travelled. Their work highlighted that both the scale of transportation and the specific thermal requirements of different food products can substantially alter emission levels. Moheb Alizadeh and Handfield (2017) further emphasized the influence of travel time, journey distance, and load volume as critical determinants of overall CO_2 output.

Beyond simple load and distance factors, a series of studies such as those by Mallidis et al. (2012), Elhedhli and Merrick (2012), Galal and El Kilany (2016), Ghahremani et al. (2016), Saif and Elhedhli (2016), Boronoos et al. (2020), and Zarbakhshnia et al. (2019) have systematically calculated emissions by integrating both the weight of transported goods and the distances covered. Their analyses converge on the conclusion that distance travelled, and load quantity are fundamental parameters in assessing CO_2 emissions within CSCs. Complementing this perspective, Pan et al. (2013), Danloup et al. (2015), Chen and Hsu (2015), Soysal et al. (2014), Musavi and Bozorgi Amiri (2017), Tordecilla Madera et al. (2018), Jiang et al. (2013; 2020), and Mohebalizadehgashti et al. (2020) have developed more comprehensive approaches that simultaneously consider load size and transport distance. This combined assessment provides a more accurate representation of emission outputs and better supports the design of efficient distribution routes.

An alternative line of inquiry focuses on emissions derived from the energy consumed by refrigerated vehicles. Research by Validi et al. (2014), Hsiao et al. (2017), Bottani et al. (2019), and Babagolzadeh et al. (2020) has quantified carbon emissions primarily as a function of energy consumption, emphasizing the substantial share of fuel or electricity used to maintain low temperatures during transport. A more nuanced perspective is offered by Chen and Hsu (2015) and Stellingwerf et al. (2018), who extended their models to incorporate emissions generated during door openings and unloading operations, recognizing that such activities can cause significant temperature fluctuations and additional energy demands. Building on this,

Zhang and Chen (2014) demonstrated that unloading products in high temperature environments can further amplify CO_2 emissions, reinforcing the importance of operational discipline in managing environmental impacts.

Finally, more holistic approaches have emerged in recent years. Stellingwerf et al. (2018), for instance, accounted for multiple interacting variables including vehicle load weight, route distance, road gradient, and driving speed, when estimating fuel consumption and emissions in CFSCs. Their study also incorporated the energy required to maintain refrigeration during transit, demonstrating that when such cooling related emissions are factored in, route optimisation strategies may change considerably, leading to both lower costs, and reduced environmental impacts.

Building on these insights, the present research identifies five primary parameters that collectively influence CO_2 emissions in CFSCs: (1) travel distance, (2) transported load, (3) frequency of unloading operations (linked to door openings), (4) energy consumption for refrigeration during transport, and (5) emissions associated with the primary refrigeration of stored products. These variables form the analytical foundation for evaluating carbon footprint in CFSCs and are summarized, along with key contributions from existing studies, in Table 2.

Table 2: Major Research Insights

			IRP Features						*Environmental Features*					
#	*Author*	*Year*	*Deterministic/ Stationary/ Non-stationary*	*Fixed dispatching cost*	*Fixed ordering cost*	*Linear travel costs*	*Penalty cost/ Service level requirement*	*Holding cost*	*Empty vehicle travelling emission*	*Load transferring emission*	*Primary refrigeration emission*	*Chill transfer emission*	*Unloading emission*	*Multi-objectivity*
1	*Al Theeb et al.*	*2020*	*D*			*	*P*	*						
2	*Allaoui et al.*	*2018*	*D*			*								*
3	*Amin and Zhang*	*2013*	*S*			*								*
4	*Amorim and AlmadaLobo*	*2014*	*D*			*								*
5	*Bortolini et al.*	*2016*	*D*			*		*		*				*
6	*Bottani et al.*	*2019*	*D*			*	*P*		*	*				*
7	*Bozorgi et al.*	*2014*	*D*	*		*			*	*				*
8	*Bozorgi*	*2016*	*D*			*		*		*				*
9	*Chen and Hsu*	*2015*	*D*							*			*	

10	*Danloup et al.*	*2015*	*D*			*			*	*			
11	*Elhedhli and Merrick*	*2012*	*D*			*				*			
12	*Fichtinger et al.*	*2015*	*D*		*	*							
13	*Hariga et al.*	*2017*	*D*	*				*	*	*			
14	*Hsiao et al.*	*2017*	*D*	*		*			*				
15	*Li et al.*	*2019*	*D*			*			*	*			
16	*Mallidis, I. et al.*	*2012*	*D*			*		*	*	*			*
17	*Meneghetti and Ceschia*	*2015*	*D*										
18	*Mohammed and Wang*	*2017*	*D*			*							*
19	*Musavi and Bozorgi-Amiri*	*2017*	*D*			*			*	*			*
20	*Torabi et al.*	*2019*	*D*			*	*P*			*			*
21	*Pan et al.*	*2013*	*D*			*			*	*			*
22	*Tordecilla Madera et al.*	*2018*	*D*	*	*	*		*		*			*
23	*Saif and Elhedhli*	*2016*	*D*		*	*		*		*			
24	*Shamayleh et al.*	*2019*	*D*		*	*		*		*			
25	*Soysal et al.*	*2014*	*D*	*		*	*P*	*	*	*			*
26	*Stellingwerf et al.*	*2018*	*D*			*		*		*	*		
27	*Validi et al.*	*2014*	*D*		*	*				*			*
28	*Zarbakhshnia et al.*	*2019*	*D*			*		*		*			*
29	*Babagolzadeh et al.*	*2020*	*S*	*			*P*	*	*	*			
30	*Jiang et al.*	*2020*	*S*			*	*P*			*			*
31	*Solyalı et al.*	*2012*	*S*	*		*		*					
32	*Galal and El-Kilany*	*2016*	*S*			*	*S*	*		*	*		
33	*Ghahremani et al.*	*2016*	*S*		*	*	*P*	*		*			*
34	*Moheb-Alizadeh and Handfield*	*2017*	*S*		*	*		*	*	*			*
35	*Mohebalizadehgashti et al.*	*2020*	*S*			*				*			*
36	*Soysal and Bloemhof-Ruwaard*	*2018*	*S*			*	*S*	*					
37	*Yavari and Geraeli*	*2019*	*S*		*	*		*					*
38	*Zhen et al.*	*2019*	*S*			*		*		*			*
39	*Soysal et al.*	*2015*	*S*			*	*S*	*		*			
40	*Lida*	*2002*	*NS*				*P*	*					

41	*Tarim and Kingsman*	*2006*	*NS*		*		*P*	*								
42	*Tarim and Smith*	*2008*	*NS*		*		*S*	*								
43	*Seth and Pandey*	*2009*	*NS*				*P*	*								
44	*Tunc et al.*	*2011*	*NS*	*	*		*P*	*								
45	*Zhang*	*2013*	*NS*				*S*									
46	*Pauls-Worm et al.*	*2014*	*NS*		*		*S*	*								
47	*Purohit et al.*	*2015*	*NS*	*	*		*S*	*								
48	*Gutierrez-Alcoba et al.*	*2016*	*NS*			*	*P*	*								
49	*Sinaga et al.*	*2016*	*NS*			*	*S*	*								
50	***Jahdi et al.***	***2024***	***NS***	*****	*****	*****	***S***	*****	*****	*****	*****	*****	*****	*****	*****	*****

Effective SCM represents another critical pathway toward reducing the carbon footprint of CFSCs. Strategic planning, precise execution, and the adoption of efficient inventory management systems can significantly reduce overproduction, optimise resource use, and enhance overall profitability while lowering CO_2 emissions (Tiwari and Tiwari, 2024). By aligning operational decisions with sustainability objectives, SCM enables firms to balance environmental goals with financial performance. In addition to improved design and efficient routing, a central aspect of sustainable SCM in CSCs lies in the integration of advanced refrigeration technologies with precise temperature control systems. As Govindan et al. (2021) emphasize, the deployment of high-performance refrigeration equipment can minimize energy consumption while ensuring product safety and quality. This integration not only reduces food spoilage and waste but also curtails unnecessary emissions, thereby promoting greener operations. Moreover, effective SCM extends beyond technology adoption to encompass collaboration across stakeholders, demand forecasting, and optimised logistics planning. Coordinated efforts among SC actors ensure that perishable products are handled in the most energy efficient and environmentally responsible manner. In this sense, SCM functions as the unifying framework through which digital technologies, energy efficient practices, and sourcing strategies are operationalized, ultimately fostering a CSC that is both profitable and sustainable.

In summary, sustainability in CFSCs is shaped by the interaction of cost efficiency, environmental impact, and operational decisions, particularly in relation to refrigeration and transportation. Although key drivers of emissions and costs are well identified, existing studies often treat these elements in isolation. This creates a clear need for integrated, quantitative approaches that can jointly model trade-offs and chain complexity. The next section therefore turns to quantitative methodologies for improving CFSCP.

2.4. Methodologies to improve CFSCP

Building on the preceding discussion of CFSC characteristics and sustainability challenges, this section turns from problem definition to performance improvement. Specifically, it reviews

the methodological approaches used in prior research to enhance CFSCP, with emphasis on decision-support methods that can reduce cost and emissions while maintaining service and product integrity.

As discussed in the previous sections, CFSC plays a crucial role in food sector and various theories and qualitative and quantitative methodologies have been proposed to address the operational, environmental, and managerial challenges associated with long-distance transport, long-term storage, and strict temperature control (Chaudhuri et al., 2018). To overcome the challenges in long period storage and transport and proper control of temperature, research has proposed different strategies. For example, Ndraha et al. (2018) suggestions are stated in the categories of using technologically advanced continuous recording of temperature along the time devices, use of modelling software for transportation and storage of perishables along time, and legal policies imposed by authorities. In another study Akram (2023) mentions adoption of the pull based lean management system, stand-alone renewable energy systems, hybrid renewable energy systems, green food preservation methods, and isolated container optimisation of CSCL as the methods that could be used to improve the CFSCP.

Against this background, the present section focuses specifically on quantitative optimisation-based methodologies for improving CFSC performance. It examines how mathematical models are used to support decision making at different planning levels, how key cold-chain-specific components are selected and represented within optimisation frameworks, and how data analytics enables model parameterisation and decision support. Accordingly, Section 2.4.1 is structured into three complementary subsections: Hierarchical Optimisation, which organises models by strategic, tactical, and operational decision levels; Model Components, which defines the scope of phenomena included in optimisation models; and Data Analytics, which examines how information and monitoring technologies support, but do not replace, optimisation-based decision making.

2.4.1. Quantitative methods

Scholars working in the field of decision making and optimisation have increasingly focused on the use of mathematical and algorithmic models to enhance the performance of CSC. A substantial share of the literature, estimated at about 45% of reviewed studies, centres on optimisation approaches designed to support distribution-related decisions in CSCs (Awad et al., 2021). Despite this shared focus, these models vary considerably in how they are formulated, the objectives they pursue, and the assumptions or constraints that underpin them.

Within the broader context of CFSCs, mathematical modelling has proven to be a key analytical tool for understanding and optimising complex decision processes. Such models enable researchers to quantify trade-offs, evaluate alternative strategies, and explore how operational, economic, and environmental factors interact. A common objective across most studies is the reduction of total distribution cost (Hsiao et al., 2017; Li et al., 2019). However, definitions of "total cost" differ significantly between models. This variation reflects an ongoing challenge in the literature: integrating economic efficiency with product quality preservation and environmental sustainability within a unified optimisation framework.

2.4.1.1. Hierarchical Optimization

Empirical studies in SCM have consistently shown that the effectiveness of performance measurement systems (PMSs) depends on how well selected metrics align with organisational objectives and decision-making contexts (Lambert and Pohlen, 2001). Because SCs operate through multiple planning layers, performance indicators must also reflect differences between strategic, tactical, and operational decision levels. Measures that guide long-term network design, for example, differ fundamentally from those used to manage medium-term production or short-term distribution activities. This distinction is not only relevant for performance measurement but also reflects the underlying structure of decision making in SCs, where planning responsibilities and optimisation problems are distributed across strategic, tactical, and operational levels (Chopra and Meindl, 2022; Stadtler, 2015).

In CFSCs, this alignment becomes even more critical due to product perishability, strict temperature requirements, and heterogeneous product–route conditions, which make performance measurement highly context-specific and time-sensitive. As a result, decisions about network configuration, replenishment frequency, routing, and temperature control cannot be treated uniformly, but must be matched to the appropriate planning horizon and level of managerial responsibility (Iyer, 2025; Nakandala et al., 2016). Empirical research has therefore moved beyond simply identifying "what to measure" toward determining "what to improve first" within each planning layer. Studies using structured, analytical, and practice-driven approaches to metric selection show that different decision levels prioritise different performance dimensions, such as cost efficiency and sustainability at the strategic level, inventory and energy efficiency at the tactical level, and delivery reliability and quality preservation at the operational level (Gunasekaran et al., 2004; Chia et al., 2009; Bhagwat and Sharma, 2007, 2009).

With rising environmental concerns, green performance indicators such as energy use and CO_2 intensity have become increasingly prominent in performance frameworks, alongside traditional cost and service measures (Gulledge and Chavusholu, 2008; Martin and Patterson, 2009). Taken together, these empirical studies indicate that SC objectives, constraints, and performance priorities vary systematically across planning horizons. This layered structure of decision responsibilities provides the conceptual basis for hierarchical optimisation models, which explicitly structure decision making into strategic, tactical, and operational levels to reflect how real SCs are planned and managed (Stadtler, 2015; Iyer, 2025).

Using this hierarchical logic, recent reviews of CSC optimisation organise models according to the decision level they support, allowing clearer comparison of model scope, objectives, and practical relevance. Iyer (2025) classifies optimisation models for CSCs across three decision-making layers of strategic, tactical, and operational, aligning them with broader SC logistics theory. According to this framework, model objectives commonly address cost or profit optimisation, product quality and shelf life, service responsiveness, and emission reduction. However, Iyer notes that an overarching, integrated model capable of simultaneously capturing all these dimensions has yet to be developed. At the strategic level, models typically focus on SC collaboration, network design, and the configuration of temperature-controlled facilities. Tactical models tend to address production planning, inventory and storage decisions, and order coordination, while operational models deal with the real-time aspects of distribution planning, routing, and monitoring.

In addition to Iyer's hierarchical classification, Zhang and Mohammad (2024) offers a complementary perspective by categorising decision-making models into four major types: (1) routing optimisation models, (2) location and inventory optimisation models, (3) integrated optimisation models, and (4) specialised models. The first two categories largely correspond to Iyer's tactical and strategic decision levels, respectively. Routing models are primarily concerned with operational and tactical decisions related to delivery scheduling, vehicle routing, and temperature maintenance, whereas location or inventory models focus on higher-level strategic design issues such as facility placement and storage capacity planning. The integrated and specialised optimisation models identified by Zhang (2024) extend beyond this three-layer hierarchy, combining multiple decision levels or addressing domain-specific challenges such as carbon footprint reduction, microbial control, or technology-enabled monitoring. These model types are discussed in greater detail in the following subsections. Reviewing these models by decision level and model type makes it possible to identify where existing research is concentrated, where important gaps remain, and how the present study positions itself within the broader landscape of CSC optimisation.

2.4.1.1.1. Strategic Design

A CSC network consists of a series of interconnected nodes such as production, processing, packaging, storage, and retail facilities and arcs that represent the transportation routes linking these nodes. Strategic network design is one of the most critical decision problems in SCM, as it establishes the overall configuration of the chain and directly influences its cost efficiency, service quality, and environmental performance. In the context of CSCP, effective network design determines how temperature-controlled resources are allocated, how transport routes are structured, and how product flows are coordinated to balance economic, operational, and sustainability objectives (Iyer, 2025). These strategic design models primarily address long-term structural decisions and therefore operate at a different decision horizon from studies that focus on short- and medium-term operational planning, such as inventory control and routing.

1. Cost Structure and Optimisation Objectives

The total logistics cost in a CSC network encompasses several interrelated components. These include fixed costs associated with establishing facilities and acquiring vehicles, as well as variable costs related to ordering, inventory holding, and transportation. In addition, CSCs incur specific costs arising from refrigeration requirements, product deterioration, and waste management (Wangsa et al., 2023). The primary objective of most network design models is to minimise this total cost, thereby determining the optimal number, location, and capacity of DCs (Li and Zhou, 2021). Such decisions are typically made infrequently and are difficult to reverse, distinguishing them from tactical inventory or routing decisions that are adjusted repeatedly over shorter planning cycles (Stadtler, 2015; Chopra and Meindl, 2022).

The placement of DCs has far-reaching implications for both infrastructure investment and operational efficiency. Location decisions influence construction and facility maintenance costs (Dou et al., 2020), while some models further account for competitive dynamics among existing DCs and their product flow interactions (S. Y. Zhang et al., 2021). In line with growing sustainability concerns, several recent studies also integrate the carbon cost associated with storage and transportation emissions directly into the objective function (Wang et al., 2018), linking economic optimisation with environmental performance in CSC network design.

2. Handling Variability and Quality in Network Design

Network design models for CSCs increasingly incorporate uncertainties and product quality considerations specific to temperature-sensitive logistics. Product freshness, for instance, depends not only on investments in refrigeration but also on stochastic factors such as weather variations, transport delays, or power interruptions, all of which affect the proportion of goods that reach retailers at acceptable quality levels (Cai et al., 2010; D. Zhang et al., 2023). In vaccine distribution chains, particularly in developing regions where high ambient temperatures and unreliable electricity are common, network design must also consider the availability and reliability of cold storage equipment at each echelon as a critical constraint (Lim et al., 2019).

To address such uncertainties, researchers have applied methods including robust optimisation (F. Yang et al., 2022) and scenario-based linearisation (Babagolzadeh et al., 2020), which enable decision makers to maintain feasible and cost-effective solutions under variable conditions. Some models additionally incorporate operational flexibility, such as the option to choose between chilled and frozen storage modes depending on product characteristics and trade-offs between energy consumption, storage cost, and quality degradation, as demonstrated in the case of green peas (Zanoni et al., 2019). By integrating these stochastic and quality-based dimensions, CSC network design models move closer to reflecting the complexities of real-world cold logistics chains. At the strategic level, uncertainty is therefore primarily managed through robust facility configuration and capacity choices, rather than through frequent operational adjustments, which are more characteristic of tactical and operational planning (F. Yang et al., 2022; Iyer, 2025).

3. Multi-Level Decision Making and Government Role

Some CSC network design models adopt bi-level optimisation frameworks to represent the interaction between public policy objectives and enterprise-level decision making. In these models, the upper level typically reflects the role of government or regulatory authorities, who aim to minimise overall emissions and develop effective subsidy or incentive schemes. The lower level, by contrast, captures the response of firms seeking to maximise their own profit while operating under those policy constraints (Zhang et al., 2019). This dual-layered structure enables researchers to analyse how policy interventions such as carbon taxes, emission caps, or investment subsidies, affect firm behaviour and overall chain performance, thereby linking environmental regulation with strategic CSC network planning. These policy–firm interaction models are inherently strategic, as they influence long-term investment and network configuration rather than day-to-day distribution or replenishment decisions (Zhang et al., 2019; Stadtler, 2015).

4. Advanced Modelling Approaches

When network design decisions are integrated with Vehicle Routing Problems (VRP), for example, determining both the optimal facility locations and the most efficient delivery routes, the resulting models become highly complex and computationally demanding. To manage this complexity, researchers often employ metaheuristic algorithms such as genetic algorithms and tabu search, which provide near-optimal solutions within reasonable computational times (Li, 2022). These approaches are particularly useful for large-scale CSCs where exact optimisation methods may be infeasible due to the combinatorial nature of location-routing interactions. By linking network configuration with routing efficiency, such models offer a more realistic and integrated perspective on cold chain design and operations. However, in most of these models,

location decisions dominate the formulation, meaning that routing is treated as a consequence of strategic network structure rather than as a primary tactical control variable (Li, 2022; Zhang and Mohammad, 2024).

5. Location (Inventory) Optimisation Models

Location and inventory optimisation models have received comparatively less attention in the CSC literature. Unlike classical inventory management models, which primarily focus on stock control and replenishment policies (Marchi et al., 2020), most CSC-related studies emphasise the strategic placement of logistics and DCs to support temperature-controlled operations (Golestani et al., 2021; Li and Zhou, 2021). The objectives of these models typically span three main dimensions:

- Economic efficiency, encompassing facility establishment, fixed, and operational costs.
- Environmental sustainability, captured through the carbon emissions associated with facility location and transport distances.
- Customer service performance, measured in terms of service levels, delivery lead times, or proximity to demand points.

Although these studies have provided valuable insights into optimal facility siting and resource allocation, they remain limited in scope. With few exceptions such as Golestani et al. (2021), most models neglect the complexity of handling multiple product types within a single network. Furthermore, real-world factors such as vehicle heterogeneity, variable travel speeds, and dynamic customer demand are rarely considered, leaving substantial opportunities for future research to develop more comprehensive and realistic optimisation frameworks.

A broader methodological review by Shashi (2021) of the CFSC literature indicates that a range of quantitative approaches have been employed to address such challenges since 1995. These include heuristic and metaheuristic algorithms (e.g., tabu search), time-window and simulation-based models, as well as mathematical programming and statistical optimisation techniques. Despite this methodological diversity, the integration of location and inventory decisions in temperature-sensitive SCs remains underexplored, underscoring a persistent gap between theory and practice. Overall, the strategic design literature demonstrates how long-term facility location, capacity, and policy choices shape the structure and sustainability of CSCs. While these studies provide essential foundations, they are less suited to analysing how day-to-day replenishment, routing, and delivery decisions perform under demand uncertainty. These shorter-horizon decisions are the focus of tactical and operational planning models, which are reviewed in the following subsection (Stadtler (2015), Chopra and Meindl (2022), Iyer (2025)).

2.4.1.1.2. Tactical Planning

Tactical planning in CSCs addresses medium-term decisions that span multiple planning periods and significantly influence the chain's efficiency, cost structure, product quality, and sustainability performance. These decisions typically encompass procurement strategies, production scheduling, storage allocation, and order fulfilment policies. Unlike conventional SCs, tactical planning in CSCs must explicitly account for product perishability, quality degradation over time, and temperature-dependent storage constraints, as well as resource availability and demand fluctuations. Balancing these interrelated factors is crucial for

maintaining consistent service levels while minimising waste, energy use, and overall operational cost (Iyer, 2025). Because these decisions are revised regularly and directly respond to demand and operational variability, the tactical level is where inventory control and replenishment policies, such as (R, S) or (R, Q), can play a central role in shaping cost and sustainability performance (Silver et al., 1998; Tarim and Kingsman, 2006).

1. Procurement Planning

In CSCs, procurement decisions extend beyond basic sourcing and replenishment considerations to encompass a broader set of interdependent factors related to product perishability and quality maintenance. Ordering policies must account for the limited shelf life of perishable goods (Zanoni and Zavanella, 2012), as well as the cooling and energy costs associated with temperature-controlled storage (Bozorgi et al., 2014). Quality inspection processes also play a critical role, as defects or deterioration identified during inspection can alter replenishment schedules and lead to inventory losses (Alamri et al., 2017). As a result, many procurement models in perishable SCs rely on structured replenishment rules or policy-based ordering frameworks to balance service level targets against spoilage risk and holding cost (Silver et al., 1998; Tarim and Kingsman, 2006).

2. Production Planning

Production planning in CSCs involves determining the optimal quantity and timing of production based on demand forecasts, supply constraints, and available resources. These decisions are commonly formulated using Mixed Integer Linear Programming (MILP) models, which provide optimal solutions under deterministic conditions (Pasha et al., 2021). Applications in this domain include multi-period agricultural production models, where harvesting schedules and product deterioration rates are explicitly integrated into the decision-making framework (Aliano Filho et al., 2023).

Broader tactical models extend this perspective by incorporating climatic variability and its impacts on yield and commodity prices, linking environmental uncertainty with decisions on planting, harvesting, and transportation (Flores and Villalobos, 2018). In addition, some studies adopt multi-objective optimisation approaches that go beyond cost and quality considerations to include social factors such as labour stability and employment balance (Chaabane et al., 2022). To address the uncertainty inherent in demand and production forecasts, researchers frequently employ rolling horizon planning techniques, allowing production schedules to be continuously updated as new information becomes available (Lejarza and Baldea, 2020). This adaptability is especially relevant in perishable CFSCs, where both timing and quality constraints are highly sensitive to dynamic environmental and market conditions. While production planning is a core tactical activity in many agri-food chains, studies focusing on inventory–routing coordination typically treat production as exogenous or fixed, to concentrate on downstream distribution and replenishment decisions (Soysal et al., 2015; Zhang and Mohammad, 2024).

3. Storage Planning

Tactical storage planning in CSCs focuses on the allocation and utilisation of space within cold storage facilities, including the activation of specific freezer units according to operational requirements (Hariga et al., 2017). Decisions at this level directly affect both cooling performance and product quality (Marchi et al., 2020). For instance, storage temperature has been shown to significantly influence mass loss and sweetness levels in perishable products

such as blueberries (Casagrande et al., 2021). To mitigate quality deterioration and physiological disorders like chilling injuries, intermittent warming techniques have been explored to achieve more uniform temperature and humidity conditions while simultaneously reducing energy consumption (Han et al., 2021).

Flexibility in capacity management also plays a critical role in tactical storage decisions. Strategies such as renting additional cold storage space during peak harvest periods can enhance cost efficiency and resource utilisation (Mateo Fornés et al., 2023). When facilities handle multiple product types, storage allocation must balance temperature-specific storage costs against the risk of cross-product quality degradation (Borghi et al., 2009). In some specialised cases, non-traditional temperature regimes are intentionally adopted, for example, certain ready-to-eat meals can be stored at slightly higher temperatures to reduce microbial safety risks without compromising product integrity (Tufano et al., 2020). Collectively, these tactical storage models underscore the importance of balancing energy efficiency, space utilisation, and product quality within CSC operations). From an operations research perspective, these storage choices translate into inventory holding costs, spoilage risks, and capacity constraints that directly influence optimal replenishment frequency and order quantities at the tactical level (Marchi et al., 2020; Tarim and Kingsman, 2006)

4. Fulfilment Planning

Given that product freshness continuously declines over time, shelf-life-based fulfilment policies are often found to outperform traditional First-In, First-Out (FIFO) approaches in CSCs (Koutsoumanis et al., 2002). These policies prioritise inventory allocation according to remaining shelf life, thereby reducing spoilage and waste. Moreover, such models can be extended to support dynamic pricing strategies, where selling prices are adjusted in real time based on residual shelf life and expected demand (Tromp et al., 2012). Operational factors within retail environments, such as periodic store closures, can also influence spoilage rates, particularly when product deterioration exhibits stochastic behaviour (Chołodowicz and Orłowski, 2021).

Retail replenishment policies must further balance the trade-off between quality preservation and inventory availability (Wang and Wang, 2022). Synchronising replenishment schedules with upstream production cycles has proven effective in minimising overall SC costs, as demonstrated by Chen et al. (2022) in a study of orange juice production. Collectively, these fulfilment-oriented models highlight the tactical complexity of coordinating ordering, pricing, and replenishment in perishable product SCs, where time, temperature, and quality degradation are interdependent decision factors. Such fulfilment rules are often embedded within broader inventory control policies that specify when and how much to reorder, thereby linking allocation decisions with replenishment timing and order size (Silver et al., 1998; Wang and Wang, 2022).

Although tactical planning includes procurement, production, storage, and fulfilment, its effectiveness ultimately depends on how replenishment and inventory decisions interact with distribution and routing under uncertain demand conditions (Soysal et al. (2015), Awad et al. (2021)), which are addressed in the following section on distribution planning and vehicle routing.

2.4.1.1.3. Distribution Planning

Distribution planning in CSCs encompasses a set of tactical and operational decisions related to inventory allocation, vehicle assignment, routing, delivery scheduling, and dynamic rerouting. Owing to the perishable nature of products and the need to maintain strict temperature control, distribution activities in CSCs are inherently more complex than in conventional logistics chains. These operations must simultaneously address time sensitivity, energy efficiency, and product quality, often under uncertain environmental and traffic conditions. As a result, researchers have increasingly relied on advanced optimisation and simulation techniques to design distribution strategies that achieve higher levels of efficiency, minimise quality loss, and support environmental sustainability across the cold chain (Iyer, 2025). Because distribution decisions directly determine delivery frequency, route structure, and vehicle utilisation, this decision level is particularly influential for inventory–routing coordination and for analysing cost–emission trade-offs under demand uncertainty (Soysal et al., 2015; Zhang and Mohammad, 2024).

1. Vehicle Routing and Problem Formulation

At the core of distribution planning lies the VRP, a well-established extension of the classical Travelling Salesman Problem (TSP), which seeks the most cost-effective routes for delivering goods from DCs to customers (Iyer, 2025). Within the CSC literature, routing optimisation models represent the most prevalent research category, accounting for approximately 36% of decision-making studies in cold food logistics (Zhang and Mohammad, 2024). These models primarily aim to enhance the economic and environmental sustainability of perishable CFSC (Zhou et al., 2022), although a smaller body of work has also integrated social objectives, such as customer satisfaction and service quality, into multi-objective frameworks. Zhang and Mohammad (2024) groups routing objectives into three main categories: economic, environmental, and social. Economic goals typically involve minimising vehicle operating costs, product deterioration losses, and penalty costs linked to delivery time windows; environmental objectives focus on reducing carbon emissions and fuel consumption, while social objectives capture dimensions such as service reliability and customer satisfaction. In practice, routing decisions are closely interlinked with inventory and replenishment policies, as delivery frequency and shipment size jointly determine vehicle utilisation, holding cost, and spoilage risk (Beyer and Ward, 2000; Soysal et al., 2015).

In CSC contexts, routing decisions must address a diverse range of operational constraints, reflecting both logistical and temperature-sensitive challenges. Common constraints include vehicle capacity, weight limitations, travel time windows, variable vehicle speeds, urban traffic restrictions, quality thresholds and customer delivery preferences (Wu et al., 2021, Jia, 2022, Xie and Li, 2019, Shi et al., 2022). Awad et al. (2021) categorises these constraints into three principal groups. Transportation constraints ensure that each customer is served once, fleet capacities and time windows are respected, and sub-tours are avoided (Stellingwerf et al., 2018; Amorim and Almada-Lobo, 2014). Quality constraints safeguard product integrity by enforcing temperature and freshness limits and incorporating spoilage or waste considerations (Mejjaouli and Babiceanu, 2018). While many models incorporate detailed time-window and quality constraints, others deliberately simplify these features to focus on the interaction between routing structure, inventory decisions, and cost–emission performance (Stellingwerf et al., 2018; Zhang and Mohammad, 2024).

Because of the specific requirements of cold logistics, CSC routing problems often necessitate specialised model extensions. These include the use of MCVs and multi-depot networks to handle diverse temperature settings and product categories (Li and Li, 2022). Collaborative routing approaches involving vehicle or product sharing have also been proposed to improve fleet utilisation and reduce empty returns (Ren et al., 2019). Several comprehensive reviews summarise advances in CSC routing optimisation (Awad et al., 2021) and MCV applications (Ostermeier et al., 2021).

More recent models further capture real-world complexities that influence routing performance, including:

- Multiple DCs, which require coordinated planning across regional networks (Liu et al., 2020).
- Heterogeneous vehicle fleets with varying capacities, operating costs, and energy efficiency (S. Zhang et al., 2023).
- Dynamic vehicle speeds influenced by traffic conditions, weather, or temperature control requirements (Meneghetti and Ceschia, 2020).
- Multiple product types with distinct temperature and handling requirements (Khan A. S. et al., 2020).
- Dynamic or stochastic customer demand, which necessitates real-time route adjustments and adaptive scheduling (Stellingwerf et al., 2018).

Together, these developments demonstrate how CSC routing models have evolved from simple cost-minimisation frameworks into complex, multi-criteria chains that integrate quality, energy, and sustainability considerations to reflect the realities of cold logistics operations.

2. Quality, Time Windows, and Decay Modelling

Maintaining product quality during distribution remains one of the key challenges in CSCs, as product decay is closely linked to time and temperature exposure. The deterioration of quality during transport is commonly modelled as either a linear (Hsiao et al., 2018) or exponential (Li et al., 2019) function of travel time, depending on the nature of the product and its sensitivity to temperature fluctuations. To capture these dynamics, many researchers apply the Vehicle Routing Problem with Time Windows (VRPTW) framework, which enables scheduling deliveries within predefined time limits to minimise freshness loss and spoilage (Hsiao et al., 2017).

Time window constraints are a defining feature of CSC routing models. In most cases, they are implemented as soft time windows, which allow limited deviations from preferred delivery times while imposing penalty costs to preserve service quality (Liu et al., 2020). More advanced formulations extend this concept through flexible or fuzzy time windows, where deliveries outside acceptable intervals incur graded penalties or reflect uncertainty in delivery conditions (Ali et al., 2021). By embedding these temporal constraints within routing optimisation, researchers can better balance efficiency, product integrity, and customer satisfaction under realistic distribution conditions. Although explicit decay functions provide detailed insight into product deterioration, such formulations require biological and thermal parameters that are often unavailable at the tactical planning level; consequently, many

inventory–routing studies capture perishability indirectly through service-level, waste, or penalty-cost assumptions (Soysal et al., 2015; Stellingwerf et al., 2018).

3. Solution Approaches

Because VRPs are NP-hard and computationally intensive, exact optimisation methods are rarely feasible for large-scale CSC applications. Consequently, most studies rely on metaheuristic algorithms that can generate near-optimal solutions within reasonable computational times. These include search-based algorithms (Hübner and Ostermeier, 2019) and population-based approaches such as genetic algorithms and particle swarm optimisation (Ning et al., 2021). Hybrid methods are also increasingly popular, combining genetic algorithms with other optimisation strategies such as simulated annealing (Nakandala et al., 2016), or k-shortest path algorithms (Liu and Zhang, 2023) to balance exploration and exploitation in the search process. Among metaheuristic techniques, Ant Colony Optimisation (ACO) and its variants have been particularly prominent in CSC routing models (Feng et al., 2023).

Awad et al. (2021) notes that the dominant mathematical formulation for routing optimisation remains MILP, although other model types, such as LP, Integer Linear Programming (ILP), Nonlinear Programming (NLP), and Multi-Objective Programming (MOP), are also used. Earlier studies predominantly relied on exact solvers such as CPLEX, GAMS, and LINGO, but more recent research (2013–2019) demonstrates a clear methodological shift towards heuristic and metaheuristic approaches, often in hybrid combination with exact methods (Stellingwerf et al., 2018). This evolution reflects the growing complexity and scale of modern CFSC problems, where exact optimisation becomes computationally prohibitive. Consequently, metaheuristic techniques, often supported by clustering or decomposition strategies, have become the dominant tools for efficiently solving large, multi-constraint CSC routing problems, most of which still assume commodity flow formulations for single-product distribution, while others apply set-partitioning or clustering-based approaches to manage problem size and solution tractability (Iyer, 2025). The need for heuristic and hybrid solution methods reflects the high dimensionality of routing-based CSC models, particularly when routing is combined with inventory decisions and environmental objectives (Awad et al., 2021; Zhang and Mohammad, 2024).

4. Cost, Emissions, and Policy Considerations

Distribution cost modelling in CSCs extends beyond conventional logistics expenses such as fuel, vehicle operation, and labour, to include additional factors related to refrigeration, product quality deterioration, and waste disposal (Yang et al., 2017). According to Awad et al. (2021), these cost components generally fall into three major categories.

The first category encompasses transportation costs, which include fuel consumption for both vehicle propulsion and refrigeration units, driver wages, tolls, and parking fees (Hsiao et al., 2017; Li et al., 2019; Tordecilla Madera et al., 2018). The second category comprises quality-related costs, arising from temperature control requirements, product degradation, rerouting to prevent spoilage, lost sales, and waste disposal (Yifeng and Ruhe, 2013). Finally, environmental costs reflect the carbon footprint of vehicle operations, refrigeration energy consumption, and potential refrigerant gas leakage (Stellingwerf et al., 2018; Saif and Elhedhli, 2016). These emissions are affected by dynamic operational factors such as vehicle load, road

gradient, and traffic congestion, all of which influence energy demand and fuel efficiency (Stellingwerf, et al., 2018; Leng et al., 2020).

To capture environmental impacts more explicitly, emissions are often modelled as either objective functions or constraints within optimisation frameworks, reflecting different regulatory mechanisms. These include:

- Carbon Cap, where total emissions must remain below a fixed threshold.
- Carbon Cap-Offset, where excess emissions require purchasing carbon credits.
- Carbon Cap-and-Trade, allowing firms to trade emissions allowances.
- Carbon Tax, which imposes a direct cost per unit of emitted CO_2 (Li et al., 2019).

By integrating these environmental cost mechanisms into routing and distribution models, researchers aim to align operational efficiency with sustainability goals, enabling firms to make balanced decisions between cost, service, and carbon performance. This has led to a growing stream of bi-objective and multi-objective routing and inventory–routing models that explicitly trade off economic efficiency against environmental impact (Soysal et al., 2014; Bortolini et al., 2016; Musavi and Bozorgi Amiri, 2017).

5. Fleet and Mode Selection

Distribution planning in CSCs also encompasses decisions regarding vehicle configuration, transport mode selection, and temperature control strategies. The use of MCVs has proven particularly effective for transporting products that require different temperature settings within the same delivery operation, thereby improving vehicle utilisation and reducing energy waste (Frank et al., 2021). Mode selection, whether by road, rail, or maritime transport, depends heavily on route-specific temperature profiles, transit duration, and product sensitivity to environmental variations (Meneghetti et al., 2021).

In maritime cold chains, routing and scheduling decisions must carefully balance fuel costs with the risk of product deterioration, as extended travel times and ambient conditions increase the likelihood of spoilage (Fan et al., 2021). Similarly, in multimodal transport chains, trade-offs emerge between cost efficiency and customer satisfaction, requiring models that integrate transit reliability, temperature control, and quality preservation (Zheng et al., 2022). These interrelated decisions underscore the complexity of designing sustainable and resilient transport strategies for temperature-sensitive logistics networks. In many inventory–routing studies, however, fleet type and transport mode are treated as given parameters, allowing the analysis to focus on how routing and replenishment policies affect cost and emissions within a fixed fleet structure (Soysal et al., 2015; Stellingwerf et al., 2018).

6. Vehicle Routing under Uncertainty

In real-world SCs, decision-making inherently involves a degree of risk and uncertainty, and modelling these uncertainties can provide decision makers with more reliable and realistic tools for optimisation. Much of the early research in SCM and inventory control assumed that demand parameters were either known or followed a stationary stochastic distribution, that is, their probability structure remained stable over time (Silver and Meal, 1973; Zhang and Chen, 2014). Under this assumption, determining the level of precautionary or safety stock was relatively straightforward, as demonstrated by several studies (Yavari and Geraeli, 2019; Soysal et al., 2015; Zhen et al., 2019; Torabi et al., 2015).

Several CSC studies have adopted stationary stochastic demand formulations to analyse routing and distribution decisions. For instance, Soysal et al. (2015) proposed an optimisation framework aimed at minimising total costs while simultaneously satisfying carbon emission and service level constraints under uncertain yet stationary demand conditions. Similarly, Babagolzadeh et al. (2020) introduced a two-stage stochastic programming model using stationary stochastic data to minimise both the economic and environmental impacts of temperature-sensitive food distribution, while Mohebalizadehgashti et al. (2020) developed a multi-objective MILP model and applied decision tree analysis to address stationary uncertainty. These studies demonstrate that incorporating stochastic demand improves the robustness of routing and inventory decisions; however, they largely rely on the assumption that demand variability is stationary over time.

In practice, demand in CFSCs is rarely stationary. CFSCs operate in environments characterised by dynamic and time-varying demand patterns, driven by seasonality, promotional activities, changing consumer preferences, and evolving regulatory requirements (Montanari, 2008; Cawston, 2018). Such demand dynamics alter both the level and variability of demand across planning periods, creating challenges that cannot be adequately captured by stationary models. From a distribution planning perspective, demand surges may necessitate more frequent deliveries to preserve freshness and service levels, increasing vehicle movements and refrigeration energy use. Conversely, demand downturns can lead to longer storage durations, requiring lower temperatures to slow product deterioration, thereby increasing energy consumption and potentially affecting product quality (Nakandala et al., 2016).

The distinction between stationary and non-stationary stochastic demand is well established in the inventory literature (Graves and Willems, 2008). While stationary demand exhibits a stable distribution, non-stationary demand fluctuates unpredictably over time due to structural changes in market conditions (Silver and Meal, 1973). Despite its practical relevance, non-stationary demand has received limited explicit attention in CSC routing and inventory–routing models, where stationary assumptions remain dominant. Tunc et al. (2011) show that neglecting non-stationary demand characteristics can lead to significant underestimation of costs and misaligned replenishment and routing decisions, particularly in chains with perishable products.

The lot-sizing problem under non-stationary stochastic demand has been examined in a range of classical inventory studies (Bollapragada and Morton, 1999; Beyer and Ward, 2000; Iida, 2002; Seth and Pandey, 2009; Purohit et al., 2015). However, most of this literature focuses on inventory control in isolation and does not explicitly consider the interaction between inventory decisions and vehicle routing, even though these decisions jointly determine distribution cost, service performance, and environmental impact (Beyer and Ward, 2000). Addressing this gap, the present study analyses the effects of non-stationary stochastic demand on both inventory management and vehicle routing within a CFSC, using policy-based inventory control frameworks.

By embedding demand uncertainty within an inventory–routing optimisation context, this line of research enables a more realistic assessment of how replenishment frequency, shipment size, routing structure, and vehicle utilisation respond to fluctuating demand conditions. This perspective is particularly relevant for cold food distribution, where routing inefficiencies and

inappropriate inventory policies can amplify energy consumption, emissions, and product waste. A summary of reviewed studies distinguishing between deterministic, stationary stochastic, and non-stationary stochastic demand models is presented in Table 2.

Overall, the distribution planning literature demonstrates that routing, delivery frequency, and vehicle utilisation are central drivers of cost, emissions, and product quality in CSCs. While many studies integrate routing with environmental objectives, relatively few jointly consider inventory control and routing under non-stationary stochastic demand (Soysal et al. (2015), Awad et al. (2021), Zhang and Mohammad (2024)). This gap motivates the present study, which focuses on inventory–routing coordination at the tactical–operational interface, comparing (R, S) and (R, Q) policies under stochastic demand to analyse cost–emission trade-offs.

2.4.1.1.4. Integrated Models

According to Zhang and Mohammad (2024), Integrated optimisation models represent a more advanced and comprehensive class of decision-making approaches within CSC research, as they simultaneously address multiple decision layers, such as location, routing, inventory (storage), and transportation. With 19 studies identified, accounting for approximately 34.5% of the literature, this category constitutes the second most extensively studied area of decision-making optimisation in CSCs. The central objective of integrated models is to capture the interdependencies among SC decisions and optimise them jointly, rather than treating them as isolated problems. While such models provide a comprehensive representation of CSC decisions, their high dimensionality often leads to substantial computational complexity, limiting their applicability for large-scale or uncertainty-rich planning environments (Babagolzadeh et al., 2020; Zhang and Mohammad, 2024).

Within this category, location–routing optimisation models often incorporate all three pillars of sustainability, economic, environmental, and social, reflecting a holistic perspective on cold chain performance. In contrast, inventory (storage)–transportation models primarily focus on economic and environmental dimensions, emphasising cost efficiency and emission reduction. Most location–routing models also integrate multiple DCs, recognising that strategic facility placement directly affects routing structures, transportation efficiency, and overall network resilience (Zhang and Mohammad, 2024). Moreover, most integrated models emphasise strategic–tactical integration, particularly location–routing, whereas fewer studies focus specifically on the tactical integration of inventory control and routing under stochastic demand (Soysal et al., 2015; Awad et al., 2021).

Despite these advances, existing integrated models still face practical limitations. Relatively few studies account for heterogeneous vehicle fleets (Babagolzadeh et al., 2020; Hariga et al., 2017; Qiu et al., 2020) or dynamic vehicle speeds influenced by road, traffic, or environmental conditions (Hariga et al., 2017; Leng; 2020). These omissions restrict the applicability of many models under real-world operational scenarios, underscoring the need for more realistic and data-driven formulations that can adapt to variable logistics conditions (Zhang and Mohammad, 2024). These limitations suggest that, rather than maximising the number of decision layers, there is value in developing focused integrated models that concentrate on the most decision-sensitive interfaces, such as the interaction between inventory policies and routing under demand uncertainty (Soysal et al., 2015; Awad et al., 2021; Zhang and Mohammad, 2024).

2.4.1.1.5. Other Models

The final category of decision-making approaches in perishable CFSCL comprises a broad and heterogeneous group of models, including simulation-based frameworks, supplier selection models, and other specialised analytical techniques. These models are designed to tackle distinct operational, strategic, or sustainability-related challenges that extend beyond the traditional optimisation paradigms of routing, location, or integrated models. By focusing on context-specific issues such as supplier evaluation under uncertainty, risk mitigation, or technology adoption, these specialised approaches complement the more conventional optimisation techniques and contribute to a more comprehensive understanding of decision-making in CSCs (Iyer, 2025; Zhang and Mohammad, 2024). Although these approaches contribute valuable insights into specific cold chain challenges, they typically do not focus on the optimisation of inventory and routing decisions that dominate day-to-day cost and emission performance in distribution planning (Iyer, 2025; Zhang and Mohammad, 2024).

1. Simulation Models

Simulation techniques are increasingly employed to replicate real-world operating conditions and evaluate CSCP under diverse scenarios. By modelling complex and dynamic logistics environments, simulation approaches enable researchers to observe chain behaviour, test alternative strategies, and predict outcomes prior to implementation. Notable applications include simulations of maritime shipping routes for banana distribution (Fan et al., 2021), railway-based SC networks within the Belt and Road Initiative (Abbas et al., 2021), and transshipment operations between DCs (Vu and Ko, 2023). The outcomes of such studies have been instrumental in assessing how logistical configurations influence economic performance, environmental sustainability, and social welfare (Abbas et al., 2023). Consequently, simulation modelling provides decision makers with a powerful, evidence-based tool for analysing trade-offs and guiding optimisation in CSCs. Simulation models are particularly useful for evaluation and what-if analysis, but they are less suited to identifying optimal replenishment and routing policies, which remains the strength of mathematical optimisation approaches (Stadtler, 2015; Iyer, 2025).

2. Supplier Selection Models

Supplier selection represents another important area of decision-making research in CSCs, where multiple evaluation criteria and methodological approaches are used to identify the most suitable partners. Selection decisions typically consider a combination of economic, environmental, and social sustainability dimensions (Khan A.U. and Ali, 2021) alongside indicators of service level and responsiveness, and measures of product quality, safety, and information system integration or standardisation (Khan A.U. and Ali, 2021). These models primarily support strategic and managerial decision making, rather than the tactical optimisation of inventory and routing policies in daily distribution operations (Khan A.U. and Ali, 2021; Iyer, 2025). Given the inherently multi-criteria nature of supplier evaluation, researchers have applied a wide range of advanced decision-making tools. Among these, Multi-Criteria Decision-Making (MCDM) method (Khan A.U. and Ali, 2021) has been used to capture uncertainty and subjectivity in expert judgments. As such, MCDM methods are most applied where expert judgement and qualitative criteria dominate, rather than in operational settings where decisions must be generated algorithmically under uncertainty (Rodriguez, 2023; Stadtler, 2015).

3. Mult-criteria decision Making

MCDM methodologies are widely applied in CFSC research to address complex decision problems that involve multiple, often conflicting, evaluation criteria and expert judgments. These approaches provide a structured and transparent framework for analysing trade-offs, prioritising alternatives, and supporting more informed and balanced decision making (Rodriguez, 2023).

Among the most frequently used techniques, the Analytic Hierarchy Process (AHP) has proven particularly valuable for identifying and evaluating key factors influencing FSC sustainability. Applications include assessing the role of packaging and packing in reuse and recycling systems (Yontar and Ersoz, 2020) and analysing their impacts on energy consumption, industry structure, and GHG emissions (Susanty et al., 2019). AHP has also been combined with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to evaluate risks in storage, facility management, and transportation due to inadequate food handling, thereby informing waste reduction strategies and assessing technology management efficiency for maintaining product shelf life (Rathore et al., 2017).

4. Multi Objective Optimisation Models

Multi-objective optimisation refers to the simultaneous optimisation of two or more conflicting objectives, where no single solution can fully satisfy all goals at once (Mavrotas, 2009). Instead of identifying one global optimum, these models produce a set of Pareto-optimal (non-dominated) solutions that represent trade-offs among competing objectives. In such solutions, improvement in one objective typically results in the deterioration of another (Baron et al., 2011). The purpose of multi-objective optimisation is to generate this Pareto frontier of feasible trade-offs, thereby enabling decision makers to select solutions that best align with their preferences and strategic priorities (Ehrgott, 2005).

Given the aim of this research, to develop a bi-objective model that enhances the sustainability performance of the CFSCs, a review was conducted of multi-objective optimisation models in logistics and cold chain contexts. These models typically pursue multiple, often competing, objectives such as maximising revenue, maintaining product quality and safety, ensuring customer satisfaction, and simultaneously minimising GHG emissions, delivery time, and total costs. For example, Soysal et al. (2014) developed a bi-objective LP model using the Epsilon Constraint (EC) method to minimise both transportation cost and CO_2 emissions. Similarly, Bortolini et al. (2016) proposed a multi-objective optimisation framework for emerging CFSCs aimed at reducing cost, carbon emissions, and delivery time. Musavi and Bozorgi Amiri (2017) formulated a multi-objective model addressing facility location and vehicle routing in CFSCs, balancing product quality improvements with reductions in transportation costs and emissions through a heuristic optimisation approach. These studies demonstrate the feasibility of embedding environmental objectives directly within logistics optimisation models, but most still assume deterministic or stationary demand and do not explicitly compare alternative inventory control policies under uncertainty (Soysal et al., 2014; Bortolini et al., 2016).

Across the literature, the EC and weighted-sum methods emerge as the most used techniques for solving multi-objective optimisation problems. The weighted-sum approach, applied by Yavari and Geraeli (2019) and Ghahremani et al. (2016), converts multiple objectives into a single aggregated function to identify a representative set of Pareto solutions. The EC method, used in several studies (Allaoui et al., 2018; Amorim and Almada Lobo, 2014; Amin and

Zhang, 2013; Mohammed and Wang, 2017; Mohebalizadehgashti et al., 2020; Tordecilla Madera et al., 2018; Soysal et al., 2014), treats one objective as the primary goal while converting others into constraints bounded by permissible thresholds. However, as noted by Baron et al. (2011), this technique can produce both efficient and weakly efficient solutions, requiring further refinement. To address this limitation, Mavrotas (2009) proposed an enhanced version, the lexicographic EC method, which ensures the generation of only strictly Pareto-efficient solutions by applying hierarchical ordering to the optimisation process. The lexicographic and augmented EC variants are particularly relevant for problems where decision makers prioritise one objective but still wish to explore structured trade-offs, making them suitable for tactical planning contexts with strong economic and environmental pressures (Mavrotas, 2009; Ehrgott, 2005).

The reviewed studies summarised in Table 2 demonstrate the range of approaches adopted to address multi-objectivity in CSC optimisation. Although several models successfully integrate economic and environmental goals, only Soysal et al. (2014) explicitly account for the effects of temperature sensitivity on product quality during distribution, highlighting an important research gap in the modelling of perishability within multi-objective frameworks.

5. Storage Design

Effective storage design is a fundamental component of CSCP, spanning multiple levels, from primary packaging to warehouse infrastructure, and directly influencing temperature control, product quality, energy consumption, and operational efficiency. Across these levels, researchers have applied analytical models, simulation tools, and optimisation techniques to enhance thermal regulation, shelf-life preservation, and cost-effectiveness.

At the primary packaging level, which encloses individual products, design features play a pivotal role in controlling the microclimate, including temperature, humidity, and gas composition, during storage, transport, and retail. Packaging characteristics strongly influence respiration rates and degradation patterns, particularly for fresh produce. For example, Jalali et al. (2017) developed an analytical model based on permeability and heat transfer to optimise micro-perforations that regulate humidity and gas exchange.

At higher packaging levels, secondary (cartons) and tertiary (pallets) packaging facilitate handling, transportation, and uniform cooling. Cooling efficiency depends on design parameters such as carton type (open versus closed tops) (Wu et al., 2019). The quaternary packaging layer, encompassing insulated or refrigerated containers, introduces further design complexities. CFD-based studies have optimised factors such as airflow configuration, door positioning (Zhang et al., 2018), fan speed, and insulation thickness (B. Li et al., 2020). Although storage and packaging design models are essential for improving thermal performance and product quality, they primarily address engineering and facility-design questions rather than the tactical planning of inventory and routing decisions and therefore fall outside the core scope of the present study (Wu et al., 2019; Zhang et al., 2018; Iyer, 2025).

Table 3 Hierarchical optimisation models in CSCs and scope of the present study

#	*Model type (Decision level)*	*Typical decisions addressed*	*Common objectives*	*Included in this study*	*Justification for inclusion / exclusion*	*Key references*
1	*Inventory optimisation (Tactical)*	*Replenishment timing, order quantities, safety stock levels*	*Holding cost, spoilage reduction, service level*	***Yes***	*Core decision layer influencing delivery frequency and routing*	*Tarim and Kingsman (2004, 2006); Nahmias (2011)*
2	*Inventory–transportation (Tactical)*	*Coordination of replenishment and delivery planning*	*Cost, emissions*	***Yes***	*Directly aligned with inventory–routing integration*	*Soysal et al. (2014); Amorim and Almada-Lobo (2014)*
3	*Vehicle routing (Operational)*	*Route design, delivery sequencing, vehicle assignment*	*Transportation cost, emissions, service reliability*	***Yes***	*Routing strongly affects emissions and interacts with inventory*	*Fikar (2018); Bottani et al. (2019)*
4	*Network design (Strategic)*	*Facility location, DC capacity, long-term fleet sizing, infrastructure investment*	*Minimise total system cost; reduce long-term emissions; ensure service coverage*	*No*	*Long-term structural decisions; outside tactical inventory–routing scope*	*Govindan et al. (2020); Akkerman et al. (2010)*
5	*Location–routing (Strategic)*	*Joint facility placement and routing structure*	*Cost, emissions, service level*	*No*	*High complexity and strategic focus limit short-term policy analysis*	*Meneghetti and Monti (2014); Coelho et al. (2014)*
6	*Production planning (Tactical)*	*Lot sizing, production*	*Cost, yield stability, labour balance*	*No*	*Production treated as exogenous to*	*Amorim et al. (2013)*

		schedules, harvest timing			*focus on distribution decisions*	
7	*VRP with time windows / decay (Operational)*	*Delivery timing, freshness preservation*	*Quality loss, penalty costs*	*No*	*Represented indirectly to preserve tractability*	*Hsu et al. (2007)*
8	*Fully integrated models*	*Location, inventory, routing, fleet, policy*	*Cost, emissions, service*	*No*	*Excessive integration reduces tractability and interpretability*	*Accorsi et al. (2016); Govindan et al. (2020)*
9	*Simulation models*	*Scenario evaluation, system behaviour*	*Cost, emissions, resilience*	*No*	*Evaluation-oriented rather than optimisation-focused*	*Behdani et al. (2019); Mangla et al. (2020)*
10	*MCDM / supplier selection*	*Partner evaluation, technology adoption*	*Economic, environmental, social*	*No*	*Qualitative focus; not suited to operational optimisation*	*Shashi et al. (2018); Govindan et al. (2015)*

Taken together, the literature shows a wide spectrum of modelling approaches, ranging from highly integrated strategic frameworks to specialised simulation, MCDM, and engineering-based models. However, a clear gap remains at the tactical–operational interface, where inventory control and routing decisions jointly determine cost, emissions, and service performance under demand uncertainty. Addressing this gap requires models that are integrated enough to capture key interdependencies yet focused enough to remain tractable and applicable in uncertain planning environments. (Soysal et al. (2015), Awad et al. (2021), Zhang and Mohammad (2024), Iyer (2025)) This rationale directly motivates the present study's focus on inventory–routing optimisation under stochastic demand with bi-objective cost–emission trade-offs.

2.4.1.2. Models Components

To date, there is no unified theoretical framework for CSC optimisation. Using an inductive review of existing models, Iyer (2021), building on the approach of Seuring et al. (2021), identifies nine core components that are commonly addressed in CSC optimisation studies. These range from product-related processes (e.g. temperature-driven decay, respiration, microbial growth) to physical chain characteristics (e.g. cooling dynamics, heat and mass

transfer), and operational and environmental factors such as delivery time windows, fuel and energy use, emissions, and technology-enabled monitoring and control.

While many studies incorporate one or more of these dimensions, none has yet integrated all nine within a single optimisation framework, reflecting both the complexity of CSCs and the need for problem-specific model design. In this study, Iyer's classification is therefore used explicitly as a structuring device to define the scope of the proposed optimisation model. The analysis focuses on components that directly inform tactical and operational decision-making in distribution planning, namely inventory control and stochastic demand (introduced as the core decision layer of this study). Other components identified by Iyer (2021) such as microbial growth, physiological product behaviour, cooling dynamics, and monitoring technologies are recognised as important for cold chain design and quality assurance but are not modelled explicitly, as they fall outside the scope of the present inventory–routing and emission-oriented optimisation framework.

Table 4 operationalises Iyer's (2021) nine-component classification by mapping each component to its disciplinary roots, typical modelling purpose, and relevance to the present study. Rather than using this framework only descriptively, it is applied analytically to justify the selection of model features and the exclusion of others. The table shows that several components, such as microbial growth, physiological product behaviour, cooling dynamics, and monitoring technologies, are primarily rooted in food science, thermal engineering, and information systems. These components are essential for product design, storage technology, and quality assurance (De Venuto and Mezzina, 2018; Jalali et al., 2017; Wu et al., 2019; Shoji et al., 2022), but they require highly detailed biological or physical data and are therefore more relevant to strategic facility design or real-time control than to tactical distribution planning (Accorsi et al., 2018; Nakandala et al., 2016).

By contrast, the components that directly support operational planning decisions in cold distribution, namely fuel and energy requirements, emissions, and delivery time windows, are typically addressed within operations research and logistics modelling (M. Wang et al., 2021; L. X. Li et al., 2019; F. Li et al., 2022). These dimensions can be meaningfully integrated into inventory-routing models without requiring laboratory-level biological data or detailed thermal simulations. Consequently, the present study adopts a selective approach that combines classical inventory and routing decisions from operations research (Tarim and Kingsman, 2006; Soysal et al., 2015) with those components that most strongly influence cost and environmental performance. This positioning allows the model to remain analytically tractable while still capturing the energy-intensive and emission-intensive nature of cold food distribution (Neusel and Hirzel, 2022; Abbas et al., 2023).

Table 4 Model components in CSC optimisation and scope of the present study

#	*Model component*	*Main discipline*	*Typical purpose in CSC optimisation models*	*Included in this study*	*Justification for inclusion / exclusion*
1	*Fuel and energy requirements*	*Logistics / industrial engineering*	*Estimate transportation and refrigeration energy use and*	***Yes***	*Required to represent realistic distribution costs and energy-intensive nature of CFSC operations*

			related operating costs		
2	*Emissions (CO2 and GHG)*	*Environmental modelling / sustainability*	*Quantify environmental impact of transport and refrigeration activities*	***Yes***	*Explicitly modelled as a second objective function to analyse cost–emission trade-offs*
3	*Microbial growth*	*Food science / microbiology*	*Model spoilage and food safety as a function of temperature and time*	*No*	*Requires detailed biological parameters; outside the scope of tactical distribution planning*
4	*Product quality and shelf life*	*Food science / operations*	*Link logistics decisions to freshness and waste generation*	*No (indirect)*	*Captured indirectly through service level assumptions rather than explicit decay functions*
5	*Demand vs. price and quality*	*Economics / SCM*	*Capture demand response to price and freshness*	*No*	*Price–quality elasticity not modelled; demand treated as exogenous and stochastic*
6	*Transpiration and respiration*	*Post-harvest biology*	*Model physiological changes affecting weight and appearance of produce*	*No*	*Relevant for storage design rather than inventory–routing optimisation*
7	*Cooling dynamics*	*Thermal engineering*	*Analyse temperature distribution and airflow in storage and vehicles*	*No*	*Data intensive and primarily relevant for facility and equipment design*
8	*Delivery time windows*	*Operations research*	*Represent service constraints and customer time requirements in routing and scheduling*	*No*	*Assumed feasible deliveries; no explicit time-window constraints, to focus on inventory–routing and cost–emission trade-offs.*
9	*Monitoring and control technologies*	*Information systems / IoT*	*Enable real-time temperature tracking and dynamic control*	*No*	*Implementation-level concern rather than optimisation model structure*

Source: Iyer, 2021

As summarised in Table 4, this selective focus highlights how different disciplines address complementary challenges within CSCs and at different levels of analysis. Food scientists and engineers contribute detailed knowledge on spoilage dynamics, cooling processes, and packaging design (Zhang and Chen, 2014; Jalali et al., 2017; Schudel et al., 2022), while operations research translates key performance drivers such as distance travelled, load carried, and temperature requirements into decision variables that support tactical and operational planning (B. Xu et al., 2023; Y. Wang et al., 2021). The present study does not seek to replace these disciplinary perspectives but rather builds upon them by embedding their most policy-relevant implications specifically fuel and energy use and associated emissions within an optimisation framework for inventory and routing decisions. Accordingly, the following subsections examine how Fuel and Energy Requirements and Emissions are represented in CSC optimisation models and incorporated into the scope of the proposed bi-objective framework.

1. Fuel and Energy Requirements

Fuel and energy consumption are central drivers of performance in cold food distribution chains and directly shape both operating cost and environmental impact (Stellingwerf et al., 2018; Neusel and Hirzel, 2022). In refrigerated logistics, energy is required not only for vehicle propulsion but also for maintaining low temperatures throughout transport and handling, leading to substantially higher energy intensity compared with conventional distribution chains (L. X. Li et al., 2019). Energy demand is influenced by routing distance, vehicle loading, frequency of stops, ambient temperature, and refrigeration efficiency, commonly represented through the coefficient of performance of cooling units (Shui and Li, 2020).

In the present study, fuel and energy requirements are embedded directly within the optimisation structure rather than treated as external performance indicators. In the mixed-integer programming model, transportation distance, vehicle utilisation, and delivered quantities determine fuel-related operating costs, while refrigeration-related energy use is represented through cost parameters linked to routing and replenishment decisions. This allows the model to capture how alternative inventory–routing policies, such as (R, S) and (R, Q), influence energy consumption through their effects on replenishment frequency, shipment size, and route structure. For example, policies that trigger more frequent deliveries increase vehicle movements and door openings, which in turn raise both propulsion and refrigeration energy demand (Liu et al., 2020; L. X. Li et al., 2019).

This selective focus, as summarised in Table 4, highlights how different disciplines address complementary challenges within CSCs across distinct decision levels. Food scientists and engineers contribute detailed knowledge on spoilage dynamics, cooling processes, and packaging design (Zhang and Chen, 2014; Jalali et al., 2017; Schudel et al., 2022), while operations research translates key performance drivers such as distance travelled, load carried, and delivery frequency into decision variables that support tactical and operational planning (B. Xu et al., 2023; Y. Wang et al., 2021). The present study therefore does not seek to replace these perspectives, but rather to build upon them by embedding their most policy-relevant implications—specifically fuel and energy consumption and associated emissions—within an optimisation framework for inventory and routing decisions under demand uncertainty. Accordingly, the following subsections focus on how Fuel and Energy Requirements and

Emissions are represented in CSC optimisation models and incorporated into the proposed bi-objective framework.

2. Emissions

Because cold supply chains are highly energy intensive, they typically exhibit a larger environmental footprint than conventional SCs (Vu and Ko, 2023; Neusel and Hirzel, 2022). Emissions arise mainly from fuel combustion for transportation, electricity generation for refrigeration, and the release of GHGes such as CO_2, CH_4, N_2O, and refrigerants (Vu and Ko, 2023). Although refrigerant leakage is often difficult to measure, it can significantly increase global warming potential and is increasingly recognised as a critical sustainability concern (F. Li et al., 2022).

Recent research argues that optimisation models for CSCs should move beyond cost-only objectives and explicitly incorporate environmental performance (Abbas et al., 2023; Zhang and Mohammad, 2024). In line with this stream, the present study models emissions as a second objective alongside total cost. Emissions are expressed as functions of routing distance, vehicle usage, and energy consumption, using emission factors to convert fuel and energy use into carbon-equivalent units (F. Li et al., 2022; B. Hu et al., 2021). This formulation allows environmental impact to be analysed in the same optimisation framework as economic performance.

The bi-objective structure, solved using the AEC method, enables systematic exploration of trade-offs between cost efficiency and emission reduction. Rather than assuming a fixed carbon penalty, the model generates a Pareto frontier that shows how reductions in CO_2 emissions require changes in inventory–routing policies, delivery frequency, and route design. Through Monte Carlo simulation, these trade-offs are evaluated under stochastic demand, allowing assessment of how uncertainty affects both economic and environmental robustness of (R, S) and (R, Q) policies.

By embedding emissions directly into the optimisation model, the study provides a bridge between sustainability research and operations research. Environmental insights, such as emission factors and carbon pricing concepts (B. Hu et al., 2021), are translated into operational decision variables that guide inventory and routing planning. In this way, challenges traditionally addressed by environmental science and engineering are converted into actionable criteria for tactical logistics decision-making.

Having established which cold-specific components are included in the model and why, the next step is to consider how these components relate to different decision-making levels within the SC. Inventory control, routing, energy use, and emissions are primarily operational and tactical concerns, yet they are shaped by strategic choices such as network structure, technology investment, and collaboration arrangements (Iyer, 2025; Chopra and Meindl, 2022). To position the present model within this broader decision context, the following section therefore examines hierarchical optimisation frameworks, which distinguish between strategic, tactical, and operational decision layers and clarify the role of optimisation model within each level of SC planning.

2.4.1.3. Data Analytics

While optimisation models define how decisions should be made, data analytics determines what information is available to support those decisions and at which planning levels they can

be realistically implemented. In the context of CFSCs, analytics plays a complementary role by transforming temperature, demand, and operational data into inputs for strategic, tactical, and operational decision-making models (Chaudhuri et al., 2018; Nakandala et al., 2016). Understanding the capabilities and limitations of data analytics is therefore essential for defining the scope of optimisation models and for distinguishing between decisions that can be supported through planning models and those that require real-time monitoring and control.

Data analytics has emerged as a critical enabler of informed decision making across all stages of the CFSCs. However, its level of adoption remains uneven across different sectors and phases of the chain (Chaudhuri et al., 2018). In a comprehensive review of 17 studies, Chaudhuri et al. (2018) found that most data-driven applications have been implemented in the fresh fruit and vegetable sector, followed by dairy, meat, and fish SCs. The use of analytics is most prevalent in distribution, transportation, and storage operations, with relatively limited implementation in upstream processes such as harvesting or downstream stages like retail. This uneven adoption has direct implications for optimisation modelling, as the availability and reliability of data constrain the level of detail and dynamism that can be incorporated into decision-support models at different stages of the CFSC (Chaudhuri et al., 2018; Stadtler, 2015).

A major focus of these applications is on temperature data collection and monitoring, which serves as the foundation for performance evaluation and decision support in cold logistics. For example, Raab et al. (2011) identified the use of temperature control systems at both the company and SC levels to ensure product safety and quality, while Ringsberg (2014) demonstrated how temperature tracking and variation analysis can help detect early signs of decomposition and identify its underlying causes. Despite these technological advances, the overall implementation of data analytics in CFSCs remains limited, largely due to organisational and structural barriers, including fragmented data systems, lack of digital infrastructure, and limited analytical capability within firms.

Chaudhuri et al. (2018) further categorised data analytics applications across the different stages of the CFSC, highlighting distinct functions and challenges at each stage, as summarised below:

1. **Harvesting and Procurement**

In the early stages of the CFSC, such as harvesting, data collection practices are often inconsistent and underutilised. Moccia, (2013) observes that, despite the availability of field data, researchers and practitioners continue to rely predominantly on traditional decision-making methods. Integrating real-time data on temperature, picking rate, and transfer time into Decision Support Systems (DSS) can substantially enhance the quality and speed of operational decisions at this stage (Moccia, 2013).

In the procurement stage, data-driven optimisation has also gained attention. Rijpkema et al. (2014) applied what-if analysis to evaluate trade-offs among transportation efficiency, inventory levels, waste generation, and shelf-life management. Together, these studies highlight the potential of data analytics to improve early-stage cold chain operations, where information integration and real-time decision support remain critical yet underdeveloped areas. Although these applications demonstrate the value of real-time data in early-stage CFSC operations, they predominantly support local operational decisions and are less directly

connected to downstream inventory–routing optimisation, which is the focus of the present study (Moccia, 2013; Rijpkema et al., 2014).

2. Quality Optimisation Across the CSC

Data collected throughout the CSC, from farm to retail, provide valuable insights for estimating product decay rates and devaluation costs, forming a foundation for the strategic redesign of CSC networks (Nakandala et al., 2016). Advanced decision models that utilise microbial growth data and TTIs have demonstrated significant improvements in shelf-life prediction and inventory optimisation (Aiello et al., 2012). In addition, RFID-based systems have enabled the dynamic assignment and tracking of perishable goods in real time (Askin et al., 2010), facilitating adaptive logistics decisions that respond to changing product conditions.

Beyond operational efficiency, these analytical tools also contribute to simulation-based assessments of market performance, particularly by modelling how varying product quality thresholds influence sales and pricing outcomes (Aiello et al., 2015). Collectively, such data-driven chains enhance traceability, regulatory compliance, and quality assurance across cold chain operations, while providing decision makers with actionable information for maintaining product integrity and minimising waste (Gessner et al., 2007). From an optimisation perspective, such analytics-driven quality models primarily inform parameter estimation (e.g. decay rates, shelf-life constraints, penalty costs), rather than the structural design of tactical inventory–routing models (Nakandala et al., 2016; Aiello et al., 2012).

3. Logistics, Distribution, and Storage

Data analytics also plays a pivotal role in enhancing decision making across production scheduling, network design, and transportation planning within CSCs. Bilgen and Çelebi (2013) developed production scheduling models that incorporate residual shelf life as a key decision variable, enabling more accurate alignment between manufacturing output and product perishability. Similarly, Shi et al. (2010) integrated RFID and sensor data into real-time planning models to improve chain visibility and minimise operational costs.

Continuous data monitoring supports dynamic adjustments in route selection, transportation speed, and storage conditions, allowing decision makers to respond proactively to variations in temperature, traffic, or product condition (Nakandala et al., 2016). Furthermore, shelf-life-based distribution strategies, such as the Least Shelf Life First Out (LSFO) policy, have proven effective in improving inventory rotation and reducing waste (Koutsoumanis and Taoukis, 2005). Collectively, these data-driven approaches strengthen the responsiveness, transparency, and sustainability of decision-making processes across multiple stages of the CFSC. Analytics-enabled visibility in distribution and storage supports tactical decisions on replenishment timing, delivery frequency, and route design, which are central to inventory–routing optimisation under uncertainty (Koutsoumanis and Taoukis, 2005; Nakandala et al., 2016).

4. Risk Management and Real Time Monitoring

Temperature data and RFID-based monitoring systems play a vital role in risk detection and mitigation throughout the CSC. Studies by Hafliðason et al. (2012) demonstrate how temperature tracking technologies can identify critical control points and trigger automated alarms when deviations occur, thereby preventing product spoilage and ensuring compliance with safety standards. Building on this, Kim et al. (2016) developed a real-time, context-aware risk management framework that integrates RFID and sensor data to detect disruptions and initiate responsive corrective actions. In addition to real-time control, traceability solutions

based on these technologies facilitate targeted product recalls, strengthen quality assurance, and support regulatory compliance across the SC (Gessner et al., 2007). While these systems are critical for real-time intervention and risk mitigation, they operate at a different decision layer than planning-oriented optimisation models, which rely on aggregated representations of uncertainty rather than continuous real-time feedback (Kim et al., 2016; Stadtler, 2015).

Table 5: Data analytics applications in CFSCs and scope of the present study

Data analytics application (CFSC stage)	Typical data used	Decision support purpose	Primary decision level	Included in this study	Justification for inclusion / exclusion	References
Analytics for optimisation inputs	Aggregated demand, cost, emission factors	Parameterise optimisation models	Tactical	Yes	Enables stochastic demand and emission modelling	Chaudhuri et al. (2018); Iyer and Robb (2025); Babagolzadeh et al. (2020)
Distribution and routing analytics	Demand data, vehicle location, temperature logs	Support routing, delivery scheduling, inventory rotation	Tactical / Operational	Yes (indirect)	Informs demand profiles and routing cost parameters	Awad et al. (2021); Chen et al. (2020); Chaudhuri et al. (2018)
Harvesting analytics	Field temperature, harvest timing, transfer time	Improve harvesting efficiency and product handling	Operational	No	Supports local operational control; outside distribution planning scope	Casagrande et al. (2021, 2023); FAO (2019)
Procurement analytics	Supplier lead times, temperature history, order data	Improve sourcing and replenishment coordination	Tactical	No	Procurement treated exogenously to focus on downstream decisions	Mateo-Fornés et al. (2023); Akkerman et al. (2010)
Quality and shelf-life analytics	Microbial growth data, TTIs, decay indicators	Estimate shelf life and spoilage risk	Tactical / Strategic	No (indirect)	Used to inform parameters, not explicitly modelled	Mercier et al. (2017); Ndraha et al. (2018); Koutsoumanis et al. (2002,

						2005, 2015); Aung and Chang (2014)
Storage analytics	Warehouse temperature, energy use, dwell time	Improve storage utilisation and energy efficiency	Tactical	No	Storage design and control assumed given	Evans et al. (2014); Marchi and Zanoni (2022); Marchi et al. (2020)
Real-time monitoring and traceability	RFID, IoT sensor streams	Detect deviations and trigger corrective actions	Operational	No	Focused on real-time control rather than optimisation	Verdouw et al. (2016); Kumari et al. (2015); Al Talib et al. (2020); De Venuto and Mezzina (2018); Ruiz Garcia and Lunadei (2010)
Risk management analytics	Disruption alerts, temperature excursions	Mitigate spoilage and compliance risks	Operational	No	Risk handled implicitly via stochastic demand	Kim et al. (2016); Wu and Hsiao (2021); Rathore et al. (2017)

As summarised in Table 5, data analytics applications in CFSCs predominantly support monitoring, traceability, and real-time operational control across different stages of the chain. While these applications are essential for quality assurance and risk mitigation, they rarely function as direct optimisation mechanisms for tactical inventory and routing decisions. Accordingly, the present study adopts data analytics as an enabling layer that informs demand characterisation, cost estimation, and emission parameters, rather than as a real-time decision engine. This positioning ensures consistency with the hierarchical optimisation framework and reinforces the study's focus on inventory–routing optimisation under stochastic demand using aggregated, decision-relevant data.

2.5. Chapter Summary

As the literature reviewed in this chapter unfolds, a clearer picture begins to emerge of how CFSCs operate in a space where biology, logistics, and sustainability constantly intersect. Much of the research to this point has helped us understand why chilled products behave differently from ambient goods, why their distribution networks are more fragile, and why their

planning processes demand far more precision. Yet this growing body of knowledge also shows that our current tools, models, and assumptions still fall short of capturing the full complexity of these chains.

Although CFSCs have been widely examined in the literature, this chapter has shown that several critical gaps remain in existing planning and optimisation approaches. The review highlighted that many models continue to rely on assumptions of stable or stationary demand, or they treat temperature control as a static constraint rather than an operationally dynamic process. As noted by Soysal and Bloemhof-Ruwaard (2018), such simplifications often yield solutions that appear efficient in theory but become unsustainable when confronted with the realities of chilled logistics. Routing models that ignore inventory interactions and demand uncertainty may increase partial loads, trigger excessive refrigeration cycles, and lead to avoidable energy consumption. Conversely, inventory-focused models frequently generate replenishment schedules that are difficult to implement once transportation constraints, vehicle capacities, and routing feasibility are considered.

Taken together, the literature reviewed in this chapter demonstrates that while valuable conceptual and methodological insights exist, current research remains limited in its ability to represent the full operational complexity of chilled food distribution chains. There is a clear need for integrated modelling approaches that explicitly capture demand uncertainty, inventory dynamics, routing decisions, and sustainability considerations within a unified framework. These gaps provide the motivation for the modelling approach adopted in this thesis. Accordingly, the next chapter builds directly on the insights of this review by formulating an integrated inventory and routing model tailored to CFSCs, with explicit consideration of cost efficiency and environmental performance under uncertain demand.

As the literature review unfolds, a clearer picture begins to emerge of how CFSCs operate in a space where biology, logistics, and sustainability constantly intersect. Much of the research to this point has helped us understand why chilled products behave differently from ambient goods, why their distribution networks are more fragile, and why their planning processes demand far more precision. Yet this growing body of knowledge also shows that our current tools, models, and assumptions still fall short of capturing the full complexity of these chains.

This Chapter brings these threads together. It weaves the key insights into a cohesive narrative that explains not only what is known, but also what remains uncertain, and how this thesis positions itself within that landscape. The subsections that follow move step by step from the operational realities of CFSCs, to the gaps in existing research, to the development of the proposed model, and finally to its contributions, limitations, and practical value. Taken together, they provide the bridge between the broader literature and the specific research approach that this thesis advances.

3. Analytical Framework

Chapter 3 develops the analytical foundation of this thesis by formulating the integrated inventory–routing optimisation model used to analyse CFSCs under uncertainty. Building on the conceptual insights and challenges identified in the literature review, the chapter translates the operational realities of CFSCs such as demand variability, perishability, routing complexity, and environmental pressure into a formal mathematical framework. The purpose of this chapter is not to present numerical results, but to define the decision structure, modelling assumptions, and optimisation logic that underpin the computational experiments and managerial insights discussed in subsequent chapters.

CFSCs operate under persistent and interrelated pressures. Products have short shelf lives, customers expect high availability, and demand rarely follows a predictable pattern. At the same time, transportation costs, refrigeration energy consumption, and environmental expectations continue to rise. In such an environment, decisions about when to replenish retailers and how much to deliver cannot be separated from decisions about how vehicles are routed. A change in replenishment timing affects inventory levels, product freshness, energy use, and delivery patterns, while a change in routing affects the feasibility, cost, and environmental impact of replenishment. These decisions are tightly connected, yet many planning approaches still treat them independently or rely on assumptions of stable demand that rarely hold in food logistics.

Against this background, this chapter formulates an integrated inventory–routing framework that explicitly accounts for the stochastic and non-stationary nature of demand in CFSCs. The central challenge addressed is to replenish retailers frequently enough to maintain freshness and service reliability, while avoiding excessive transportation activity, unnecessary emissions, and avoidable operational costs. Traditional replenishment policies, particularly fixed-quantity approaches such as the (R, Q) policy, struggle under these conditions because they offer limited adaptability when demand fluctuates across periods and locations. To overcome these limitations, this chapter adopts the static–dynamic (R, S) policy as the foundation of the proposed model. The (R, S) structure is more responsive to demand variability, allowing replenishment quantities to adjust dynamically while maintaining coordinated review periods. Building on this policy, the chapter develops a mixed-integer inventory–routing model that integrates service-level protection under uncertainty with explicit consideration of transport- and refrigeration-related CO_2 emissions.

The chapter is organised as follows. Section 3.1 defines the operational context and formally states the decision-making problem addressed in this research. Section 3.2 presents the complete mathematical formulation of the integrated inventory–routing model, including decision variables, parameters, objective functions, and constraints. Section 3.3 details the treatment of non-stationary stochastic demand and the probabilistic service-level mechanism used to safeguard customer availability. Section 3.4 introduces the environmental component of the model and explains how emissions arising from transportation and refrigeration activities are quantified. Finally, Section 3.5 brings the economic and environmental dimensions together, establishing the basis for the bi-objective optimisation approach and the computational analysis presented in the subsequent chapter.

Together, these sections form the conceptual and mathematical backbone of the thesis. They translate the practical challenges of CFSCs—including uncertainty, perishability, routing complexity, and sustainability requirements—into a structured optimisation framework that can be systematically analysed and evaluated through the computational experiments presented in the following chapter.

The optimisation model developed in this thesis is constructed around a bi-objective formulation that captures both economic and environmental considerations. One objective function minimises operational costs, including ordering, holding, and transportation expenses. The second objective minimises total expected emissions. This aligns the model with the sustainability frameworks discussed earlier in the literature review and reflects wider calls for environmentally responsible logistics made by Seuring and Müller (2008) and by the European Commission (2018). By quantifying the trade-offs between cost performance and environmental impact, the model provides decision makers with access to operational plans that are not only financially sound but also compliant with contemporary sustainability expectations.

3.1. Problem Context and Motivation

CFSCs have repeatedly been shown to operate under conditions fundamentally different from those of ambient supply networks. Earlier chapters of this review established that their defining characteristics include dependence on strict temperature control, susceptibility to rapid quality decay, and consistently high energy requirements across storage and transport operations (Aung and Chang, 2014; Mercier et al., 2017). These operational realities place chilled chains at a heightened level of vulnerability. Even seemingly small deviations in temperature or handling practices can accelerate microbial activity, reduce remaining shelf life, and compromise product safety. As Gustavsson et al. (2011) illustrate, the biological behaviour of perishable products is tightly bound to temperature integrity, meaning that logistics decisions have immediate consequences for both product quality and consumer well-being.

Because chilled chains sit at the intersection of biological fragility and logistical complexity, they are uniquely exposed to demand uncertainty, spoilage risks, and elevated CO_2 emissions. This dual exposure arises from both their operational configuration and their sensitivity to external shocks. Demand in food service and retail markets can fluctuate dramatically due to weather, seasonality, and behavioural shifts, causing frequent mismatches between inventory levels and consumption patterns. In parallel, refrigeration energy consumption increases with delivery frequency, load configuration, and transport conditions, creating a measurable environmental footprint across the chain (Ndraha et al., 2018).

As the literature review established, CFSCs are among the most complex and energy-intensive logistics chains within modern SCM. Maintaining temperature integrity throughout the distribution process is essential not only to preserve food quality and safety but also to comply with sustainability and environmental requirements. Despite its critical economic role, the CFSC faces major challenges related to high energy use, refrigeration inefficiency, GHG emissions, and product perishability. These challenges make the CFSC fundamentally different from conventional ambient SCs and turn its optimization into an interdisciplinary problem that

involves logistics, operations research, and environmental science (Montanari, 2008; Zhang and Mohammad, 2024).

These intertwined challenges help explain why traditional logistics planning tools are often not sufficient for CSCs. Many conventional models assume stable demand or neglect the influence of temperature on product quality and operational efficiency. As noted by Soysal and Bloemhof-Ruwaard (2018) and Zhang and Mohammad (2024), neglecting these factors oversimplifies the reality of CSC operations and limits the ability of planners to make informed, resilient decisions. Such models may appear operationally efficient on paper but fail once the biological behaviour of food products and the variability of demand are introduced. The inability of traditional models to capture these dynamics frequently leads to stockouts, product deterioration, and excess safety stocks, all of which increase cost and waste.

A significant gap in the literature concerns the treatment of temperature dynamics. The majority of optimisation models approach temperature as a static, binary condition by assuming that if a vehicle is refrigerated, products remain within the required thermal band (Ndraha et al., 2018). Temperature fluctuates throughout the journey. Variations occur across compartments, between different product types, and even within the same load. Temperature also changes because of operational actions, such as door openings, loading patterns, or the order in which products are delivered. Existing models, however, do not incorporate these thermal behaviours or account for the ways in which they interact with routing and loading decisions. As a result, they cannot fully capture the spoilage dynamics or shelf-life implications that emerge from real-world distribution processes. Recent studies point to these neglected areas as promising opportunities for future research, particularly in relation to quality decay functions, microbial growth, and thermal modelling (Iyer, 2025).

Vehicle configuration is another domain where current models impose simplifying assumptions. In practice, many distribution chains rely on dual-temperature or multi-compartment vehicles to deliver mixed chilled and frozen loads. Yet many optimisation frameworks, including commonly used inventory–routing models, assume single-compartment vehicles. This mismatch between practical vehicle configurations and model assumptions further limits the applicability of many existing CSC optimisation frameworks.

Demand modelling remains another considerable gap. Although some recent studies incorporate non-stationary or uncertain demand, most models still rely on known probability distributions or regular consumption patterns. The reality within decentralised food service networks is quite different. These markets experience fluctuations driven by weather, seasonality, menu rotations, local events, and consumer preferences. Demand patterns can shift rapidly and unpredictably. Against this backdrop, the CFSC is examined as an integrated network that converts perishable food inputs into consumer-ready products through a sequence of temperature-controlled operations influenced by time, temperature, and demand uncertainty. Figure 1 presents the schematic structure of the network investigated in this study. The network consists of a single DC and several geographically dispersed retailers. The DC replenishes retailers according to stochastic and non-stationary customer demand that varies over a finite planning horizon. Food demand is subject to seasonal effects, market fluctuations, and consumer preferences; therefore, it is treated as a random variable. Each retailer's demand must be met at a predefined minimum service level, while unmet demand results in backorders that accumulate until satisfied.

The integrated nature of the model helps avoid common pitfalls in CSC planning. For example, routing decisions made without reference to inventory dynamics may lead to frequent partial loads, wasted capacity, or unnecessary energy use. On the other hand, inventory plans developed without attention to routing feasibility may produce delivery schedules that are impractical in real distribution environments.

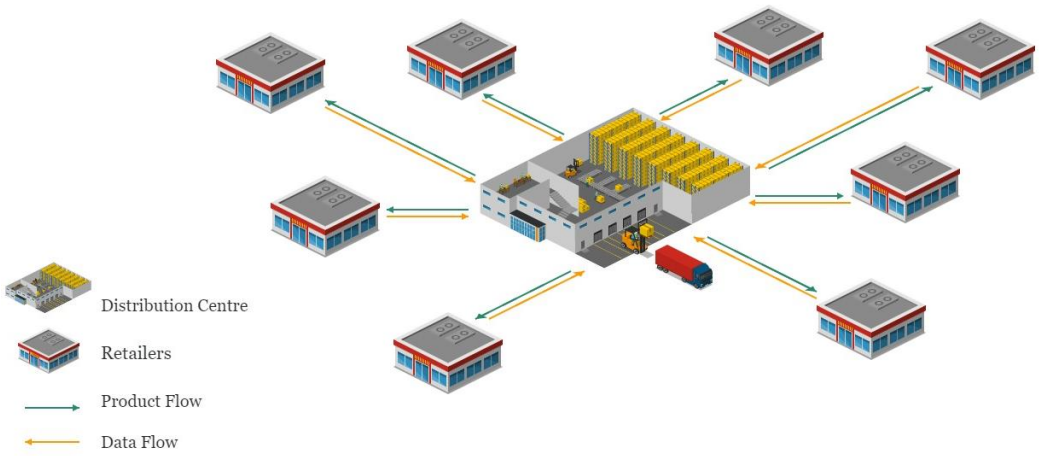


Figure 1: Schematic representation of the SC network

To manage this uncertainty, the study adopts the (R, S) inventory policy, where the review period (R) and the order-up-to level (S) are jointly determined. This policy allows decision-makers to adjust replenishment quantities dynamically in response to realised demand, which is essential in chains affected by non-stationary stochastic conditions. The reasons for selecting this policy, and its comparison with the traditional (R, Q) approach, are explained in Section 3.2. In contrast, the (R, Q) policy fixes both the order interval and quantity in advance, which limits flexibility in uncertain environments (Tarim and Kingsman, 2004).

To maintain model clarity and tractability, several simplifying assumptions are introduced. A single vehicle with sufficient capacity is available in each period to distribute products from the DC to retailers. The vehicle performs one route per period, beginning and ending at the DC, and visits only those retailers that require replenishment. The initial inventory of all retailers is assumed to be zero at the beginning of the planning horizon. Lead times are ignored because their inclusion would complicate the notation without significantly altering the model's fundamental structure.

The total expected chain cost consists of five major components:

- Inventory holding cost for carrying excess stock between periods
- Fixed replenishment cost incurred whenever a retailer places an order
- Purchasing cost for products obtained from the DC
- Vehicle dispatching cost incurred each time the vehicle departs the depot
- Transportation cost associated with travelling between retailers along the route

Because of the strong sensitivity of temperature-controlled operations, even minor changes in delivery frequency, route sequencing, or unloading duration can alter the thermal environment of the vehicle and accelerate product deterioration (Soysal and Bloemhof-Ruwaard, 2018). In addition to cost, environmental effects are explicitly considered. Cold logistics activities are recognised as major contributors to GHG emissions, mainly due to refrigeration and fuel use. The model includes five emission-generating processes:

- Travelling of empty vehicles between nodes
- Product transfer between nodes during delivery
- Primary refrigeration of the vehicle load at the depot before dispatch
- Additional load chilling during transfers between retailers
- Emissions generated when maintaining load temperature during unloading

Each of these processes contributes to the overall carbon footprint of the chain. Within this context, optimisation modelling extends beyond cost minimisation and becomes a mechanism for jointly addressing economic efficiency and environmental responsibility. Prior studies show that integrating inventory and transportation decisions can reduce logistics costs while simultaneously lowering energy consumption and waste generation in perishable goods SCs (Govindan et al., 2020; Iyer, 2025).

Therefore, optimizing inventory and routing decisions affects both cost and environmental performance. For example, reducing delivery frequency or optimizing route sequences can lower fuel and refrigeration energy consumption, but it may also increase inventory holding costs or affect service levels. This interdependence between economic and environmental outcomes represents the central motivation for the model developed in this study.

The main objective of this research is to determine replenishment schedules, order quantities, and routing plans that jointly minimise the total expected cost and total carbon emissions of the CFSC. The model captures the trade-off between these two goals: striving for lower cost can increase emissions, while emission reduction efforts may raise operational costs. This dual perspective highlights the importance of integrating sustainability into SC decision-making (Iyer, 2025).

To achieve this, a bi-objective mixed-integer stochastic model is developed. The formulation combines traditional inventory-routing decision variables with emission-related parameters, providing a framework that quantifies the trade-offs between financial performance and environmental impact.

The mathematical model, presented in Section 3.3, includes the expected cost and emission objectives, inventory balance equations, probabilistic service-level constraints following Tarim and Kingsman's (2004, 2006) approach, and routing constraints that link inventory and transportation decisions into one unified structure.

While this thesis adopts a bi-objective formulation to explicitly represent sustainability trade-offs, subsequent extensions of the model explored a single-objective cost-minimisation variant in which emissions were internalised within the cost structure. During collaborative refinement and preparation for journal publication, the formulation was simplified into a single-objective cost-minimization model that internalised emissions within the total cost function. This

adjustment, explained in Section 3.6, improved computational efficiency while maintaining environmental awareness in the cost structure.

Taken together, these characteristics highlight the need for optimisation models that explicitly integrate demand uncertainty, temperature-dependent operations, and environmental impacts within a unified decision framework. The next sections discuss the rationale for selecting the (R, S) policy, describe the mathematical formulation of the proposed model, and present the theoretical basis for the probabilistic service-level constraint used to represent demand uncertainty.

3.2. Justification of the (R, S) Policy

In any inventory setting, the choice of replenishment policy defines how frequently orders are placed and how much is ordered. Two of the most established frameworks in stochastic inventory management are the (R, Q) and (R, S) policies. Understanding the difference between them is essential before selecting a policy suitable for CFSCs.

The modelling approach developed in this research is shaped directly by the challenges identified throughout the literature review. CFSCs operate in an environment where demand is uncertain, temperature control is critical, and distribution networks are fragmented. In response to these conditions, this study adopts a replenishment framework that can cope with variability. The (R, S) policy provides such a structure. By specifying a fixed review interval together with an order-up-to level, it creates a replenishment rhythm that can absorb fluctuations in demand while still meeting service-level targets, as demonstrated in the foundational work of Tarim and Kingsman (2004). This policy becomes significantly more powerful when combined with a multi-period routing structure, allowing replenishment timing and routing decisions to be determined together. Integrating these decisions offers the possibility of reducing fuel consumption, improving vehicle utilisation, and lowering emissions, an outcome particularly relevant for energy-intensive CFSC operations, as underlined in the research of Soysal and Bloemhof-Ruwaard (2018).

Under the (R, Q) policy, the replenishment mechanism operates with a fixed-order quantity. Inventory levels are continuously monitored, and whenever the stock position drops to or below a specified reorder point (R), a replenishment order of constant size Q is triggered. The interval between orders is therefore variable, depending on how quickly demand depletes inventory, while the order quantity remains constant. This structure offers simplicity and predictability: once R and Q are established, the entire ordering mechanism runs automatically with minimal computational effort. However, because both parameters are predetermined, managers have little flexibility to adjust the plan when demand patterns shift unexpectedly.

The (R, S) policy follows a different logic. Here, inventory levels are reviewed every R periods rather than monitored continuously. At each review, the stock position is raised up to an order-up-to level (S). The order quantity is therefore the difference between the target level S and the current inventory at the time of review, meaning that order sizes vary according to realised demand. The review period R is usually fixed for planning coordination, but the replenishment amount adapts dynamically. This policy thus combines elements of both static and dynamic decision-making: timing is predetermined, while quantity responds to uncertainty.

Choosing between these two policies depends on the characteristics of the SC environment. The (R, Q) policy performs well in stable settings with stationary demand, whereas the (R, S) structure is better suited to volatile and uncertain conditions where adaptability is required.

The influential work of Soysal et al. (2015) extended the (R, Q) concept to a multi-period IRP that determined delivery routes and replenishment decisions simultaneously. Their model minimised the total expected cost consisting of transportation and holding components. Although the (R, Q) policy was advantageous for its simplicity, it lacked responsiveness when applied to CFSCs, where demand is both non-stationary and uncertain. Once a planning horizon begins, a fixed-quantity structure cannot react to unexpected demand fluctuations, forcing managers to rely on large safety stocks or risk product shortages.

Cold chains add further complexity through temperature requirements, perishability, and energy-intensive logistics. Under the (R, Q) framework, high safety stocks are often maintained to buffer against variability, but this approach increases holding costs and may lead to product spoilage or energy waste due to extended refrigeration. Hence, despite its computational convenience, the (R, Q) replenishment mechanism can be economically and environmentally inefficient for perishable products.

To address these shortcomings, this research reformulates the (R, Q) approach into a static–dynamic (R, S) structure, following Bookbinder and Tan (1988) and Tarim and Kingsman (2004), and adapts it to the CFSCs by explicitly including CO_2 emissions in the objective function. The (R, S) policy offers a practical balance between the rigidity of purely static models and the complexity of fully dynamic ones. Replenishment periods (R) are predetermined for coordination across the network, while order-up-to levels (S) are set in advance to guide decisions. The actual replenishment quantity, however, is calculated after demand is realised, allowing responsiveness to stochastic conditions.

This structure provides two important advantages. First, it maintains planning stability because review times are known in advance, enabling synchronized routing and transportation schedules. Second, it introduces flexibility by letting managers adjust order sizes without reconstructing the entire plan. The static–dynamic principle therefore creates a manageable yet adaptive mechanism that reflects how decisions are made in real CSC operations.

Fully dynamic strategies such as rolling-horizon models theoretically achieve optimal results because decisions are revised after every demand observation. Nevertheless, these methods are computationally demanding and often infeasible for daily operations in CFSCs, where each re-optimization would require new routing, vehicle dispatching, and refrigeration start-ups. Frequent rescheduling leads to excessive computation and high operational cost.

The bi-objective (R, S) inventory and routing model expands these concepts further by embedding them in a single integrated structure. Combining a replenishment strategy with a multi-period routing plan enables the model to represent two interdependent decision layers simultaneously. The first concerns the timing of replenishment for each retailer under non-stationary and uncertain demand conditions. The second concerns the construction of vehicle routes that limit transportation cost and emissions. The (R, S) policy thus provides a practical compromise between optimality and practical implement ability. It captures the key stochastic features of demand while keeping the decision process structured and computationally efficient. This makes it particularly appropriate for CFSCs, where decisions must be both

flexible and feasible in practice. By incorporating CO_2 emissions into the (R, S) framework, the model developed in this research also extends beyond economic efficiency to include environmental performance, allowing the evaluation of sustainability trade-offs in an integrated way.

In summary, the motivation for adopting the (R, S) policy in this study is threefold:

- Flexibility under uncertainty. The (R, S) framework accommodates stochastic demand by adjusting order quantities dynamically while retaining fixed review periods.
- Operational practicality. It reduces computational and scheduling burdens compared with fully dynamic methods, which require frequent re-optimization.
- Alignment with sustainability objectives. Integrating CO_2 emissions into the (R, S) formulation provides a more comprehensive assessment of CSCP, balancing economic and environmental goals.

The (R, S) policy therefore serves as the methodological foundation for the mathematical formulation presented in the next section, where both economic and environmental objectives are operationalized within a unified optimization framework.

3.3. Model Formulation under Demand Uncertainty

This section presents the formulation of the (R, S) inventory–routing model developed for a CFSC. The model integrates both economic and environmental objectives under stochastic demand conditions. It builds on classical inventory–routing frameworks but extends them to capture the specific characteristics of cold logistics, including temperature maintenance, energy intensity, and GHG emissions.

The SC considered in this study consists of a single item chain with one DC that serves multiple retailers. Customer demand at each retailer is stochastic and non-stationary, varying over time and location. Let the random variable d_{it} denote the demand of retailer i in period t. Each d_{it} follows a known probability density function $f_{it}(d_{it})$ and a cumulative distribution function $F_{it}(d_{it})$. Demands across retailers and time periods are assumed to be independent, reflecting the spatial and temporal variability typically observed in food markets.

Building on the multi-period IRP developed by Soysal et al. (2015) under the classical (R, Q) policy, this study reformulates the model using the static–dynamic (R, S) policy introduced by Tarim and Kingsman (2004). The (R, S) structure provides greater flexibility in responding to stochastic demand because replenishment timing is predetermined at the start of the planning horizon, while order quantities are calculated dynamically as actual demand is realised. This approach improves adaptability without compromising computational tractability. In addition, the model is extended to the CSC context by explicitly accounting for CO_2 emissions generated by transportation and refrigeration activities. This dual economic–environmental perspective allows the assessment of trade-offs between operational efficiency and sustainability performance.

The problem is represented on a complete directed graph $G = (V, A)$, where $V = \{0,1, \dots, |V|\}$ denotes the set of all nodes. Node 0 represents the DC, and the remaining nodes $V' = \{1,2, \dots, |V|\}$ correspond to retailers. The set of arcs $A = \{(i,j) \mid i,j \in V, i \neq j\}$ includes all possible travel paths between nodes. The planning horizon is divided into T discrete periods,

$t \in \{1,2,\dots,T\}$. A fleet of K identical vehicles is available, each with a finite capacity C. The vehicle set is denoted by $K = \{1,2,\dots,K\}$. For simplicity, both the DC and retailers are assumed to have unlimited storage capacity so that the analysis can focus on inventory and routing coordination rather than storage limitations.

During each period, each vehicle can perform at most one route, starting and ending at the DC. Vehicles may visit a subset of retailers that require replenishment, carrying the corresponding orders. It is not necessary to serve every retailer in every period; only those whose inventory positions reach or fall below their reorder points R_i are replenished. The initial inventory level of each retailer is set to zero ($I_{i0} = 0$) to represent the start of a new planning cycle. Replenishment lead times are ignored to maintain clarity of formulation, although they could be introduced in future versions of the model without altering its structure.

A probabilistic service-level constraint is imposed to ensure that demand in each period is met with a minimum probability α. When demand cannot be fully satisfied, backordering is permitted, and the unsatisfied portion is carried over to the next period. Products are assumed to have an indefinite shelf life under proper temperature control, meaning that no deterioration or spoilage occurs within the planning horizon. This assumption allows the model to concentrate on the coordination of logistics and environmental aspects rather than product decay.

The objective of the model is to determine the optimal replenishment periods, order-up-to levels, and delivery routes that minimise both the total expected chain cost and the total CO_2 emissions generated across the CFSC. The resulting problem is formulated as a bi-objective mixed-integer stochastic programming model with two interdependent objective functions, one economic and one environmental, linked through shared operational decision variables.

Table 6: Notations of the proposed (R, S) model

Sets and Indices	
$\mathcal{T} = \{1,2,\dots,\mathrm{T}\}$	Set of discrete planning periods indexed by t, t'
$\mathcal{R} = \{1,2,\dots,\mathrm{R}\}$	Set of retailers indexed by i, j
$\mathrm{C} = \lvert\mathcal{R}\rvert$	Number of retailers (used in MTZ subtour constraints)
$\mathcal{N} = \{0\} \cup \mathcal{R}$	Set of network nodes including depot node 0
Parameters	
$\mathrm{d_{it}}$	Retailer i random variable demand in period t with mean $\mu_{\mathrm{d_{it}}}$ and standard deviation $\sigma_{\mathrm{d_{it}}}$
ρ_{it}	Coefficient of demand variation ($\sigma_{\mathrm{d_{it}}}/\mu_{\mathrm{d_{it}}}$)
$\mathrm{f_{it}(d_{it})}$	Probability density function of demand
$\mathrm{F_{it}(d_{it})}$	Cumulative distribution function of demand
$\mathrm{F}^{-1}_{\mathrm{d_{i,t-s+1}+d_{i,t-s+2}+\cdots+d_{i,t}}}$	Inverse cumulative distribution function of the total demand for retailer i as of period t since the last replenishment in period $\mathrm{t} - \mathrm{s} + 1$.
α	Customer service level
f	Fixed dispatch cost incurred when the vehicle leaves the depot
$\mathrm{o_i}$	Fixed ordering cost per replenishment at retailer i
$\mathrm{h_i}$	Unit inventory holding cost at retailer i

q	Unit purchasing cost
v_{ij}	Transportation cost from node i to node j
a_{ij}	Base (load-independent) emissions between nodes i and j
g_{ij}	Emission factor per unit of load from node i to node j
l	Unit CO_2 emission of load primary refrigeration
n_{ij}	Unit CO_2 emission of load chill transfer from node i to node j
e	Unit CO_2 emission per replenishment event (Unloading)
M	A sufficiently large number
Decision Variables	
K_{it}	The replenishment variable is equal to 1 if a replenishment order for retailer i is placed in period t, otherwise 0
Y_{ijt}	The routing variable is equal to 1 if travelling from node i to node j in period t, otherwise 0
Z_t	The vehicle dispatching variable is equal to 1 if at least one retailer is visited in period t, otherwise 0
$P_{itt'}$	The decision variable for the latest replenishment is equal to 1 if the latest order prior to period t was in the period $t - t' + 1$, otherwise
I_{it}	Inventory level of retailer i at the end of period t
B_{it}	The order quantity of retailer i to the warehouse in period t
W_{ijt}	The load transferred from retailer i to retailer j in period t
U_{it}	Auxiliary variable for sub-tour elimination

The proposed model is designed to minimise both the total expected cost of the CFSC and the total GHG emissions associated with its operations. Accordingly, two objective functions are formulated.

- **Objective Functions:**

$$minimise\ \mathrm{E}\{TC\} = \sum_{i\in\mathcal{R}}\sum_{t\in\mathcal{T}}(o_i\,K_{it} + h_i\,\mathrm{E}\{I_{it}\} + q\,\mathrm{E}\{B_{it}\}) + \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\sum_{t\in\mathcal{T}} v_{ij}\,Y_{ijt} + \sum_{t\in\mathcal{T}} f\,Z_t \quad (1)$$

$$minimize\ TG = \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\sum_{t\in\mathcal{T}} a_{ij}Y_{ijt} + \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\sum_{t\in\mathcal{T}} W_{ijt}(g_{ij}+n_{ij}) + \sum_{j\in\mathcal{R}}\sum_{t\in\mathcal{T}} W_{0jt}l + \sum_{j\in\mathcal{R}}\sum_{t\in\mathcal{T}} eK_{jt} \quad (2)$$

The first objective function, Equation (1), minimises the total expected cost of the chain's inventory–routing over the planning horizon T. This cost consists of several components.

- The first summation represents the total cost incurred at retailer $i$in period t, including fixed ordering cost (o_iK_{it}), expected inventory holding cost ($h_iE[I_{it}]$), and expected backorder cost ($qE[B_{it}]$).

- The second summation accounts for transportation costs, expressed as the cost per distance or per unit of load moved between nodes $i$and j($v_{ij}Y_{ijt}$).
- The final term represents the fixed vehicle dispatching cost (fZ_t) associated with operating a vehicle during period t.

Together, these components capture the primary economic drivers of the chain, balancing ordering, holding, shortage, and routing costs in an integrated framework. The expectation operator $E\{\cdot\}$ is used because the demand is stochastic, which implies that the inventory levels (I_{it}) and backorders (B_{it}) are also random variables. Consequently, the total chain cost must be represented in expected terms.

The second objective function, Equation (2), aims to minimise the total GHG emissions generated across all logistical activities within the CFSC. These emissions are the result of multiple energy-intensive processes related to both transportation and refrigeration.

- The first term represents the emissions produced by vehicle movement without load (empty travel) from node $i$to node j in period t.
- The second term captures emissions from product transfer and additional cooling during transportation between nodes i and j. These emissions depend on the vehicle load weight (W_{ijt}) and on the distance-based factors g_{ij} and n_{ij}.
- The third term accounts for primary refrigeration emissions, indicating the energy required to cool the vehicle load before departure from the DC to retailer j.
- The final term represents unloading emissions, which occur when the vehicle doors are opened at delivery points and additional cooling energy is required to maintain product temperature stability.

Together, these components quantify the environmental footprint of CSCL operations, linking routing and inventory decisions to the chain's total CO_2 emissions. The combination of the two objective functions forms a bi-objective mixed-integer stochastic programming model, which allows for analysing trade-offs between cost efficiency and environmental sustainability.

The proposed model is governed by a set of constraints that describe the logical and operational relationships among inventory, replenishment, and routing decisions. These equations define the feasible region of the bi-objective inventory–routing problem under stochastic demand. Each constraint serves a specific purpose in linking inventory management with vehicle routing while ensuring service quality and practical operability.

- **Constraints:**

$$I_{i0} = 0 \tag{3}$$

$$E\{I_{it}\} + E\{d_{it}\} = E\{B_{it}\} + E\{I_{it-1}\} \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \tag{4}$$

$$E\{B_{it}\} \leq M\, K_{it} \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \tag{5}$$

$$E\{W_{ijt}\} \leq M\, Y_{ijt} \qquad \forall t \in \mathcal{T}, i \in \mathcal{N}, i \neq j \tag{6}$$

$$K_{it} \leq Z_t \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \tag{7}$$

$$\sum_{i \in \mathcal{N}} E\{W_{ijt}\} - \sum_{i \in \mathcal{N}} E\{W_{jit}\} = E\{B_{jt}\} \qquad \forall t \in \mathcal{T}, j \in \mathcal{R} \tag{8}$$

$$E\{I_{it}\} \geq \sum_{t' \in \mathcal{T}} \left(F^{-1}_{d_{i(t-t'+1)} + d_{i(t-t'+2)} + \cdots + d_{it}}(\alpha) - \sum_{k=t-t'+1}^{t} E\{d_{ik}\} \right) P_{it't} \tag{9}$$

$$\forall t \in \mathcal{T}, i \in \mathcal{R}$$

$$P_{itt'} \geq K_{i,t-t'+1} - \sum_{k=t-t'+2}^{t} K_{it} \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \tag{10}$$

$$\sum_{t' \in \mathcal{T}} P_{itt'} = 1 \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \tag{11}$$

$$\sum_{i \in \mathcal{N}, i \neq j} Y_{ijt} = K_{jt} \qquad \forall t \in \mathcal{T}, j \in \mathcal{R} \tag{12}$$

$$\sum_{j \in \mathcal{N}, i \neq j} Y_{ijt} = K_{it} \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \tag{13}$$

$$U_{it} - U_{jt} + C\, Y_{ijt} \leq C - 1 \qquad \forall t \in \mathcal{T}, i, j \in R, i \neq j \tag{14}$$

$$0 \leq U_{it} \leq C - 1 \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \tag{15}$$

$$E\{W\}, E\{B\}, E\{I\}, U \geq 0 \tag{16}$$

$$Y, Z, K \in \{0,1\} \tag{17}$$

Constraint (3) sets the initial inventory level of each retailer to zero. This assumption represents the start of a new planning cycle in which all retailers begin without stock and must rely on subsequent replenishments from the DC.

Constraint (4) defines the expected inventory balance for each retailer and period. It states that the expected inventory at the end of period t, plus the expected demand during that period, must equal the expected backorders and the inventory carried over from the previous period. In other words, it ensures that all inflows (orders received) and outflows (demand and backorders) remain consistent over time. This balance is the foundation of every inventory control model, representing the physical law of stock conservation.

Constraint (5) is a logical linking condition that ties the backorder variable to the replenishment decision. The binary variable K_{it} equals one if retailer $i$places an order in period t, and zero otherwise. The constant M is a large number used to deactivate the constraint when no replenishment occurs. This formulation ensures that backorders can only exist if a replenishment decision has been made for that retailer.

Constraint (6) links the expected vehicle load W_{ijt} to the routing variable Y_{ijt}. It states that load transfer between nodes i and j can occur only if the vehicle travels along the corresponding arc. If $Y_{ijt} = 0$, meaning the arc is not used, the expected load on that path must also be zero. This constraint prevents infeasible flow of goods through unused routes.

Constraint (7) connects replenishment and vehicle dispatching decisions. The binary variable Z_t equals one if a vehicle is dispatched in period t. This restriction ensures that a vehicle can only depart if at least one retailer places an order during that period.

Constraint (8) expresses load conservation. It ensures that the difference between the load entering and leaving a retailer equals the expected quantity that retailer receives (or backorders) from the DC. This condition maintains a consistent flow of goods along each route and enforces that vehicle capacity and customer orders remain balanced.

In inventory mechanisms with uncertain demand, it is important to ensure that a minimum service level is maintained. Tarim and Kingsman (2006) proposed a probabilistic reformulation that defines inventory and service-level relationships through Constraints (9) to (11).

Constraint (9) enforces the service-level condition that the expected inventory at the end of each period should be sufficient to satisfy at least a proportion α of total demand occurring between the most recent replenishment and the current period. Here, $F^{-1}_{d_i(t-t'+1,t)}(\alpha)$ denotes the inverse cumulative distribution function of demand, representing the stock level required to achieve a service probability of α. The binary variable $P_{it't}$ equals one if the most recent replenishment before period $t$occurred in period $t - t' + 1$. This formulation ensures that each retailer holds enough stock to cover unpredictable fluctuations in demand between two consecutive orders.

Constraint (10) identifies the most recent replenishment period. It activates the corresponding $P_{it't}$ variable if a replenishment was made in period $t - t' + 1$ and none occurred afterward before period t. This mechanism allows the model to trace back to the latest order and correctly allocate the demand intervals used in the service-level formulation.

Constraint (11) ensures uniqueness by requiring that each period has exactly one most recent replenishment reference. This avoids ambiguity about which prior order period applies when calculating safety stock levels. The probabilistic constraint can be interpreted more intuitively by expressing it in terms of service level probability:

$$Pr\ \{I_{it} \geq 0\} \geq \alpha \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \tag{18}$$

This means that the inventory level at the end of each period must be non-negative with at least probability α. So, the stock available should be sufficient to satisfy at least α proportion of potential demand realizations. If the random demand follows a normal distribution, Tarim and Kingsman (2004) derived the following linear equivalent of Constraint (9):

$$E\{I_{it}\} \geq \sum_{t' \in \mathcal{T}} z_\alpha\, \rho_{it} \left(\sum_{m=max\,(1,t-t'+1)}^{t} E^2\{d_{im}\} \right)^{\frac{1}{2}} P_{it't} \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \tag{19}$$

Here, z_α is the standard normal quantile corresponding to service level α, and ρ_{it} denotes the standard deviation of demand. This expression linearizes the probabilistic constraint, allowing it to be handled more efficiently by optimization solvers.

The next group of constraints governs vehicle routing and ensures logical flow between nodes. Constraints (12) and (13) ensure route continuity. They guarantee that if a retailer is visited in each period, there is both an inbound and outbound connection for that node. In other words, if a vehicle arrives at retailer i, it must also leave the retailer and continue its route. These constraints prevent incomplete or infeasible tours.

Constraints (14) and (15) are sub-tour elimination constraints, commonly used in vehicle routing models. The continuous variable U_{it} represents the position of retailer i in the visiting sequence during period t. Together, these constraints ensure that each vehicle forms a single continuous route that starts and ends at the DC, without creating isolated loops among subsets of retailers.

Constraint (16) specifies non-negativity for expected inventory, backorder, load, and routing order variables, reflecting their real-world meaning.

Constraint (17) defines the binary nature of the main decision variables. Y_{ijt} indicates whether the route between nodes i and j is used in period t, Z_t shows whether a vehicle is dispatched in period t, and K_{it} represents whether retailer i places an order in that period.

Together, Constraints (3) to (17) provide a complete logical description of the mechanism. They link inventory dynamics with vehicle routing, ensure service-level reliability, prevent sub-tours, and maintain consistency between ordering, transportation, and emission-related activities. The model therefore captures the interdependence of logistical and environmental decisions, allowing for realistic and sustainable optimisation of cold food distribution under uncertainty.

3.4. Analytical Derivation of Equation Nine

This section explains the analytical steps leading to Equation (9), which defines the probabilistic service-level constraint in the model. The derivation follows the classical stochastic inventory formulation of Tarim and Kingsman (2004, 2006) and extends it to the CFSC context, where ensuring both product availability and temperature reliability is critical. The aim of this derivation is to express the minimum expected inventory required at each period to achieve a desired service level α, while considering the uncertain and time-dependent nature of demand. The reasoning builds gradually from a single-period perspective to a multi-period cumulative formulation that accounts for the time elapsed since the last replenishment.

We begin with the concept of the order-up-to level, denoted by S_t. This represents the stock position immediately after a replenishment at the start of period t. It serves as the maximum inventory available to satisfy the stochastic demand during that period. If no new order is placed in period t, meaning $Q_t = 0$, the order-up-to level is simply equal to the ending inventory of the previous period. When a replenishment is made, the expected ending inventory can be expressed as:

$$E\{I_{it}\} = E\{S_{it}\} - E\{d_{it}\} \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \qquad (20)$$

Equation (20) shows that the expected stock at the end of each period equals the order-up-to level minus the expected demand. This identity captures the fundamental balance between what is available and what is consumed. The goal of service-level control is to ensure that this available stock can meet demand with a high probability. Therefore, the probabilistic condition is formulated as:

$$P(d_{it} \leq S_{it}) \geq \alpha \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \qquad (21)$$

This means that the probability of stock being sufficient to cover demand in each period must be at least α. The service level α is typically chosen according to managerial or contractual requirements, such as 95 % or 99 % (see Tarim and Kingsman, 2006). In practical CSC operations, such a target ensures that products like dairy, meat, or fresh produce are available at retail outlets almost all the time, avoiding both stockouts that interrupt sales and unnecessary emergency shipments that increase energy use.

Cold food retailers do not always place orders every period. The replenishment cycle can span several periods, depending on demand variability, temperature constraints, and transport capacity. Suppose the last replenishment before period t occurred in period $t - t' + 1$. The stock received then must satisfy cumulative demand over t' periods, from $t - t' + 1$ up to t. To maintain the required service level over this entire replenishment cycle, we need:

$$P\left(\sum_{n=t-t'+1}^{t} d_{in} \leq S_{i,\ t-t'+1}\right) \geq \alpha \qquad \forall t, t' \in \mathcal{T}, i \in \mathcal{R} \qquad (22)$$

Equation (21) ensures that the total demand occurring between two consecutive orders does not exceed the stock available immediately after the last replenishment with probability α. Let $F^{-1}_{d_i(t-t'+1,t)}(\cdot)$ be the inverse cumulative distribution function of this aggregated demand. Using the quantile concept, we can restate the service-level requirement as:

$$S_{i,t-t'+1} \geq F^{-1}_{d_{i,\ t-t'+1,t}}(\alpha) \qquad \forall t, t' \in T, i \in R \qquad (23)$$

This expression defines the minimum starting inventory level that guarantees a service level α across several periods. The larger the uncertainty in demand, the higher the quantile value and thus, the greater the safety stock needed to maintain reliability. In CSCs, such safety stock represents buffer capacity not just in physical inventory but also in refrigeration energy and space. Too little stock risks empty shelves and lost freshness, while too much stock increases energy costs and CO_2 emissions due to longer cooling times. By substituting Equation (23) into the single-period inventory relationship (20), we obtain:

$$E\{I_{it}\} \geq F^{-1}_{d_{i,\ t-t'+1,t}}(\alpha) - \sum_{n=t-t'+1}^{t} E\{d_{in}\} \qquad \forall t, t' \in \mathcal{T}, i \in \mathcal{R} \qquad (24)$$

Equation (24) states that the expected ending inventory must be at least the difference between the α-quantile of cumulative demand and the expected cumulative demand since the last replenishment. The right-hand side represents the safety stock required to achieve the desired service level. This term measures the "insurance inventory" that protects against unexpected surges in demand. In food distribution, this reserve also protects against minor temperature-related losses or variations in customer purchases.

The value $F^{-1}_{d_i(t-t'+1,t)}(\alpha)$ can be pre-calculated for all relevant combinations of t' and t, provided that the demand distribution parameters are known or estimated from historical data. To connect this analytical expression with the model's decision structure, we define a binary variable $P_{it't}$, which takes the value 1 if the most recent order before period t was placed in period $t - t' + 1$, and 0 otherwise. With this definition, the service-level condition can be rewritten as:

$$E\{I_{it}\} \geq \left(F^{-1}_{d_{i,t-t'+1,t}}(\alpha) - \sum_{n=t-t'+1}^{t} E\{d_{in}\} \right) . P_{it't} \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \qquad (25)$$

This condition ensures that the appropriate safety stock is applied only to the relevant demand interval that corresponds to the latest replenishment. Since each period must have exactly one "most recent" replenishment, the following uniqueness constraint applies:

$$\sum_{t'=1}^{T} P_{it't} = 1 \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \qquad (26)$$

To maintain logical consistency between the ordering variable and the binary indicator, we add:

$$P_{it't} \geq K_{i,t-t'+1} - \sum_{n=t-t'+2}^{t} K_{i,n} \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \qquad (27)$$

Equation (27) ensures that $P_{it't} = 1$only when an order was placed in period $t - t' + 1$ and no subsequent orders occurred before t. Here K_{it} is the binary decision variable indicating whether

retailer i places an order in period t. Considering expected values explicitly, the final relationship becomes:

$$E(I_{it}) \geq \left(F^{-1}_{d_{i,t-t'+1,t}}(\alpha) \; - \sum_{n=t-t'+1}^{t} E(d_{in}) \right) . P_{it't} \qquad \forall t \in \mathcal{T}, i \in \mathcal{R} \qquad (28)$$

Equation (28) corresponds directly to Equation (9) in the mathematical model. It expresses the probabilistic service-level constraint in an expected-value form that can be handled efficiently by the mixed-integer optimisation solver. Conceptually, this equation ensures that for every retailer and period, the model maintains enough expected inventory to meet cumulative demand between two consecutive orders with at least probability α. In other words, the formulation mathematically enforces a reliability level that balances service quality with cost and emissions.

In practice, this means that vehicles are dispatched and inventory is held in such a way that product availability at each retailer is almost certain, yet without excessive energy consumption from over-cooling or unnecessary replenishments. This balance between reliability and sustainability is what differentiates the proposed CSC model from classical cost-only formulations (see Montanari 2008; Soysal et al. 2015; Zhang and Mohammad 2024). Therefore, Equation (9) can be interpreted as the bridge between stochastic inventory theory and sustainable cold logistics. It transforms the abstract concept of service level into a quantifiable constraint that directly influences both economic and environmental objectives. By integrating this equation, the model ensures that CSC operations remain efficient, resilient, and environmentally responsible even under uncertain and variable demand conditions.

3.5. Performance interpretation and KPIs

A final component of the model relates to its alignment with the broader KPI landscape discussed earlier in the literature. The model reflects several of the most important indicators used to evaluate CSCP. Some of these indicators are integrated directly through its objective functions and constraints. Others arise indirectly through the model's optimisation logic. This dual alignment ensures that the framework remains connected to established performance measures while still offering analytical flexibility.

Beyond numerical optimisation outcomes, the results can also be interpreted through a performance measurement perspective. The model also engages deeply with the measurement of performance through key indicators. SC monitoring tools offer practical guidelines for bridging planning and execution, as described by Chae (2009), and benchmarking is widely seen as an important mechanism for evaluating performance effectiveness (Shah and Singh, 2000). CFSCs, however, span a wide array of performance dimensions, including efficiency, sustainability, technology use, quality, and logistics responsiveness. As noted by Gunasekaran et al. (2004), Shashi et al. (2018), Turan and Ozturkoglu (2020), Akram (2023), and Chermala et al. (2024), these indicators collectively capture the multifaceted challenges of CSC operations.

Yet many KPIs proposed in the literature require real-time sensing, biochemical assessments, or behavioural data that extend beyond the boundaries of mathematical optimisation. For this reason, the proposed optimisation model evaluates performance using a subset of KPIs that can

be meaningfully operationalised through decision variables, constraints, and objective functions. Economic indicators feature prominently in the model. Total chain cost, transportation cost, and cost minimisation objectives are embedded directly in the first objective function, reflecting the emphasis on cost performance in performance frameworks such as those developed by Kaplan and Norton (1992) and applied more recently to perishable SCs by Shashi et al. (2018) and Akram (2023).

Environmental indicators are also central to the model. CO2 emissions and carbon reduction are incorporated explicitly within the second objective function, with emissions estimated through distance-based routing decisions and standard fuel emission factors. This reflects the perspective of recent sustainability-oriented studies that interpret emissions as a direct outcome of routing configuration and travel behaviour, including the work of Chen et al. (2019) and Farrukh et al. (2022). Inventory-related KPIs such as inventory levels, safety stock compliance, and demand satisfaction are also represented directly through the (R, S) policy and associated inventory balance constraints. These elements support adherence to service-level requirements while reducing stockout risk, and the incorporation of non-stationary demand strengthens the model's alignment with the growing recognition that CSCs increasingly face fluctuating and uncertain demand conditions (Aiello et al., 2012).

Taken together, these indicators illustrate the subset of performance dimensions that can be operationalised effectively within a mathematical optimisation framework. To clarify this alignment and show how the developed model maps onto the broader performance landscape discussed in the literature, Table 6 provides a consolidated summary of key CFSC KPIs, their definitions, supporting references, and the extent to which each is addressed in this research.

Table 7: Summary of CFSC-KPIs and Extent of Coverage in the Present Study

	#	KPI	Description	Key References	Addressed in this Research
Economic and Cost Performance	1	Cost efficiency / cost minimisation	Ability to reduce total operating cost while maintaining service and quality.	Kaplan and Norton (1992); Gunasekaran et al. (2004); Akram (2023)	Yes
	2	Total CFSC cost	Combined expenditure for raw materials, warehousing, energy, labour, transport, and handling.	Shashi et al. (2018)	Yes

	3	Total cost reduction	Measurable decrease in cumulative SC cost across periods.	Shashi et al. (2018); Akram (2023)	Yes
	4	Economic performance / profitability	Financial returns, profit margins, and economic value created along the chain.	Kaplan and Norton (1992); Farrukh et al. (2022); Belhadi et al. (2021)	-
	5	Market share growth	Change in firm's share of target market.	Shashi et al. (2018)	-
	6	Operational efficiency	Ratio of effective output to resource input.	Akram (2023)	Yes (Indirect)
	7	Energy consumption (efficiency)	Total energy used in CFSC operations.	Farrukh et al. (2022); Shashi et al. (2018)	Yes (Indirect)
	8	Dynamic pricing performance	Responsiveness of pricing strategies to perishability and market conditions.	Shashi (2021)	-
Time, Reliability and Responsiveness	9	Lead time	Total time required to fulfil an order.	Shashi et al. (2018); Akram (2023)	Yes (Indirect)
	10	Cycle time	Time required to complete one operational cycle.	Martin and Patterson (2009); Gunasekaran et al. (2004)	Yes (Indirect)
	11	Time optimisation	Extent to which processes minimise delays.	Chermala et al. (2024)	-

	12	Responsiveness	Ability to react quickly to demand or operational changes.	Akram (2023); Cerchione et al. (2018)	Yes (Indirect)
	13	Delivery reliability / delivery interruption	Consistency in on-time deliveries.	Turan and Ozturkoglu (2020); Chermala et al. (2024)	Yes (Indirect)
	14	Hard time-window compliance	Meeting strict delivery windows for perishables.	Chermala et al. (2024)	-
	15	Product quality	Nutritional, sensory, and microbiological attributes.	Chermala et al. (2024); Turan and Ozturkoglu (2020)	-
	16	Food safety compliance	Conformity with hygiene and hazard control standards.	Turan and Ozturkoglu (2020)	-
	17	Shelf-life (extension/monitoring)	Duration for which product remains safe and saleable.	Shashi et al. (2018); Akram (2023)	-
	18	Microbial risk monitoring	Measurement of microbial hazards.	Akram (2023)	-
Quality and Food Safety	19	Temperature-verified delivery	Deliveries completed at validated temperatures.	Chia et al., 2009; Chae, 2009	-
	20	Spoilage / waste rate	Percentage of product deteriorated or discarded.	Shashi et al. (2018)	Yes (Indirect)

	21	Packaging quality / standard packaging	Appropriateness of material, design, and hygiene.	Turan and Ozturkoglu (2020); Chermala et al. (2024)	-
	22	Protein level / water content / fibre content / pH value	Biochemical quality attributes used in quality tracking.	Chermala et al. (2024)	-
	23	Sanitation compliance	Hygiene in storage and transportation environments. biological/physical hazards.	Turan and Ozturkoglu (2020)	-
	24	Contamination risk control	Ability to prevent	Turan and Ozturkoglu (2020); Akram (2023)	-
	25	Inventory levels	Amount of stock across the chain.	Shashi et al. (2018)	Yes
	26	Inventory holding days	Time products remain in storage.	Shashi et al. (2018)	-
Inventory and Storage Performance	27	Handling and rotation performance	Efficiency of FIFO/FEFO and handling processes.	Turan and Ozturkoglu (2020)	-
	28	Cold storage capacity	Available temperature-controlled storage volume.	Akram (2023); Chermala et al. (2024)	-
	29	Temperature maintenance / temperature control	Stability of required temperature inside storage/transport.	Turan and Ozturkoglu (2020); Chermala et al. (2024)	-

	30	Mishandling rate	Errors in loading, unloading, and shelf placement.	Chermala et al. (2024)	-
	31	CO_2 emissions / CO_2 intensity	Carbon footprint generated by transport, storage, and manufacturing.	Shashi et al. (2018); Chen (2019)	Yes
	32	Carbon emission reduction	Extent of emission mitigation.	Shashi et al. (2018)	Yes
	33	Energy usage reduction	Lowering energy consumption in CFSC operations.	Shashi et al. (2018)	Yes (Indirect)
	34	Water usage reduction	Optimisation of water use in production/logistics.	Shashi et al. (2018)	-
	35	Food waste reduction	Reducing edible losses.	Shashi et al. (2018)	Yes (Indirect)
Environmental and Sustainability Indicators	36	Solid waste reduction	Minimising non-food waste.	Shashi et al. (2018)	-
	37	Toxic material reduction	Lower reliance on hazardous substances.	Shashi et al. (2018)	-
	38	Green packaging adoption	Use of eco-friendly materials.	Shashi et al. (2018)	-
	39	Recycling rate	Proportion of recycled materials.	Shashi et al. (2018)	-

	40	Empty running reduction	Percentage reduction of vehicles running without loads.	Chia et al. (2009); Zhang et al. (2011)	Yes (Indirect)
	41	Fuel efficiency	Fuel consumed per kilometre.	Shashi et al. (2018)	Yes (Indirect)
	42	Environmental responsibility / sustainability performance	Broader ecological performance.	Shashi (2021); Chermala et al. (2024)	Yes (Indirect)
	43	Traceability accuracy	Ability to track product location and history.	Shashi et al. (2018); Shashi (2021)	-
	44	Temperature monitoring accuracy	Reliability of temperature sensors/loggers.	Shashi et al. (2018)	-
	45	Information sharing and security	Integrity and speed of data exchange.	Chermala et al. (2024); Akram (2023)	-
	46	RFID/barcode/IoT system performance	Accuracy, read range, and reliability of identification technologies.	Shashi (2021); Turan and Ozturkoglu (2020); Chermala et al. (2024)	-
	47	Technological readiness	Maturity of digital infrastructure.	Zhang et al. (2011)	-
Technology and Digitalisation	48	Digital CSC tracking systems	Use of digital tools to monitor CFSC operations.	Akram (2023)	-
	49	Blockchain-based traceability	Immutable tracking of product data.	Akram (2023)	-
	50	Laser scanning microscopy / calibration tools	Precision tools for quality/safety validation.	Akram (2023)	-

	51	Data management reliability	Accuracy and reliability of digital records.	Shashi (2021)	-
	52	Transportation consolidation efficiency	Extent to which loads are combined to reduce trips.	Leng et al. (2020)	Yes
	53	Transport cost	Cost associated with distribution activities.	Leng et al. (2020)	Yes
	54	Vehicle routing performance	Efficiency of routing and planning algorithms.	Chermala et al. (2024); Shashi (2021)	Yes
	55	Intermodal transportation availability	Flexibility in using multimodal transport.	Chermala et al. (2024)	-
	56	Chilled transportation performance	Temperature-controlled transport compliance.	Turan and Ozturkoglu (2020)	-
Transportation and Logistics	57	Refrigerated vehicle deployment	Availability of specialised vehicles.	Akram (2023)	-
	58	Weather/traffic disruption impact	Influence of external disturbances on logistics.	Chermala et al. (2024)	-

Collaboration, Governance and Stakeholders	59	Collaboration effectiveness	Quality of horizontal/vertical collaboration.	Prajogo et al. (2018); Ataseven and Nair (2017)	-
	60	Information sharing efficiency	Speed and quality of shared information.	Cerchione et al. (2018); Chermala et al. (2024)	-
	61	Stakeholder responsibility fulfilment	Extent to which parties meet obligations.	Aday and Aday (2020); Govindan et al. (2017)	-
	62	Customer satisfaction	Perceived quality and service performance.	Kaplan and Norton (1992); Chermala et al. (2024)	-
	63	Performance pressure	Influence from powerful buyers/retailers.	Michalski et al. (2018)	-
Demand and Market Factors	64	Demand forecasting accuracy	Accuracy of predicting demand.	Chermala et al. (2024)	-
	65	Socioeconomic/environmental consumer behaviour	Consumer behaviour affecting CFSC performance.	Chermala et al. (2024)	-
	66	Market position	Competitive standing in the market.	Michalski et al. (2018)	-

Routing performance indicators are embedded through the structure of routing decisions themselves. Since distances travelled determine both cost and emissions, they serve as a direct proxy for logistics efficiency. Several KPIs emerge indirectly as well. Lead time and cycle time emerge naturally from the choice of review interval, since the model optimises replenishment frequency together with routing. This integrates temporal performance indicators that have been emphasised in studies by Martin and Patterson (2009) and Chermala et al. (2024). Operational efficiency also surfaces through the consolidation of routes and the reduction of unnecessary vehicle movements, reflecting the logistical sustainability perspectives of Fabbe-Costes et al. (2011).

Consistent with Turan and Ozturkoglu (2020), the results show that policies which reduce stockouts and excessive overstocking also mitigate deterioration risks. In parallel, energy efficiency is reflected indirectly through distance minimisation, with CO_2 emissions acting as a recognised proxy for fuel and refrigeration energy use (Zhang et al., 2011).

3.6. Simplified Publication Model

The model developed in this thesis was initially formulated as a bi-objective stochastic IRP designed to minimise both the total expected cost and the total CO_2 emissions of a CFSC. This formulation captured the complex trade-off that decision-makers face between financial efficiency and environmental responsibility in temperature-controlled logistics, where energy use and emissions are significant operational concerns. During the collaborative process of preparing the research for publication (Jahdi et al., 2024), the original model was further refined in cooperation with a co-author. The aim of this refinement was to improve computational efficiency, enhance interpretability, and align the formulation with the expectations of an applied journal audience. In this process, the bi-objective structure developed in the thesis was simplified into a single-objective expected-value formulation**,** while retaining the same conceptual and stochastic foundations. The published version therefore represents a streamlined adaptation of the thesis model rather than a conceptual departure from it.

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Although the paper initially presented the model in deterministic form for clarity, it was subsequently extended to account for stochastic demand using the expected-value operator $E\{\}$. Hence, the final published model was not purely deterministic but an expected-value stochastic formulation, consistent with the framework used in this thesis.

Both versions assume that demand follows a known probability distribution and that decisions are made to minimise the expected chain cost over this distribution. The stochasticity is therefore handled analytically rather than through simulation, using the probabilistic service-level reformulation of Tarim and Kingsman (2004, 2006). This strategy, known as the static–dynamic uncertainty approach, fixes replenishment periods while allowing order quantities to adapt to realised demand. It captures uncertainty explicitly yet remains tractable for mixed-integer optimisation. Thus, while the published version condensed the objectives into a single cost function, it retained the same stochastic logic that underpins the thesis model. Both belong to the family of expected-value stochastic programmes, balancing realism with solvability.

The thesis model treated inventory, routing, and emission as separate but interacting modules, allowing detailed analysis of their interdependencies. In the publication, these elements were fully integrated within a single mathematical structure, linking economic and environmental dynamics more directly.

Transportation emissions were expressed as functions of vehicle load, distance, and energy consumption, following the fuel-consumption-based model of Soysal et al. (2015). Refrigeration emissions were modelled using heat-transfer and door-opening effects as described by Köseli et al. (2023). Both emission sources were converted to equivalent energy costs and added to the objective function. This consolidation meant that emission effects influenced routing and scheduling decisions automatically. Instead of minimising emissions explicitly, the optimisation process naturally favoured energy-efficient routes and delivery schedules that reduced both cost and environmental footprint. The model therefore remained sustainable in intent but was mathematically leaner and more practical to solve.

The simplified model also adopted a more standardised notation and constraint structure to align with conventional IRP literature. Key adjustments included:

- Replacing the replenishment variable K_{it} with δ_{it} for clarity.
- Substituting routing and load variables (Y_{ijt}, W_{ijt}) with X_{ijkt} and F_{ijkt}, introducing an explicit vehicle index k.
- Combining vehicle-capacity and flow-conservation constraints into a single formulation.
- Expressing the probabilistic service-level condition based on $F^{-1}_{d_i(t-t'+1,t)}(\alpha)$ in a simplified linearised form.

These refinements improved readability, reduced the number of binary variables, and allowed larger numerical experiments without altering the model's conceptual foundations. The transition from the bi-objective to the single-objective form also reflected a managerial emphasis. The thesis version served as a theoretical exploration of sustainability trade-offs, while the published model was intended for practical decision support. In real logistics operations, managers typically optimise a single measure, often total cost, while monitoring environmental outcomes as performance indicators (Zhang and Mohammad, 2024). Computationally, the simplified model offered faster solution times and easier sensitivity analysis. It enabled experiments on how delivery frequency, vehicle capacity, or energy prices affect both cost and emissions, producing insights that are directly interpretable for practitioners. In this sense, the simplification was a deliberate balance between theoretical completeness and real-world usability.

3.7. Chapter Summary

This chapter established the formal problem definition and mathematical formulation of the optimisation framework used in this thesis. By integrating inventory replenishment and vehicle routing decisions under non-stationary stochastic demand, the chapter translated the operational complexities of CFSCs into a coherent mixed-integer modelling structure. The adoption of the static–dynamic (R, S) policy enabled a balance between planning stability and responsiveness, while probabilistic service-level constraints ensured customer availability under uncertainty.

In addition to economic considerations, the chapter explicitly incorporated environmental impacts arising from transportation and refrigeration activities. By embedding CO_2 emissions within the optimisation framework, the formulation captured the inherent trade-offs between cost efficiency and environmental performance that characterise modern CFSC operations. Together, these elements form the analytical foundation upon which the computational experiments and policy comparisons in the next chapter are based.

From a research development perspective, the model presented in Jahdi et al. (2024) should be viewed as a collaboratively refined and operationally simplified version of the bi-objective stochastic model developed in this thesis. The thesis formulation provides the theoretical foundation, explicitly representing the dual sustainability objectives under uncertainty. The published version, by contrast, translates these principles into a more compact, single-objective structure that is computationally tractable and suitable for empirical analysis. Together, these two formulations demonstrate the evolution of the research, from theoretical conception to practical implementation and illustrate how rigorous analytical modelling can be adapted to deliver both academic contribution and managerial relevance in sustainable CFSC optimisation.

4. Computational Experiments and Results

The previous chapters introduced the theoretical foundations of the proposed optimisation model, presented its mathematical formulation, and described the bi-objective solution approach based on the AEC method. However, the value of an optimisation model lies not only in its theoretical formulation but also in its performance under realistic SC conditions.

For this reason, this chapter presents a series of computational experiments designed to evaluate the behaviour, robustness, and practical performance of the proposed (R, S) inventory–routing model. The model is examined through two complementary sets of analyses. The first analysis focuses on a single illustrative case, enabling a detailed comparison between the (R, S) and the traditional (R, Q) policies under a controlled environment. This case example provides an intuitive understanding of the model's operational mechanisms, including replenishment triggering, safety stock evolution, and cost responses to stochastic demand.

The second analysis extends the evaluation by generating a large collection of randomly constructed problem instances that vary across demand patterns, uncertainty levels, planning horizon lengths, and vehicle dispatching costs. This broader experimentation allows the scalability and robustness of the model to be assessed across diverse operating conditions. By combining optimisation with Monte Carlo simulation, the analysis captures not only average chain behaviour but also the variability induced by stochastic demand.

Together, these computational experiments provide a comprehensive evaluation of the proposed model. They quantify the economic and environmental performance of the (R, S) policy, examine trade-offs between competing objectives, and identify the conditions under which the (R, S) policy outperforms alternative replenishment strategies. The chapter begins with the illustrative case example in Section 4.1.

4.1. The Bi-Objective Solution Method for Experiments

The bi-objective stochastic model developed in this Chapter minimises both the total expected cost and total CO_2 emissions across the CFSC. These objectives are inherently conflicting: emission reductions may require operational adjustments such as greener transport choices, tighter routing constraints, or inventory policies that increase holding and service-related costs. Therefore, a MOO method is required to generate efficient trade-offs between economic and environmental performance.

Beyond the inherent conflict between economic and environmental objectives, the practical applicability of integrated optimisation models is further constrained by computational complexity. Inventory–routing problems are widely recognised as computationally demanding, particularly when they involve multiple objectives, non-stationary stochastic demand, and multi-period planning horizons. Even when heuristic replenishment structures such as the (R, S) policy are adopted, they can reduce decision dimensionality and do not eliminate the underlying combinatorial nature of the problem. As noted by Soysal and Bloemhof-Ruwaard (2018) and Zhang and Mohammad (2024), solving these models for larger-scale networks may become time-consuming and unsuitable for routine operational use, highlighting a persistent trade-off between model realism and computational feasibility.

Positioned within the hierarchical optimisation frameworks discussed by Iyer (2025) and Zhang and Mohammad (2024), the present research focuses on tactical and operational decision-making in CFSCs. Specifically, it develops a multi-period inventory–routing model that jointly determines replenishment schedules under an (R, S) policy and vehicle routing decisions from a single DC to multiple retailers. The resulting bi-objective mixed-integer formulation extends existing CSC optimisation models by explicitly incorporating non-stationary stochastic demand, a feature often simplified or ignored in studies based on deterministic or stationary assumptions (Soysal et al., 2015; Tunc et al., 2011). To enable a transparent and systematic evaluation of economic–environmental trade-offs in the computational experiments, a Pareto-efficient solution set is generated using the AEC method introduced by Mavrotas (2009).

Among the available MOO techniques, the AEC method is adopted in this study to support the computational experiments. The method provides a structured and computationally efficient way to generate Pareto-optimal solutions, allowing the trade-off between cost and CO_2 emissions to be analysed systematically. The AEC method was first introduced by Mavrotas (2009) as an enhancement of the classical EC technique proposed by Chankong and Haimes (1983). The AEC method has since been widely applied in logistics and SC optimisation (Pan et al., 2013; Govindan et al., 2014). Its ability to handle non-convex Pareto fronts and mixed-integer formulations makes it particularly suitable for the bi-objective inventory–routing model examined in this chapter.

The classical EC method converts a multi-objective problem into a series of single-objective ones. This is done by selecting one objective to minimise directly while the remaining objectives are transformed into constraints bounded by user-defined thresholds, referred to epsilon values. A general multi-objective minimisation problem can be expressed as:

$$\begin{aligned} &\min F(x) = (f_1(x),\ f_2(x), \dots,\ f_n(x)) \\ &\text{subject to } x \epsilon X \end{aligned} \tag{29}$$

where $f_i(x)$ represents the i-th objective, and X is the feasible solution space. Using the EC approach, one objective, $f_1(x)$, is optimised while all other objectives are constrained by epsilon values as follows:

$$\begin{aligned} &min\, f_1\,(x) \\ &\text{subject to } f_i(x) \leq \mathcal{E}_i,\ i \in \{2,3, \dots, n\},\ x \epsilon X \end{aligned} \tag{30}$$

To ensure that meaningful trade-offs are explored, a pay-off table is created by solving each objective function independently to obtain its best and worst possible values. These values define the feasible epsilon range for each constrained objective:

$$\varepsilon_i \in [\min(f_i), \max(f_i)]$$

By varying these epsilon values incrementally within their ranges, a set of Pareto-optimal solutions is generated, outlining the trade-off surface between the objectives.

While the traditional EC method is intuitive, it can produce redundant or weakly efficient solutions, particularly when the Pareto front is non-convex or when objectives are measured on different scales. To address these issues, Mavrotas (2009) developed the AEC approach, by introducing slack variables and normalisation parameters. These additions improve numerical

stability and ensure that only Pareto-efficient solutions are generated during the optimisation process.

Each secondary objective is associated with two additional components. First, a slack variable u_i is introduced to measure any deviation from the specified epsilon bound of the i-th objective. Second, a normalisation parameter ϕ_i is used to scale deviations relative to the achievable range of each objective, thereby avoiding bias caused by differences in magnitude across objectives. Following Mavrotas (2009), the normalisation coefficient is defined as:

$$\varphi_i = \frac{max(f_1) - min(f_1)}{max(f_i) - \mathrm{m}in(f_i)} \tag{31}$$

Using the normalisation coefficients, the multi-objective problem is transformed into the augmented single-objective formulation. One objective is minimised directly, while deviations from the epsilon constraints imposed on the remaining objectives are penalised through weighted slack variables. The augmented formulation is given by:

$$min\, f_1(x) + \sum_{i=2}^{n} \varphi_i u_i \tag{32}$$

subject to $f_i(x) - u_i = \mathcal{E}_i,\ i \in \{2,3,\dots,n\},\ x\epsilon X,\ u_i \geq 0$

By incorporating the slack variables directly into the objective function, this formulation ensures that any violation of the epsilon constraints is explicitly penalised in proportion to the objective's scale. As a result, dominated or weakly efficient solutions cannot be selected as optimal, and each solution generated corresponds to a truly Pareto-efficient point. In this study, the AEC method is used to solve the bi-objective (R, S) inventory–routing model, where represents the total expected cost and $f_2(x)$ represents the total CO_2 emissions generated across the CFSC.

The process begins by constructing a pay-off table, obtained by minimising each objective independently while recording their respective minima and maxima. These values define the allowable epsilon range for emissions and cost.

Next, the AEC formulation in Equation 32, is then solved iteratively represents the total expected cost and $f_2(x)$ represents the total CO_2 emissions generated across the CFSC. For each epsilon level, the model is re-solved to produce a new non-dominated solution. The resulting set of solutions forms the Pareto frontier, which represents all efficient trade-offs between economic and environmental performance.

Compared with other methods such as the weighted-sum or goal-programming approaches, the AEC method offers several advantages. In particular, it avoids the scaling bias inherent in weighted formulations, performs reliably when the Pareto frontier is non-convex, and remains computationally efficient for mixed-integer problems.

These characteristics make it particularly well-suited for this CFSC optimisation model, where discrete routing, replenishment, and service-level decisions must be evaluated jointly under stochastic demand.

Overall, the AEC method provides a structured and robust approach for solving the bi-objective inventory–routing problem considered in this study. It converts the two-objective formulation into a series of single-objective subproblems, ensuring full Pareto efficiency while maintaining computational tractability. The resulting Pareto frontier forms the basis for the computational analyses presented in the following sections, beginning with the illustrative case example in Section 5.2.

4.2. A Case Example

To provide an intuitive and transparent comparison between the (R, Q) and (R, S) policies, this subsection presents a small numerical case example. The primary aim is to examine how the (R, S) policy performs relative to the traditional (R, Q) approach in terms of total SC cost when demand is uncertain over time. For clarity of interpretation, this experiment focuses exclusively on the economic objective, represented by the cost-minimisation function in Equation (1). The environmental objective introduced in the section 5.1 is intentionally excluded at this stage so that the cost-related mechanisms and differences between the two policies can be analysed in isolation. The SC considered in this case example consists of a single DC serving seven retailers over a planning horizon of seven periods. This setting reflects a small but realistic chilled-food distribution network. Customer service is controlled through a minimum service level of 0.95. In other words, each retailer is planned so that stockouts are very unlikely. Retailer demand is assumed to be stochastic and non-stationary: it follows a normal distribution with time-varying realisations, while the expected value remains constant across periods for simplicity. The service level is translated into a safety factor z_α, which denotes the standardised quantile of the normal distribution used in the safety stock calculations.

Several cost parameters are required to evaluate the performance of the two policies. In the case example, these parameters are assigned the following numerical values: holding cost $h_i = 1$, unit ordering cost $q = 0$, fixed ordering cost $o_i = 300$, fixed dispatching cost $f = 500$, and a constant CV $\rho_{it} = 0.05$ for all retailers and periods. These assumptions create a setting that holding inventory and placing orders are costly, but the purchase price itself is normalised to zero so that differences between the two policies arise mainly from inventory, ordering, and routing decisions rather than from product cost. Table 8 summarises the main parameters used in the numerical study.

Table 8: Parameters

Parameter	Values
R (The total number of retailers)	7
T (The total number of periods)	7
z_α (Customer service level)	1.644
ρ_{it} (CV)	0.05
h_i (Holding cost for retailer i)	1
q (Unit ordering cost)	0
o_i (Fixed ordering cost for retailer i in period t)	300
f (Fixed vehicle dispatching cost)	500

The expected demand levels for each retailer over the seven-period planning horizon are reported in Table 9. For this illustrative case, expected demand is assumed to be constant over

time for each retailer, while varying across retailers (for example, retailer 1 requires 75 units in each period). This simplified demand structure is intentionally adopted to ensure that the observed performance differences between the (R, Q) and (R, S) policies can be attributed to policy design, rather than to complex or highly variable demand patterns

Table 9: Expected demands

Retailers	*Periods*						
	1	*2*	*3*	*4*	*5*	*6*	*7*
1	*75*	*75*	*75*	*75*	*75*	*75*	*75*
2	*150*	*150*	*150*	*150*	*150*	*150*	*150*
3	*300*	*300*	*300*	*300*	*300*	*300*	*300*
4	*10*	*10*	*10*	*10*	*10*	*10*	*10*
5	*5*	*5*	*5*	*5*	*5*	*5*	*5*
6	*170*	*170*	*170*	*170*	*170*	*170*	*170*
7	*240*	*240*	*240*	*240*	*240*	*240*	*240*

Finally, Table 7 provides the travel cost matrix V_{ij} between the DC (node 0) and the seven retailers (nodes 1–7), as well as among the retailers themselves. These costs represent, for example, fuel, driver time, and refrigeration expenses associated with moving a vehicle between two locations. They are essential inputs for the routing component of the optimisation model, as they influence which delivery routes are preferred under each policy.

Table 10: Travel cost between nodes

Nodes	*Nodes*							
	0	*1*	*2*	*3*	*4*	*5*	*6*	*7*
0	*0*	*20*	*30*	*80*	*90*	*100*	*95*	*80*
1	*20*	*0*	*25*	*60*	*75*	*95*	*80*	*65*
2	*30*	*25*	*0*	*65*	*80*	*85*	*100*	*65*
3	*80*	*60*	*65*	*0*	*25*	*50*	*65*	*40*
4	*90*	*75*	*80*	*25*	*0*	*65*	*75*	*55*
5	*100*	*95*	*85*	*50*	*65*	*0*	*30*	*10*
6	*95*	*80*	*100*	*65*	*75*	*30*	*0*	*25*
7	*80*	*65*	*65*	*40*	*55*	*10*	*25*	*0*

Both the (R, S) and (R, Q) models were implemented and solved using IBM ILOG CPLEX 20.1.0, which determines, for each retailer and each period, whether a replenishment should occur and what quantity should be delivered. Once optimal replenishment decisions were obtained, the performance of each policy was evaluated using a Monte Carlo simulation with 10,000 replications. This simulation step is essential because demand is stochastic; it enables the estimation of expected total cost under many possible demand scenarios rather than relying on a single deterministic outcome. The large number of replications ensures that the resulting cost estimates are statistically stable and reliable.

The simulation results reveal a clear difference between the two policies. The (R, S) mechanism achieves a total expected cost of 13,282, whereas the (R, Q) policy results in a slightly higher cost of 13,583. This difference corresponds to a 2.2% cost reduction when shifting from an (R, Q) policy to an (R, S) policy. Although this percentage may appear

modest at first glance, in SC practice, especially in CSCs where margins are tight, such improvements represent meaningful operational savings.

The underlying reason for this cost difference becomes evident when examining how each policy handles uncertain demand. Figure 2 illustrates the cumulative safety stock levels under both approaches across the seven-period planning horizon. The contrast between the two policies is immediate: the (R, S) policy consistently results in lower cumulative safety stock than the (R, Q) policy.

This behaviour can be explained by the structural characteristics of each policy. Under the (R, Q) policy, once a retailer's inventory position falls below the reorder point R, a fixed quantity Q is ordered. Because orders occur in fixed increments and at fixed times, the retailer lacks recourse actions to react to unexpectedly high demand within a cycle. As a result, the retailer must hold large safety stocks to protect against all possible demand fluctuations over the entire replenishment cycle.

In contrast, the (R, S) policy offers significantly more flexibility. Whenever the inventory position drops below the reorder level, replenishment occurs up to a target inventory position S. This allows the retailer to react more frequently and more responsively to changes in demand. Because replenishment can occur sooner and in variable quantities, safety stock only needs to cover the demand variation between the current period and the next replenishment opportunity, not the entire cycle. This structural difference explains the much lower safety stock levels visible in Figure 2.

Lower safety stock naturally translates into lower holding costs, which represent a major portion of total SC cost, particularly in CSCs where refrigeration is expensive. Additionally, the (R, S) policy leads to fewer ordering events and more efficient inventory movements, which further reduce fixed ordering and unit-level ordering costs. Together, these effects contribute to the lower total expected cost achieved by the (R, S) model.

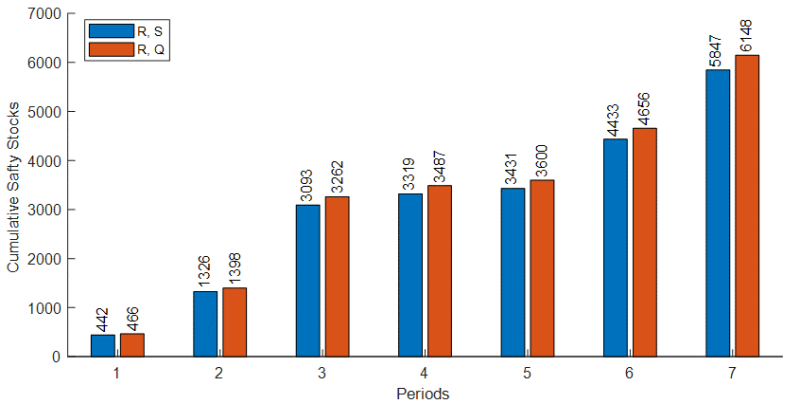


Figure 2: Case example cumulative safety stocks under (R, S) and (R, Q) policies

Because this study focuses on the FSC, where products are highly perishable and freshness are central to customer value, the differences in safety stock behaviour between the (R, S) and (R, Q) policies become even more consequential. In CSCs, lower safety stocks generally imply shorter storage times, faster inventory turnover, and products that reach consumers with a higher remaining shelf life. When retailers hold only the inventory they truly need, as is the case under the (R, S) policy, products move through the chain more quickly, reducing the

likelihood of quality deterioration, spoilage, and waste. As a result, customer satisfaction tends to increase, while the retailer's risk of profit loss due to expired products declines.

In contrast, the (R, Q) model generates relatively large safety stocks from the very first periods. While this may improve protection against uncertain demand, it also leads to longer storage durations for temperature-sensitive goods. For many fresh food categories, extended storage, even under controlled temperatures, accelerates microbial deterioration and reduces overall product quality. This can negatively affect both consumer experience and brand reputation. More importantly, from a sustainability standpoint, the unnecessary accumulation of stock increases the likelihood of disposal due to expiration, contributing to food waste and avoidable environmental burdens.

To further emphasize the structural differences between the two policies, the case study is extended to a 100-period horizon, and the resulting cumulative safety stock levels are shown in Figure 3. The contrast becomes dramatic when the horizon expands.

Under the (R, Q) policy, cumulative safety stock grows rapidly and non-linearly, reaching extremely high levels by the end of the horizon. This behaviour stems from the fixed-quantity nature of the policy: because replenishments occur in predetermined increments Q, retailers must carry large safety buffers to shield themselves from potential demand variability over each cycle. As the number of periods grows, this buffer accumulates repeatedly, causing total safety stock to escalate at an accelerating rate. Such behaviour translates into very high holding costs, making the (R, Q) policy increasingly unattractive and in many real-world CSC settings, practically infeasible.

By contrast, the (R, S) policy produces a far more stable and controlled pattern of inventory accumulation. Its cumulative safety stock increases slowly, reflecting the ability of the policy to adjust replenishment quantities dynamically in response to demand conditions. This flexibility prevents excessive inventory build-up and keeps holding costs low even over extended horizons. The smoother trajectory in Figure 3 demonstrates that (R, S) remains financially and operationally sustainable, whereas (R, Q) scales poorly when the planning period is long.

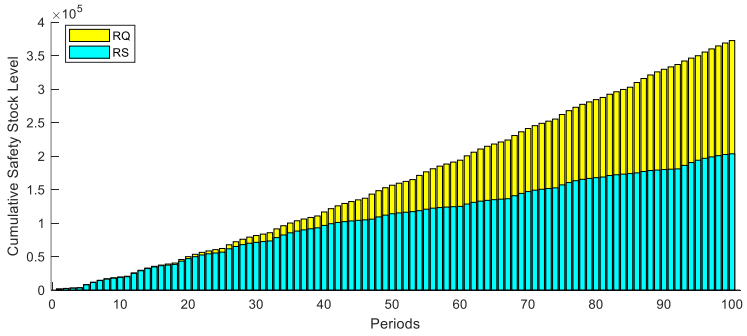


Figure 3: Cumulative safety stocks under the (R, S) and (R, Q) policies for 1000 days

Shifting from the (R, Q) to the (R, S) policy also affects individual components of the total cost. While the unit ordering cost q, the fixed dispatch cost f, and the transportation cost $v$experience only minor changes, the holding cost component decreases substantially. This reduction results directly from the lower safety stock levels under the (R, S) model. Even though the number of vehicle dispatches remains similar across the two policies, the routing

decisions differ: the (R, S) model tends to choose more cost-efficient routes, reducing total travel cost.

The observed improvements in transportation efficiency arise from the greater coordination enabled by the (R, S) policy. Because replenishment quantities can vary across periods, delivery decisions can be synchronised more effectively across retailers. This flexibility allows the optimisation model to consolidate orders, exploit favourable routing combinations, and avoid unnecessary or poorly loaded vehicle tours. In contrast, the fixed-quantity structure of the (R, Q) policy can force replenishments to occur even when delivery quantities are not well aligned with efficient routing opportunities, leading to higher travel costs.

A further consequence of reduced inventory levels and improved routing efficiency is a measurable reduction in CO_2 emissions. In refrigerated logistics, emissions arise primarily from two sources: vehicle operations, including fuel consumption and transport refrigeration units, and cold storage, which requires continuous energy input to maintain low temperatures. Under the (R, S) policy, fewer excess units are transported and stored at retailer locations, resulting in lower vehicle emissions per unit delivered and reduced energy consumption for refrigeration. Together, these effects yield a total CO_2 emission reduction of 8.5% relative to the (R, Q) policy in the case example, demonstrating that the economic gains achieved by the (R, S) policy are accompanied by meaningful environmental benefits.

One of the most important insights illustrated by the case example is the ability of the integrated inventory–routing model to generate simultaneous improvements across multiple performance dimensions. By optimising replenishment decisions and vehicle routing plans jointly, the model enhances coordination between inventory management and transportation activities. This integration leads to more efficient vehicle utilisation and improved route consolidation, which in turn reduce total travel distance, fuel consumption, and associated costs. These operational improvements are reflected in both the lower total SC cost and the measurable reduction in CO_2 emissions observed under the (R, S) policy.

Beyond transportation efficiency, timely and flexible replenishment plays a critical role in preserving CSC integrity. By avoiding excessive safety stock and reducing unnecessary storage durations, the integrated inventory–routing model limits prolonged exposure of temperature-sensitive products to refrigerated environments. Shorter storage times reduce the risk of quality deterioration and spoilage, while smoother inventory profiles help stabilise temperature control operations at retailer locations. These effects contribute not only to improved product quality outcomes but also to lower holding costs, reinforcing the economic value of coordinated inventory and routing decisions under the (R, S) policy.

Finally, the structure of the proposed model aligns well with the operational realities of fragmented food distribution networks, which are common in many CFSCs. In chains characterised by small and decentralised customer clusters such as cafés, restaurants, and institutional kitchens, rigid replenishment policies often lead to inefficient routing and underutilised vehicles. The integrated (R, S) inventory–routing approach mitigates these inefficiencies by enabling delivery plans that are responsive to local demand conditions while avoiding unnecessary travel. The performance gains observed in this illustrative case therefore provide a practical explanation for why the (R, S) policy performs well in decentralised CSC settings. To assess whether these insights generalise beyond a single example, the next section

extends the analysis to a large set of randomly generated problem instances under varying demand and cost conditions.

4.3. Random Problem Instances on Various Scales

To further evaluate the robustness and general applicability of the proposed optimisation model, a comprehensive set of computational experiments was conducted. While Section 5.1 focused on a single illustrative case, this section extends the analysis by generating 400 randomly constructed problem instances that vary across several key dimensions of uncertainty and operational cost. The aim is to assess how consistently the (R, S) policy outperforms the traditional (R, Q) approach under a wide range of realistic CSC conditions. The experiments systematically vary four critical components of the SC environment and a total of 400 test instances are created by combining these factors.

1. Demand variability, represented through five constant CVs: $\rho_{it} \in \{0.05,\ 0.10,\ 0.15,\ 0.20,\ 0.25\}$. These values capture progressively increasing degrees of demand uncertainty.
2. Planning horizon length, tested at four different scales: $T \in \{7,\ 14,\ 21,\ 28\}$. This allows the evaluation of how replenishment policies behave over short, medium, and longer operational periods.
3. Fixed vehicle dispatching cost, with four levels: $f \in \{500,\ 1000,\ 2000,\ 5000\}$. These reflect different transportation cost environments, from low-cost local deliveries to more expensive long-distance routes.
4. Non-stationary stochastic demand patterns, representing five realistic demand evolutions frequently observed in food and retail markets including constant demand, increasing demand, decreasing demand, lifecycle (rise, peak, decline), erratic or irregular demand.

As in the previous section, both the (R, S) and (R, Q) models were coded and solved using IBM ILOG CPLEX 20.1.0, which determines the optimal replenishment timing and quantities for each retailer. To account for randomness in customer demand, each replenishment plan was then evaluated using a 10,000-run Monte Carlo simulation, ensuring statistically reliable estimates of total expected cost.

The SC structure remains identical to the earlier case study: one DC serving seven retailers. All economic parameters including holding cost h_i, unit ordering cost q, fixed ordering cost o_i, minimum service level, and safety factor z_α, are kept consistent with Section 5.1. Only the parameters listed in Table 8 were varied. The primary focus of this analysis is once again the economic objective function, represented by Equation (1). For each of the 400 test instances, the difference in expected total cost between the (R, S) and (R, Q) policies was calculated.

Table 11: Changing parameters of demand pattern, , planning periods , Fixed dispatch cost, Coefficient of demand

Changing parameters			
Demand Pattern	*T (planning periods)*	*f (Fixed dispatch cost)*	*ρ*
Constant	*7*	*500*	*0.05*

Decreasing	*14*	*1000*	*0.10*
Increasing	*21*	*2000*	*0.15*
Lifecycle	*28*	*5000*	*0.20*
			0.25

The first set of analyses examines how the cost improvements achieved by the (R, S) policy vary under different types of stochastic demand behaviour. Figure 4 summarises the average percentage cost reduction of (R, S) relative to (R, Q) across five demand patterns: constant, decreasing, increasing, life cycle, and erratic.

Across all patterns, the (R, S) model consistently provides a positive cost advantage, demonstrating that its flexibility in replenishing up to a target level S makes it robust to a wide range of demand conditions. The magnitude of this improvement, however, is not uniform. The most substantial gains occur under the life-cycle demand pattern, where demand rises, peaks, and then declines. In such environments, fixed-quantity replenishment under (R, Q) becomes particularly inefficient, as the rigid order quantity leads to inventory accumulation during declining phases and insufficient replenishment during rising phases. By contrast, the (R, S) policy adapts more naturally to these changes by adjusting order quantities dynamically, resulting in significantly lower holding and ordering costs.

In comparison, the constant, increasing, decreasing, and erratic demand patterns exhibit similar and more moderate levels of improvement, typically ranging between approximately 4% and 12% depending on the planning horizon. These patterns impose fewer extreme fluctuations than the life-cycle scenario, limiting the disadvantage of fixed-quantity ordering but still leaving room for improvement under (R, S).

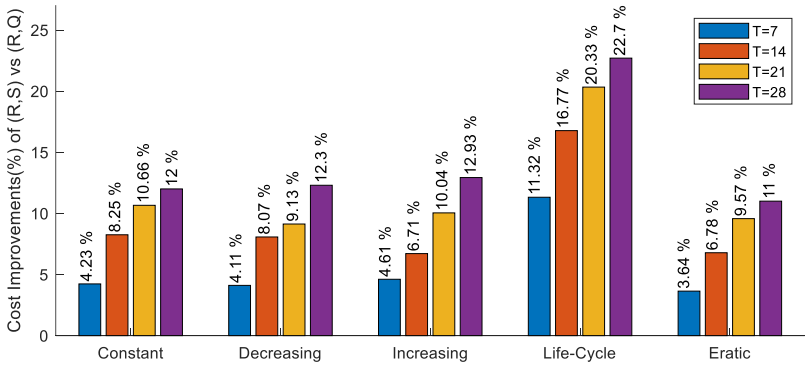


Figure 4: Cost gains of the (R, S) model across demand and horizon settings

The results clearly support the earlier insights presented in Section 4.1: the cost advantage of the (R, S) policy becomes larger as the planning horizon increases. For example, under an erratic demand pattern, with a 7-period horizon, (R, S) is 3.64% cheaper than (R, Q), at 14 periods, the improvement grows to 6.78%, at 21 periods, to 9.57%, and at 28 periods, to 11.00%. This trend is consistent across all demand patterns. The underlying explanation lies in how safety stocks accumulate under each policy. The (R, Q) policy must

hold a large quantity of safety stock to protect against possible demand variability over each reorder cycle. When the planning horizon expands, these stocks accumulate repeatedly, leading to very large cumulative inventory levels and correspondingly high holding costs. In long-horizon settings, this accumulation becomes unrealistic from both an economic and operational perspective, especially in FSCs where products expire quickly. Conversely, the (R, S) policy replenishes up to a target level Sand allows more frequent adjustments. Its safety stock increases only gradually over time, resulting in much lower cumulative holding costs. Thus, longer planning horizons magnify the difference in performance between the two policies.

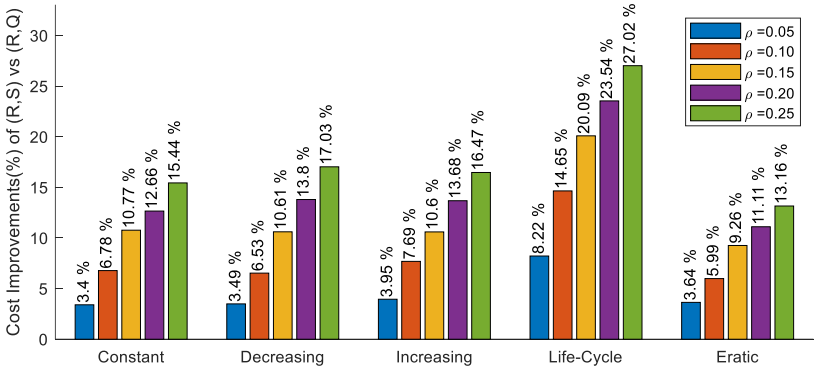


Figure 5: Cost gains of the (R, S) model across demand and CV settings

The next analysis explores how demand uncertainty, expressed through the CV of ρ, influences the relative performance of the two models. Figure 5 shows that total expected cost increases for both (R, Q) and (R, S) as the CV increases. This is expected: greater uncertainty requires higher safety stocks to maintain the same service level, inevitably raising total cost. However, the key insight is that the economic advantage of the (R, S) policy increases with higher ρ. Under higher demand variability, the rigid (R, Q) policy becomes increasingly inefficient because its fixed order quantity cannot adapt to the uncertainty. As deviations from expected demand grow, retailers under (R, Q) must hold even larger safety stock buffers, compounding holding costs. The (R, S) policy, by contrast, can adjust replenishment quantities to match the evolving demand distribution. This flexibility helps mitigate the impact of uncertainty, making the (R, S) policy significantly more cost-effective when demand variability is high. The results in Figure 5 therefore demonstrate that the benefits of adopting (R, S) are amplified in environments with substantial stochastic fluctuations, which is characteristic of many real-world CSC operations.

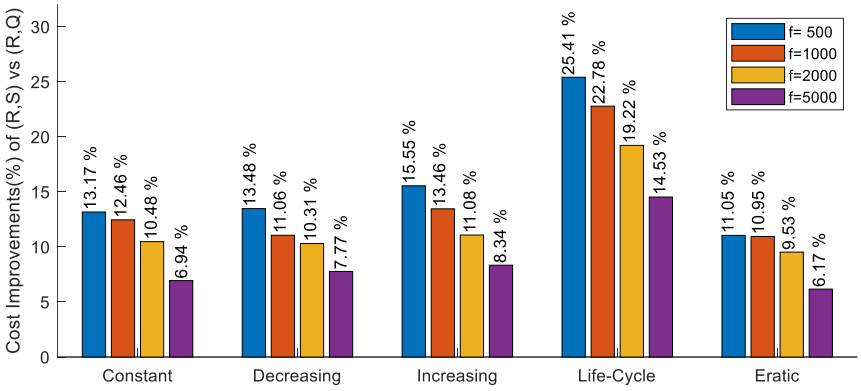


Figure 6: Cost gains of the (R, S) model across demand and dispatching cost settings

Finally, Figure 6 examines the effect of varying the fixed vehicle dispatching cost f. The results show a clear inverse relationship between dispatch cost and the relative advantage of the (R, S) policy. Specifically, as the dispatch cost increases, the cost improvement achieved by (R, S) becomes larger. This finding can be interpreted as follows. The (R, Q) policy's fixed reorder quantity often results in more dispatches or less efficient vehicle utilisation, because retailers may place orders even when the vehicle is not yet operating at an optimal load. As dispatching becomes more expensive, these inefficiencies become more financially damaging. The (R, S) policy, however, enables synchronised and flexible replenishment, which tends to produce more efficient routing decisions. It can consolidate orders more effectively, reduce unnecessary dispatches, and select routes that minimise distance or cost. When dispatching is inexpensive, this advantage is relatively small; however, as f increases, the inefficiencies of the (R, Q) policy become significantly more costly, thus widening the cost gap.

4.4. Trade-off Between Economic and Environmental Objectives

The first step in applying the AEC method is to generate an accurate pay-off Table, which identifies the extreme values of each objective when optimised individually. As discussed in Section 3.3, the Lexicographic (Lex) optimisation method is applied to compute the minimum of one objective while holding the other as secondary, thereby ensuring precise extreme solutions.

Table 12: Pay-off Table

	Objective one	*Objective two*
ε_1	*13282*	*27034*
ε_2	*208997*	*71763*

These values define the feasible ranges within which ε can vary for each objective during the AEC procedure. They also reveal the extent of conflict between the two objectives: the solution that minimises cost produces high emissions, while the solution that minimises emissions results in very high cost.

To apply the AEC method, each bi-objective formulation is converted into a single-objective optimisation model by turning the second objective into a constraint. Following Mavrotas (2009), this transformation introduces slack variables s_1 and s_2, as well as augmentation parameters ϕ_1 and ϕ_2, to ensure the generation of only efficient Pareto solutions.

Applying the general AEC formulation in Equation (32) to the present bi-objective model yields the following problem-specific formulations:

- **Minimising the economic objective with augmented environmental constraint:**

$$\begin{aligned} & min\, f_1(x) + \varphi_2 s_2 \\ \text{Subject to} \quad & f_2(x) - s_2 = \mathcal{E}_2 \\ & x \epsilon X \\ & s_2 \geq 0 \end{aligned} \tag{33}$$

- **Minimising the environmental objective with augmented economic constraint:**

$$\begin{aligned} & min\, f_2(x) + \varphi_1 s_1 \\ \text{Subject to} \quad & f_1(x) - s_1 = \mathcal{E}_1 \\ & x \epsilon X \\ & s_1 \geq 0 \end{aligned} \tag{34}$$

By systematically adjusting ε_1 or ε_2 within the pay-off ranges, a set of Pareto-efficient solutions is generated. Each solution represents a distinct balance between cost and CO_2 emissions.

The application of the AEC method produces the Pareto frontier shown in Table 13. These solutions reflect different levels of trade-off between economic and environmental performance.

Table 13: The Pareto frontier solutions

Equation (1)	*Equation (2)*
13282	*208997*
13290	*157575*
13483	*97678*
14118	*71851*
18813	*71789*
19211	*71739*

These solutions form a convex decreasing frontier, illustrating the inherent conflict: improvements in one objective inevitably cause deterioration in the other.

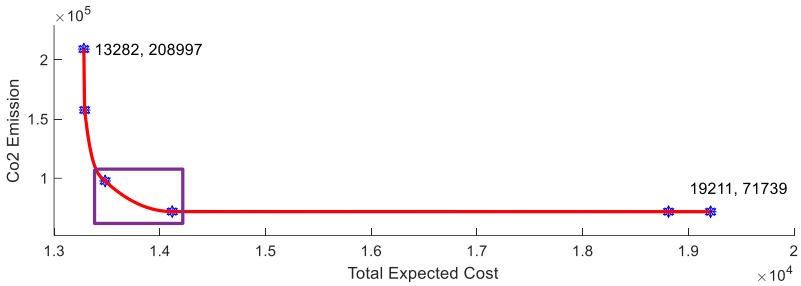


Figure 7: The trade-off between the two objectives

Figure 7 highlights a clear inverse relationship between total cost and CO_2 emissions. As emissions decrease, the total chain cost increases. However, this relationship is nonlinear, meaning that the marginal cost of reducing emissions becomes increasingly large beyond a certain point.

From the computational results, it can be observed that initial emission reductions are relatively inexpensive. The early Pareto points indicate that CO_2 emissions can be reduced substantially, from 208,997 kg to around 97,678 kg, with only a small increase in cost (from 13,282 to 13,483). This suggests that there are practical opportunities to reduce emissions without imposing significant financial strain.

The Pareto frontier also indicates that the cost of carbon reduction increases sharply near the frontier's lower bound. Reducing emissions from 71,851 kg to 71,789 kg requires the total cost to rise from 14,118 to 18,813, an increase of 4,695 units for only 62 kg of additional reduction. This demonstrates a classic diminishing returns effect: as the chain approaches very low emission levels, further improvements become disproportionately expensive.

The results further suggest that the central region of the frontier (marked in red in the diagram) represents solutions where costs remain within a manageable range, and emissions are reduced significantly relative to the cost-optimal solution.

For many organisations, especially those balancing financial pressure with sustainability goals, the solutions in this region are likely to be the most desirable. These points achieve meaningful emission reductions without the extreme cost burden associated with the lowest-emission solutions.

The Pareto frontier indicates that extreme solutions may not be practical. Although the model can identify the absolute minimum-emission solution (71,739 kg), it is economically prohibitive for most real-world operations. The associated cost (19,211) is substantially higher than the mid-range alternatives, making it unattractive unless environmental targets must be met at any cost.

The Pareto frontier clearly shows that no single solution optimises both objectives simultaneously. Decision-makers must explicitly choose their preferred balance, modest emission reductions can be achieved at low cost, deep emission cuts require disproportionately high investment, and the (R, S) policy enables a flexible exploration of these trade-offs. In practice, organisations may select any point along the frontier depending on regulatory emission limits, corporate environmental commitments, customer expectations regarding sustainability, or budget constraints. The flexibility of the AEC method allows the decision-

maker to prioritise economic efficiency, environmental performance, or a balanced compromise.

4.5. Chapter Summary

This chapter presented a comprehensive computational evaluation of the proposed bi-objective inventory–routing model for CFSCs. Building on the model formulation and solution framework developed in the preceding chapters, the analysis assessed the operational, economic, and environmental performance of an (R, S) replenishment policy relative to the traditional (R, Q) policy under stochastic demand conditions.

Section 4.1 outlined the implementation of the AEC method as the primary solution approach for addressing the conflicting objectives of cost minimisation and CO_2 emission reduction. By generating a Pareto-efficient solution set, the method enabled a transparent and systematic examination of economic–environmental trade-offs while remaining computationally tractable for the mixed-integer inventory–routing problem considered.

Section 4.2 provided a detailed case example to illustrate the structural differences between the (R, S) and (R, Q) policies. The results showed that the (R, S) policy achieves lower expected total cost through reduced safety stock requirements and more responsive replenishment behaviour. These inventory dynamics led to lower holding costs, improved routing efficiency, and measurable reductions in CO_2 emissions. Extending the planning horizon further highlighted the scalability advantage of the (R, S) policy, as cumulative safety stock growth remained controlled over time, whereas inventory levels under the (R, Q) policy increased rapidly and became operationally unsustainable.

To test the robustness of these findings, Section 4.3 expanded the analysis to a large set of randomly generated problem instances spanning multiple demand patterns, uncertainty levels, planning horizons, and transportation cost environments. Across all experimental settings, the (R, S) policy consistently outperformed the (R, Q) policy in terms of expected total cost. The magnitude of this advantage increased under higher demand variability, longer planning horizons, and higher fixed dispatching costs, confirming that the flexibility of the (R, S) policy is particularly valuable in volatile and cost-sensitive CSC contexts.

Finally, Section 4.4 examined the trade-off between economic and environmental objectives using the Pareto frontier generated by the AEC method. The results revealed a clear and nonlinear conflict between cost and CO_2 emissions, indicating that substantial emission reductions can be achieved with relatively small cost increases, while deeper reductions require disproportionately higher economic investment. This analysis demonstrated the model's ability to support balanced compromise solutions, rather than focusing solely on extreme cost- or emission-optimal outcomes.

Overall, the computational results confirm that integrating inventory and routing decisions under an (R, S) replenishment policy delivers significant economic and environmental benefits in CFSCs. The findings establish a strong empirical foundation for the concluding chapter, which discusses the broader implications of these results, their managerial relevance, and directions for future research.

5. Conclusion and Managerial Implications

This chapter concludes the thesis by synthesising the key findings, contributions, and practical insights derived from the proposed bi-objective inventory–routing model for CFSCs. Building on the computational experiments and comparative analyses presented in the previous chapters, it first summarises the main academic contributions of the research, highlighting how flexible replenishment policies, stochastic demand modelling, and environmental objectives can be integrated within a unified optimisation framework. The chapter then translates these analytical results into a set of actionable managerial implications, offering guidance for decision-makers seeking to balance cost efficiency, service reliability, product freshness, and carbon reduction in practice. Recognising the inherent complexity of CFSCs and the modelling choices adopted in this study, the chapter also outlines key directions for future research, identifying opportunities to extend the proposed framework through richer data, enhanced environmental modelling, and broader organisational and coordination perspectives. The chapter concludes with final remarks that reflect on the overall contribution of the thesis and its relevance for the design and management of more efficient and sustainable cold food distribution chains.

5.1. Research Overview

This research examined how inventory and routing decisions can be jointly optimised in CFSCs, where products are perishable, demand is uncertain, and environmental pressures are increasing. To address these challenges, the study modelled an IRP that simultaneously determines retailer replenishment decisions and vehicle routing plans under non-stationary stochastic demand. The mechanism was designed to meet a required service level while accounting for the route-dependent cost structure typical of refrigerated distribution. A bi-objective MIP model was developed using the (R, S) policy, which determines both the timing and the size of each replenishment order. The model considers the time since each retailer's last replenishment and the uncertainty that may have occurred in the intervening periods. Two objectives were incorporated: (1) minimising total expected cost and (2) reducing total CO_2 emissions arising from transportation and refrigeration. To explore the trade-off between these competing goals, the AEC method was employed, with the pay-off table derived using a lexicographic optimisation approach.

To evaluate performance, both the (R, S) model and the traditional (R, Q) model were coded and solved using CPLEX. Each policy's replenishment decisions were then assessed using 10,000-run Monte Carlo simulations to capture the effect of demand uncertainty on cost and emissions.

5.2. Key Findings

The results demonstrated that the (R, S) model consistently outperforms the (R, Q) policy across all five demand patterns studied, including constant, increasing, decreasing, life cycle, and erratic. The findings also revealed important behavioural patterns. The (R, S) model's cost-effectiveness increases with the length of the planning horizon and with higher CV, highlighting its suitability in environments characterised by volatility and long-term planning. In contrast, the cost advantage decreases as the fixed vehicle dispatching cost rises, reflecting the sensitivity of routing decisions to transportation cost structures. A key driver of these

improvements is the substantial reduction in safety stock under the (R, S) policy, which leads to significantly lower holding costs. Although both policies dispatch a similar number of vehicles, the (R, S) model selects more efficient routes and avoids unnecessary replenishments. Consequently, it reduces not only cost but also environmental impact. The study found that CO_2 emissions decrease by 8.5% under the (R, S) policy due to lower transported and stored inventory, reduced refrigeration load, and improved route efficiency.

Finally, the bi-objective analysis generated a set of Pareto-efficient solutions that reveal the non-linear nature of the cost emission trade-off. The Pareto frontier provides decision-makers with a clear picture of how economic savings and emission reductions interact, and it highlights the points where additional emission reductions become disproportionately expensive.

5.3. Research Contributions

This research makes several contributions to the academic literature on CFSC optimisation, particularly in the areas of inventory–routing modelling, multi-objective optimisation, and sustainable logistics. While prior studies in the CSC domain have addressed operational efficiency and quality-control challenges, limited work has integrated stochastic demand, environmental objectives, and flexible replenishment policies within a unified optimisation framework. By bringing these elements together, this study advances existing research and contributes a more comprehensive representation of decision-making challenges in CFSCs.

First, the research contributes by developing a bi-objective mixed-integer programming model that jointly optimises inventory and routing decisions under non-stationary stochastic demand. Traditional IRP models often assume stationary or deterministic demand and typically optimise routing or inventory decisions in isolation. By integrating demand variability, replenishment timing, and route-dependent costs, this study offers a more realistic reflection of the operational challenges faced in CFSCs.

Second, the thesis advances theoretical understanding by embedding the (R, S) replenishment policy within a rigorous optimisation framework. Although the (R, S) policy is widely recognised in the inventory literature as a practical and adaptive heuristic, it is rarely incorporated into mixed-integer inventory–routing formulations. This research shows that (R, S) can be modelled analytically and can outperform the traditional (R, Q) policy, particularly in environments characterised by demand uncertainty. The results provide theoretical insight into how the dynamic order-up-to structure of (R, S) interacts with routing decisions and demand volatility, extending existing theory on replenishment behaviour.

Third, this study contributes methodologically by applying the AEC method to a CSC-IRP. While the EC method has been used in various multi-objective optimisation contexts, its application to inventory–routing with environmental considerations is limited. The model succeeds in generating a clean and meaningful Pareto frontier, avoiding weakly efficient solutions and enabling a transparent analysis of cost–emission trade-offs. This demonstrates the suitability of AEC for complex logistical chains with sharp conflicting objectives.

Fourth, the research provides theoretical insight into how demand patterns and operational parameters influence replenishment policy performance. Based on 400 computational experiments, the study identifies generalisable behavioural trends: the (R, S) policy remains cost-effective across all five demand patterns considered; its relative advantage increases with

longer planning horizons and higher demand uncertainty; and its performance advantage diminishes as fixed vehicle dispatching costs rise. These findings offer new theoretical evidence on the structural relationship between replenishment flexibility, uncertainty, and cost behaviour, relationships that have not been systematically quantified in prior CSC inventory–routing research.

Finally, the study contributes to sustainability-oriented SC theory by embedding CO_2 emissions directly into the optimisation model. Rather than treating sustainability as a conceptual consideration, the model explicitly quantifies how emissions are affected by replenishment frequency, routing decisions, safety stock levels, and refrigeration requirements. The finding that the (R, S) policy can reduce emissions by 8.5 percent while maintaining service levels reinforces the theoretical role of flexible replenishment strategies in environmentally responsible logistics. Moreover, the resulting Pareto frontier reveals the non-linear structure of cost–emission trade-offs, offering a reference point for future analytical work.

In summary, the research advances theoretical understanding by demonstrating how flexible replenishment policies, stochastic modelling, environmental objectives, and route-dependent costs can be integrated into a unified bi-objective IRP framework. This synthesis creates new opportunities for scholars to explore richer, more realistic, and more sustainable SC models.

A central contribution of the proposed model lies in its explicit integration of economic performance and environmental sustainability within a single optimisation framework. By jointly minimising total expected cost and CO_2 emissions, the model moves beyond approaches that treat environmental performance as a secondary or ex post consideration. This integrated formulation enables rigorous evaluation of trade-offs between financial efficiency and emission reduction, demonstrating how environmentally responsible distribution strategies can be incorporated directly into operational decision making.

By embedding analytically tractable performance indicators within a single mixed-integer optimisation structure, the bi-objective inventory–routing model provides a transparent framework for evaluating CFSC performance. In contrast to prior studies that often examine distribution efficiency, carbon reduction, or service performance in isolation, this research unifies cost behaviour, emission outcomes, inventory dynamics, and routing efficiency within a coherent decision-support model. In doing so, it advances the literature by explicitly quantifying economic–environmental trade-offs and operationalising an integrated perspective on CSC optimisation.

The research further contributes to the literature on dynamic vehicle routing, an area identified as underexplored in CSC optimisation. By integrating inventory decisions based on an (R, S) policy with routing decisions under non-stationary demand, the model strengthens analytical capabilities for dynamic routing environments. This integration extends existing routing theory by demonstrating how replenishment flexibility and demand variability jointly influence routing efficiency and environmental performance.

5.4. Managerial Implications

While the mathematical formulation and computational analysis provide important theoretical insights; the primary value of this research lies in its practical relevance for decision-makers in CFSCs. Managers operate under continuous pressure to maintain product freshness, control logistics costs, reduce waste, and respond to growing environmental expectations. The findings of this study translate these analytical results into a set of actionable managerial implications that support more informed and balanced replenishment and distribution decisions.

1. **Adopt Flexible Replenishment Policies (Prefer (R, S) Over (R, Q))**

One of the clearest messages from this research is that the (R, S) policy consistently outperforms the (R, Q) policy, regardless of demand shape or planning conditions. For managers, this means that relying on fixed order quantities is rarely the most efficient strategy. Allowing the replenishment quantity to vary, while maintaining a common order-up-to level, reduces safety stocks, lowers holding costs, and ensures fresher products reach the shelves. In perishable food operations, flexibility is not a luxury; it is a necessity.

2. **Prioritise (R, S) in Environments with High Demand Uncertainty**

Many food products face unpredictable consumer behaviour, promotional fluctuations, and seasonal variations. The experiments carried out in this study show that the value of the (R, S) policy increases sharply as demand becomes more uncertain. When the CV rises, fixed quantity mechanism requires large safety buffers, driving up cost and increasing the risk of spoilage. Managers dealing with erratic or volatile demand such as fresh produce or dairy, can significantly benefit from switching to the (R, S) policy.

3. **Use Shorter Planning Cycles or Shift Policies for Longer Horizons**

Findings from both the case study and the randomised experiments demonstrate that the (R, Q) model scales poorly when the planning horizon increases, as safety stock levels grow excessively and become impractical for weekly or monthly planning cycles. In contrast, the (R, S) policy shows stable and controlled behaviour even under longer horizons. Managers planning over multi-week or seasonal time frames should therefore avoid rigid fixed-order policies and adopt adaptive strategies such as (R, S). More broadly, cold chain operations require substantial capital investment, coordinated decision making, and continuous cost control. Aligning delivery frequency with demand behaviour helps maintain product integrity, reduce waste, and improve cost efficiency, allowing managers to identify delivery intervals that balance timeliness, cost, and sustainability

4. **Reduce Waste, Improve Freshness, and Enhance Customer Experience**

Excessive safety stock directly affects product freshness, shelf life, and waste levels in food supply chains. By holding fewer units and turning over inventory more quickly, the (R, S) policy helps ensure products remain fresher for longer, reduces spoilage and shrinkage, aligns replenishment with actual consumption, and improves customer satisfaction. Managers in grocery retail, restaurant supply, or meal-kit logistics can use these insights to strengthen their freshness promise and reduce unnecessary disposal costs.

5. Leverage (R, S) to Support Sustainable Logistics Strategies

The bi-objective model demonstrates that meaningful reductions in CO_2 emissions can be achieved at relatively low cost, particularly when emissions are closely linked to transportation routing and inventory levels. Managers seeking to meet corporate sustainability targets or respond to regulatory pressure can therefore adopt the (R, S) policy as part of a balanced decarbonisation strategy that improves environmental performance without undermining cost efficiency. At the same time, the Pareto frontier highlights that extreme emission reductions become disproportionately expensive, indicating that decision-makers should focus on emission targets located within an "efficient compromise" region rather than pursuing aggressive reductions that sharply inflate logistics costs. By jointly optimising routing and replenishment decisions, the model supports the dual managerial objective of efficiency and sustainability and provides a transparent decision-support tool for visualising and managing cost–emission trade-offs. In this way, optimisation-based approaches can act as practical instruments for implementing broader sustainability strategies, including emission reduction, waste minimisation, and energy-efficient distribution planning.

6. Optimise Vehicle Routing When Dispatch Costs Are High

As vehicle dispatching costs rise due to fuel prices, labour shortages, or longer delivery distances, the relative advantage of the (R, S) policy becomes more pronounced. By enabling order consolidation and improved synchronisation across retailers, the (R, S) policy makes more effective use of vehicle capacity and supports the selection of cost-efficient routing plans. In contrast, poorly coordinated routing and replenishment decisions can lead to unnecessary trips, higher refrigeration usage, increased emissions, and deterioration in product quality, all of which collectively inflate total logistics cost. The findings of this research demonstrate that integrating inventory and routing decisions helps prevent these inefficiencies by aligning delivery schedules with actual demand and capacity constraints. For managers, particularly those operating in competitive and low-margin food service environments, this highlights the importance of integrated inventory–routing optimisation rather than treating routing and inventory planning as separate decision processes.

7. Improve Energy and Refrigeration Efficiency

Lower safety stock levels not only reduce inventory holding costs but also decrease the energy required for cold storage and reduce the operating load on refrigeration systems. By limiting excess inventory and increasing turnover, the (R, S) policy helps stabilise refrigeration demand and supports more energy-efficient facility operations. Managers facing high energy costs or pursuing sustainability initiatives can therefore use the (R, S) policy to achieve energy reduction objectives while maintaining required service levels and product integrity.

Taken together, these managerial implications demonstrate that the proposed (R, S) model is not merely a theoretical construct but a practical decision-support tool for CFSC management. The model provides managers with a structured way to navigate the inherent trade-offs between cost efficiency, service level reliability, product freshness, and carbon reduction that characterise modern CFSC operations. From a strategic perspective, the findings inform decisions related to fleet configuration, sustainability investments, and long-term logistics planning. From a tactical perspective, they support day-to-day choices concerning delivery frequency, review intervals, safety stock levels, and route consolidation. These insights are particularly valuable for food service and decentralised distribution networks with small order

sizes and volatile demand, where flexible and integrated planning is essential for achieving both operational efficiency and sustainability objectives.

5.5. Study Limitations

Although this research provides meaningful insights into the management of CFSCs, it is important to acknowledge its limitations. Recognising these limitations helps clarify the scope and applicability of the proposed model and highlights opportunities for further academic development and extension.

1. Assumptions About Demand Behaviour

The model assumes that demand follows a normal distribution with predefined patterns (constant, increasing, decreasing, life cycle, and erratic). While these patterns capture many real-world situations, actual demand for food products can be more complex, affected by weather, promotions, pandemics, supply shocks, and social behaviour. Future studies could incorporate empirical demand distributions derived from real sales data, non-normal or heavy-tailed distributions, time-series or machine-learning demand forecasts. Such extensions would allow the (R, S) policy to be tested under even more dynamic and realistic demand scenarios.

2. Single DC (Single-Echelon) Structure

The current model focuses on a single DC serving multiple retailers. In practice, CSCs often operate through multi-echelon structures involving central warehouses, regional hubs, and cross-docking platforms. Extending the model to multi-echelon or networked environments could reveal new insights about how replenishment flexibility propagates across multiple layers of the SC.

3. Deterministic Vehicle Capacities and No Disruption Modelling

Vehicle capacities, travel times, and network availability were treated as deterministic. Real CSC operations, however, frequently face traffic delays, vehicle breakdowns, temperature-control failures, road closures, or driver shortages. Future research could incorporate stochastic travel times, robust routing, or real-time dispatch adjustments, making the model even more applicable to real operational challenges.

4. Simplified Representation of CO_2 Emissions

This study focuses on emissions from transportation and refrigeration but uses simplified estimations of emissions per distance and per unit of inventory. More elaborate environmental modelling, such as life-cycle assessment (LCA) or temperature-dependent energy consumption models, could enrich the environmental component and reveal deeper insights into sustainability trade-offs.

5. Freshness and Quality Dynamics Not Explicitly Modelled

While the study emphasised the importance of product freshness and low safety stock, the model does not integrate explicit freshness deterioration or microbial growth equations. Future research could incorporate temperature-shelf-life relationships, product ageing models, or dynamic quality decay functions. This would allow the (R, S) model to optimise not only inventory and routing but also product quality outcomes.

6. Computational Complexity and Scalability

Although the model performed well for the scale of the experiments (seven retailers), the combinatorial complexity increases significantly as the number of retailers grows. Investigating decomposition approaches, metaheuristics, or hybrid optimisation-simulation frameworks could help extend the applicability of the model to large real-world networks with dozens or even hundreds of nodes.

Finally, although the broader CSC literature addresses a range of temperature-sensitive biological processes, including microbial growth, biochemical degradation, transpiration, and cooling dynamics, these processes extend beyond the operational focus of the present model. The aim of this research is to support decisions that logistics managers can influence frequently, such as routing, replenishment timing, and service levels, rather than long-term strategic investments or detailed food science modelling. This focus enhances the model's practical usability but also limits its ability to capture the full set of biological factors that influence product quality throughout the chain.

An additional practical limitation relates to the uneven implementation of sustainability practices across different geographical and institutional contexts. Empirical evidence suggests that advanced monitoring technologies, sensor systems, and energy-efficient infrastructure are more prevalent in developed economies than in developing regions. As a result, the applicability and effectiveness of optimisation-based decision-support tools may depend on local technological readiness, regulatory environments, and governance structures. Managers should therefore consider regional constraints and institutional conditions when interpreting and applying the model's insights in practice.

Finally, the present study intentionally concentrates on the transportation and distribution stage of CFSCs, where delivery frequency, routing patterns, and decentralised customer structures create significant operational complexity. By focusing on this stage, the model highlights how inventory positioning and replenishment timing directly influence emissions, product quality, and overall SCP. While this focus supports depth and tractability, it also means that upstream processing and downstream retail dynamics are not explicitly modelled.

5.6. Future Research

The proposed model aligns with broader trends toward data-driven planning in CFSCs by demonstrating how commonly available operational data can be transformed into actionable decision support. Although the model does not rely on real-time temperature monitoring or sensor-based quality tracking, it shows how non-stationary demand profiles, distance matrices, vehicle capacity constraints, and emission coefficients can be systematically integrated within a unified optimisation framework. The results indicate that even in data-constrained environments, structured optimisation models can support informed planning decisions by clarifying trade-offs across cost, service level, and environmental performance. Future research could build on this foundation by progressively incorporating richer data streams, allowing decision-support systems to evolve from periodic planning tools toward more responsive and adaptive optimisation platforms.

Although this thesis adopts Iyer's (2021) framework to define the broader scope of CSC optimisation, only a subset of the identified components is incorporated explicitly into the proposed model. The analysis focuses on inventory–routing coordination, delivery-related

constraints, fuel and energy requirements, and CO_2 emissions, which are most closely aligned with tactical planning decisions under uncertainty. Other components identified by Iyer, including microbial growth, product quality and shelf-life dynamics, demand–price–quality interactions, transpiration and respiration processes, cooling dynamics, and monitoring technologies, are not modelled explicitly. These components are typically rooted in food science, thermal engineering, and information systems and often require biological, physical, or real-time data that lie beyond the scope of optimisation-based tactical models. Their exclusion therefore reflects a deliberate modelling choice rather than an oversight, but it also highlights clear opportunities for interdisciplinary extension.

These omitted components represent promising and clearly defined directions for future research. Integrating dynamic quality decay or microbial growth functions would allow optimisation models to account explicitly for food safety risks, spoilage behaviour, and shelf-life constraints when determining replenishment and routing decisions. Incorporating cooling dynamics, packaging characteristics, or temperature-dependent energy consumption functions could improve the accuracy of emission and energy estimations, particularly for refrigerated transport and storage. In addition, coupling inventory–routing optimisation with real-time monitoring technologies, such as IoT sensors or digital twin platforms, could enable adaptive planning approaches that respond dynamically to temperature excursions, demand shocks, or operational disruptions. Research that systematically combines these disciplinary perspectives with stochastic inventory–routing and multi-objective optimisation would substantially enhance the realism and decision relevance of future cold chain models.

Beyond modelling structure, data availability represents a critical practical challenge for the implementation and further development of optimisation-based decision-support systems in CFSCs. Effective planning depends on accurate information regarding temperature histories, refrigeration equipment characteristics, energy consumption patterns, and delivery-time windows. However, many small and medium-sized food service operators lack the digital infrastructure required to collect, integrate, and maintain such data consistently. As noted by Mustafa (2024), information quality in these settings is often fragmented or incomplete. Future research could therefore investigate tiered or hybrid modelling approaches in which optimisation complexity is explicitly aligned with data maturity, allowing simpler models to support decision making where data are limited, while enabling richer formulations in digitally advanced environments.

Although the current implementation adopts CO_2 emissions as the primary environmental performance indicator, the underlying optimisation structure is intentionally designed to accommodate additional environmental and operational dimensions. Future research could extend the framework to include product-specific degradation functions, thermal profiling along routes, or dual-compartment vehicle configurations. Such extensions would allow models to differentiate between chilled and frozen products, capture heterogeneous temperature requirements, and assess trade-offs between routing efficiency and thermal stability. This flexibility illustrates how optimisation frameworks can evolve alongside advances in refrigeration technology, thermal modelling, and food quality science, reinforcing their role as integrative tools for sustainable cold chain management.

In addition to technical and data-related extensions, behavioural and organisational factors represent an important and underexplored dimension of future research in CFSCs. Prior studies

suggest that managerial routines, risk perceptions, and decision-making behaviour can constrain energy efficiency and sustainability outcomes as strongly as technological limitations or cost considerations (DeCanio, 1998; Andrews and Johnson, 2016). Organisational culture, investment horizons, regulatory pressure, and inter-firm trust also influence whether efficiency-oriented strategies are adopted in practice (Centobelli et al., 2018). Future research could explicitly integrate these behavioural dimensions into optimisation-based frameworks, for example by modelling bounded rationality, asymmetric information, or decision inertia.

While such behavioural and organisational dimensions lie outside the tactical optimisation scope of the present study, they strongly condition the effectiveness of quantitative decision-support tools in real-world settings. Fragmented decision-making structures may undermine efficiency gains even when technically sound solutions exist (Jaber and Goyal, 2008), while collaborative alignment among SC actors has been identified as a critical enabler of sustainable cold chain performance (Neusel and Hirzel, 2022). Future research that integrates optimisation models with organisational theory, governance mechanisms, or behavioural economics could therefore provide a more complete understanding of how efficiency and sustainability improvements are achieved and sustained in practice

Viewed collectively, the broader literature highlights that CFSCs operate as complex socio-technical systems in which technical infrastructure, human behaviour, and organisational arrangements are tightly interconnected. Deficiencies in any single component, such as inadequate temperature control, poor data integration, or misaligned incentives, can propagate inefficiencies across the entire network (Ndraha et al., 2018; Cawston, 2018). Consequently, long-term performance improvements often require coordinated change across technology adoption, workforce capabilities, digital monitoring, and governance structures (Akram, 2023; Zhang and Mohammad, 2024). Future optimisation research would benefit from explicitly recognising these interdependencies rather than treating operational decisions in isolation.

Within this broader context, the contribution of the present study is intentionally focused on the tactical optimisation layer of CFSC management. By demonstrating how integrated inventory–routing decisions and flexible replenishment policies improve cost efficiency and environmental performance under uncertainty, the model provides a quantitative foundation upon which broader organisational and behavioural initiatives can build. Future research that combines such optimisation-based tools with governance-oriented or behavioural approaches may offer a more holistic pathway toward CFSCs that are not only efficient and resilient but also aligned with long-term sustainability objectives.

The present thesis adopts a centralised decision-making perspective and does not explicitly model coordination or collaboration among autonomous SC actors. This represents an important direction for future research, as real CFSCs involve multiple stakeholders whose objectives and incentives are often misaligned (Iyer, 2025). Understanding how decentralised decision environments affect inventory–routing performance remains a critical challenge for both theory and practice.

Future studies could extend the proposed framework by relaxing the centralised assumption and introducing decentralised or coordinated decision structures. From a modelling perspective, this could involve actor-specific objective functions, coordination contracts such as revenue-sharing or cost-sharing mechanisms, buy-back agreements, or trade-credit arrangements embedded directly within the inventory–routing formulation. Alternative

approaches could represent vendor-managed inventory systems, joint distribution agreements, or shared routing decisions through additional information-sharing constraints. More advanced extensions could adopt game-theoretic or bilevel optimisation formulations to capture strategic interactions among actors and to evaluate the impact of regulatory interventions or subsidies. Such models would enable systematic comparison between centralised and coordinated scenarios and provide deeper insight into when collaboration enhances cost efficiency, service levels, product quality, and emission performance.

Although CO_2 emissions constitute the primary environmental indicator in the present study, future research could broaden the environmental scope to include additional sustainability dimensions. These may include energy consumption disaggregated by transport and storage stages, refrigerant leakage, or product waste resulting from temperature excursions. Extending the model in this direction would support a more comprehensive assessment of environmental performance and strengthen the linkage between operational decisions and sustainability outcomes.

Taken together, these research directions highlight the substantial gap that remains between current optimisation-based models and the full complexity of real CFSC operations. Addressing this gap will require interdisciplinary collaboration that combines optimisation, data analytics, food science, thermal engineering, and organisational research. Progress along these lines would move the field toward decision-support tools capable of capturing both operational and biological realities while supporting the efficiency, resilience, and sustainability objectives that increasingly define cold food distribution practice.

5.7. Concluding Remarks

In closing, this research integrates inventory control, vehicle routing, stochastic demand modelling, and environmental assessment into a unified bi-objective optimisation framework tailored to the operational realities of cold food distribution. By embedding a flexible (R, S) replenishment policy within an integrated inventory–routing structure, the study demonstrates that cost efficiency and environmental responsibility need not be treated as mutually exclusive objectives. The results show that, while no single solution can simultaneously minimise cost and emissions, the Pareto frontier generated by the model provides decision-makers with a clear and transparent basis for selecting solutions that reflect their operational priorities, budgetary constraints, and sustainability commitments. Beyond its analytical contribution, the proposed bi-objective (R, S) model serves as a practical decision-support tool that guides managers in designing replenishment and distribution strategies that are fresher, leaner, and more environmentally responsible. In doing so, the research offers a concrete pathway toward CFSCs that are better equipped to meet the economic and sustainability challenges of an increasingly complex and volatile marketplace.

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